AN EMPIRICAL INVESTIGATION OF CORPORATE CREDIT DEFAULT SWAP SPREADS AND RETURNS

By

John Pereira (K0949215)

Supervisors: Dr. Mohamed Nurullah and Prof. Ghulam Sorwar

A thesis submitted in partial fulfilment of the requirements of Kingston University for the Degree of Doctor of Philosophy

September 2015

ACKNOWLEDGEMENTS

Firstly, I would like to express my sincere gratitude to my Director of Studies Dr. Mohamed Nurullah and my supervisor Prof. Ghulam Sorwar for their continuous support, suggestion, feedback and encouragement for my PhD and related research. I will always be grateful and indebted for their patience and for the trust and confidence they have shown in me. Their guidance and subject matter expertise has helped me immensely throughout the last four years of my PhD research.

Besides my advisors, I take this opportunity to thank faculty members from Kingston Business School for their encouragement and support, colloquium/seminar/conference participants for their feedback and suggestions, thesis committee for their insightful comments and my PhD colleagues: Dr. Rebecca Fakoussa, (and soon to be Dr's) Marvyn Boatswain, Ratnes Alahakone, Rahul Chawdhary, Rizwan Malik, Ijeoma Udegbe, Benedetta Crisafulli and others for the stimulating discussions, for the late nights we worked together and for all the fun, discussions and disagreements we have had in the last four years. I would also like to thank Fatima Fernandes for encouraging me to join the PhD programme and helping me through the early stages of my PhD journey.

I acknowledge that my PhD would have not been possible without the financial assistance in the form of studentship funding provided by Kingston Business School, Accounting Finance and Informatics department. My sincere thanks also go to Prof. Favato Giampiero, who authorised funds to purchase the Markit Database. It would have been difficult to finish the PhD on time without access to this critical dataset. Special thanks to Dr. Irma Malafronte for all the discussions around my PhD and for her constant support, encouragement, suggestions and timely interventions in the most difficult times.

Last but not the least, I would like to thank my family: my parents and to my brother and sisters for supporting me mentally, emotionally, financially and spiritually throughout the last four year of this research and my life in general. All your prayers and best-wishes certainly helped. Words cannot express how grateful I am for all those who have believed in me.

ABSTRACT

This thesis focuses on the empirical investigation of Credit Default Swap (CDS) spreads and return dynamics for listed corporates in the US, UK and EU. Academic interest in CDS market is continuously growing and this thesis aims to provide a better understanding of the CDS market dynamics. Specifically, this thesis explores three critical areas of research interest for the CDS market with each Chapter Two, Three and Four focussing on a specific aim, objectives and research questions within the context of the overall thesis. The thesis is largely based on three separate but broadly related research studies.

The first study, Chapter Two, explores the dynamics of quarterly CDS spreads for corporates in US, UK and EU for the three major economic conditions namely; pre-crisis, crisis and post-crisis period. This study is the first to explore such a wider sample domain both in terms of the geographical coverage as well as the period of analysis. CDS spreads are regressed using both accounting based ad-hoc measures as well as theory driven market based variables, individually as well as collectively in a single combined model. This study documents the changing nature of spread predictor variables based on the sub-period of analysis and find the market based variables to be more closely aligned to spreads than their accounting counterparts. This study proposes the use of both information sets as additive rather than substitutive within the CDS pricing framework. This study also tests the effect of bond market liquidity dynamics and CDS market liquidity effect on CDS spreads and finds spreads in the post-crisis period to be plagued by both bond market and CDS liquidity dynamics. This study concludes that CDS spreads in the post-crisis period may be plagued by non-default driven factors and should not be considered as pure measure of corporate credit risk. Thus signals from CDS market should be carefully considered in conjunction with other financial market indicators before drawing policy implications.

The second study, Chapter Three, evaluates the effect of the interest rate, quantitative easing and fiscal policy announcements in US and UK on corporate CDS returns. The unprecedented interventions announced by government and Central banks to contain the effect of the financial crisis provides the motivation for this study. This study measures the effect of these announcements on corporate credit risk by estimating daily CDS returns which is a better time series measure of corporate credit risk than CDS spreads or equity returns as used in past studies. This study notes an opposite effect of interest rate announcement, where credit risk for firms following the interest rate announcement decreased for US corporate

while it increased for UK corporates. Across both US and UK, corporate credit risk tends to be lower following QE announcements; highlighting its popularity during the financial crisis. Fiscal policy announcements are characterised by minor improvement in corporate credit risk which is short lived. By comparing pre and post announcement days abnormal return, this study finds that median abnormal return following US policy interventions were higher in post announcement days in US while an opposite effect can be noted for the UK corporates. This study concludes that policy interventions in US were more effective in stabilising corporate credit risk for US corporate while policy announcements in UK were not effective. This study also tests the differential effect following policy interventions across corporates sampled based on sector, credit quality, firm size and CDS liquidity. No other study have undertaken such a detailed sub-sample analysis across policy announcements in US and UK and the findings underline the theme that firm specific heterogeneity leads to differential effect of policy announcement on corporate credit risk.

The third study, Chapter Four, attempts to provide evidence of the generalizability of the Fama and French (FF) asset pricing model to the CDS market. The test on generalizability of the FF model to the CDS market has not been attempted before and this study is the first to check the external validity of the FF model with an aim to test if the model works for the CDS market. The findings from the portfolios returns indicate the average daily excess returns are not perfectly aligned as expected to the book-to-market, operating profitability and investment factors and expose variations in average return sufficient to provide strong challenges in asset pricing tests. The relationship between the portfolio type and average excess return trend is also found to fluctuate based on the sub-period of analysis. Apart from testing the external validity of the FF model, this study also aims to access the external validity of the default risk hypothesis, by testing if the default risk is priced in the cross section of CDS returns and if the FF factors; *SMB* and *HML* factors are proxying for default risk in the CDS returns. The finding indicates that it is unlikely that *SMB* and *HML* are proxying for default risk. Overall, the findings from this study indicates the FF three factor (3F) and FF five factor (5F) model can be generalised to the CDS market, between the two models the 5F model is a better asset pricing model for the CDS market. This study goes a step further and queries if the FF factor model for the CDS market can be improved on by augmenting it with a default driven factor. Augmenting both the 3F and 5F model with default factor results in at best a marginal improvement to the models' explanatory power across the sub-periods analysed in this study. Hence for reasons of parsimony, this study suggest the FF 5F model to be preferred asset pricing model for the CDS market

Notwithstanding these separate contributions, overall this thesis contributes to a better understanding of CDS spreads, CDS returns and thus the CDS market in general. The past decade have seen a wealth of literature focussing on CDS market and the knowledge and understanding of the CDS market dynamics is being continuously refined and expanded. The findings of this thesis will provide useful insight and a deeper understanding for a variety of stakeholders including regulators, market participants, the financial community and the academic community at large to be able to better understand an important source of credit risk information.

STATEMENT OF ORIGINALITY

I, John Pereira certify that to the best of my knowledge, the content of this thesis is my own work. Where information has been derived from other sources, I confirm that this has been appropriately cited and referenced in the thesis. The work contained in this thesis has not been previously submitted for any degree or diploma in any other higher education institution.

John Pereira
September 2015

TABLE OF CONTENT

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

A

AAR – Average Abnormal Return

ACAR – Average Cumulative Abnormal Return

AIG – American International Group Inc.

AMEX – American Stock Exchange

AR – Abnormal Return

B

BE – Book Value of Equity

BIS – Bank for International Settlements

B/M – Book to Market

BMP – Boehmer, Musumeci and Poulsen

BOE – Bank of England

BP – Basis points

BSM – Black Scholes and Merton

C

CAAR – Cumulative Average Abnormal Return

CAPM – Capital Asset Pricing Model

CAR – Cumulative Abnormal Return

CBGN – Bloomberg Generic Pricing Source

CCP – Central Counterparty Clearing

CDS – Credit Default Swaps

CDX HY – North American High yield grade CDS index

CDX IG – North American Investment grade CDS Index

CMA – Conservative Minus Aggressive

CMR – Constant Mean Return

COGS – Cost of Goods Sold

CPI – Consumer Price Index

CR – Credit Rating

CRA – Credit Rating Agency

CRSP – Centre for Research in Security Prices

D

DTCC – Depository Trust and Clearing Corporation

DTD – Distance to Default

E

EBRD – European Bank of Reconstruction and Development

EU – European Union

F

FF – Fama and French

FF 3F – Fama and French three factor

FF 5F – Fama and French five factor

FIS – Fiscal Policy

FOMC – Federal Open Market Committee

G

GARCH – Generalised Autoregressive Conditional Heteroskedasticity

GDP – Gross Domestic Product

GFC – Global Financial Crisis

GICS – Global Industry Classification Standard

H

HBOS – Halifax Bank of Scotland

HML – High Minus Low

I

IFRS – International Financial Reporting Standards

INV – Investment

IOSCO – International Organisation for Securities Commission

IR – Interest Rate Cut

ISDA – International Swap and Derivatives Association Inc.

K

KMV – Kealhofer, McQuown and Vasicek

L

LHS – Left Hand Side

LIBOR – London Interbank Offer Rate

M

MBS – Mortgage Based Securities

MC – Market Capitalisation

MDA – Multivariate Discriminant Analysis

ME – Market Value of Equity

MON – Monetary Policy

N

NASDAQ – National Association of Securities Dealers Automated Quotations

NYSE – New York Stock Exchange

NYFR-OIS – New York funding rate to Overnight index swap

O

OCC – Office of Comptroller of Currency

OECD – The Organization for Economic Cooperation and Development

OIS – Overnight Indexed Swap

OLS – Ordinary Least Square

OP – Operating Profitability

OTC – Over The Counter

P

PIGS – Portugal, Ireland, Greece and Spain

Q

QE – Quantitative Easing

R

RBS – Royal Bank of Scotland

RHS – Right Hand Side

RMW – Robust Minus Weak

ROA – Return on Assets

S

SAR – Standardised Abnormal Return

SCAR – Standardised Cumulative Abnormal Return

SEC – Securities and Exchange Commission

SIFI – Systematically Important Financial Institutions

SMB – Small Minus Big

SRT – Sign Rank Test

T

TA – Total Assets

TAF – Term Auction Facility

TARP – Troubled Asset Relief Programme

TED Spreads – U.S. Treasuries and Eurodollars spreads

TSLF – Term Security Lending Facility

U

UK – United Kingdom

US – United States

V

VIF – Variance Inflation Factor

VIX – Implied Volatility Index

VMS – Vulnerable Minus Stable

CHAPTER 1

INTRODUCTION

CHAPTER 1 - INTRODUCTION

1.1 Introduction

The fiasco in the US sub-prime mortgage market fuelled the Global Financial Crisis (GFC) of 2007-2008 and had a tremendous impact on global economies. The crisis that started in US triggered large scale failure of the global banking system and brought major economies to its knees. Before the global economy could cope with it hazardous effect, recovery process was further dampened by the Sovereign debt crisis of 2010, further deteriorating the economic climate. The interconnectedness of the financial markets and the banking system has plagued the recovery process. These dire economic situations have hampered the sustainability and survival of large and small firms likewise and the dreadful aftereffects of the crisis are evident both in developed as well as the developing economies. The Financial crisis prompted large scale corporate defaults increasing the credit risk of the global financial system to unprecedented levels. The build-up of the financial crisis is closely linked to the tremendous growth and development in the Credit derivatives market; specifically Credit Default Swaps (CDS). As an Over-the-Counter (OTC) instrument, the lack of regulatory oversight and ease of speculative betting had fuelled the meteoric growth and development in the CDS market. The advent and the growth of the CDS market is often quoted as one of the most visible aspects of the intense process of financial innovation that has taken place in the last decade. The increased participation and adoption of CDS by financial institutions springs from the desire to better manage credit risk and of traders to gain exposure to credit market via arm's length financial transactions. Following the credit crisis, economists and investors around the global were quick to criticize the lack of proper regulatory mechanism and transparency in the CDS market and credited it to have exacerbated the effect of the financial crisis. However, it is not the reason why credit derivatives were created, accepted and actively used by market participants globally. CDS in theory are supposed to facilitate the transfer of credit risk from risk-averse investors to insurers, thereby facilitating risk transfer to parties better able to handle them and creating efficiency from the credit risk management perspective. However, CDS has come under intense criticism for their role in the Global Financial Crisis and the Sovereign default drama. The fact that some of the financial entities that had run into greatest difficulties during the crisis; such as Lehman Brother and AIG were leading players in the world CDS market was the major factor for the increased attention by regulators on these instruments. The possible role of CDS in destabilising the financial markets during the European Sovereign debt crisis has raised important questions on the economic relevance of these instruments and rekindled the need for more regulatory oversight. These contrasting effects make the CDS market quite fascinating to study and analyse from the research perspective.

Corporate credit risk has been a subject of a growing concern among academics and practitioners since the number of corporate defaults peaked globally following the financial crisis of 2008. Moreover, the cost of corporate default has also skyrocketed with large scale corporate defaults causing tremendous strain on the global economy. Understanding what drives corporate credit risk is crucial to evaluate firm's financial strength in the light of the changing economic conditions. Recently, majority of empirical studies have used CDS spreads as the pure measure of default risk and the extent to which this information set is a true indicator of corporate credit risk begs further exploration. As CDS spreads influences corporate debt pricing, an unexpected movement in spreads could considerably strain a firm's ability to raise new debt. It is possible that CDS spreads are driven by factors other than a firm's default risk and their movement subject to shocks in the macro economy. This warrants a closer examination of corporate CDS spreads dynamics. In the aftermath of the financial crisis, Central banks throughout the world have taken a number of policy initiatives in an effort to stabilise the financial system and to prevent the possible spillover effect on other sectors in the economy. These initiatives were taken to aid economic stability and quicken the recovery process. How effective were these policy interventions in stabilising the corporate credit risk market is crucial to understand if the policies achieved its desired goals. This needs to be explored and understood to be better equipped to handle future crisis situations.

CDS market is relatively new compared to the equity and bond markets and its economic relevance to the financial system and use by market participants is growing globally. Research interest in the CDS market is also increasing with a wealth of academic studies exploring the market dynamics and its role in the financial crisis. However, in spite of the growing research interest in the CDS market, there is much confusion in public debate about the role CDS played during the crisis. Observers tended to overstate the potential evil emanating from such instruments and call for more regulation and potential curtailment of these instruments. However, the role of CDS as a risk management tool and a means of allocating credit risk more efficiently should not be forgotten.

This thesis provides a detailed study on the dynamics of the CDS market by exploring firstly, the drivers of CDS spreads with an aim to model corporate CDS spreads before, during and after the financial crisis. Secondly, this study aims to assess the effect of policy intervention on corporate credit risk environment to gauge if the policies were effective in stabilising the corporate credit risk market. Lastly, this study applies the Fama and French asset pricing model to explain the dynamics of CDS returns with an aim to propose an asset pricing model for the CDS market. Although each chapter within this thesis focusses on a separate research interest with specific aim and objectives relevant to the chapter's scope of inquiry, the general aim of this thesis is to provide a better understanding of the CDS market.

1.2 Credit Default Swap

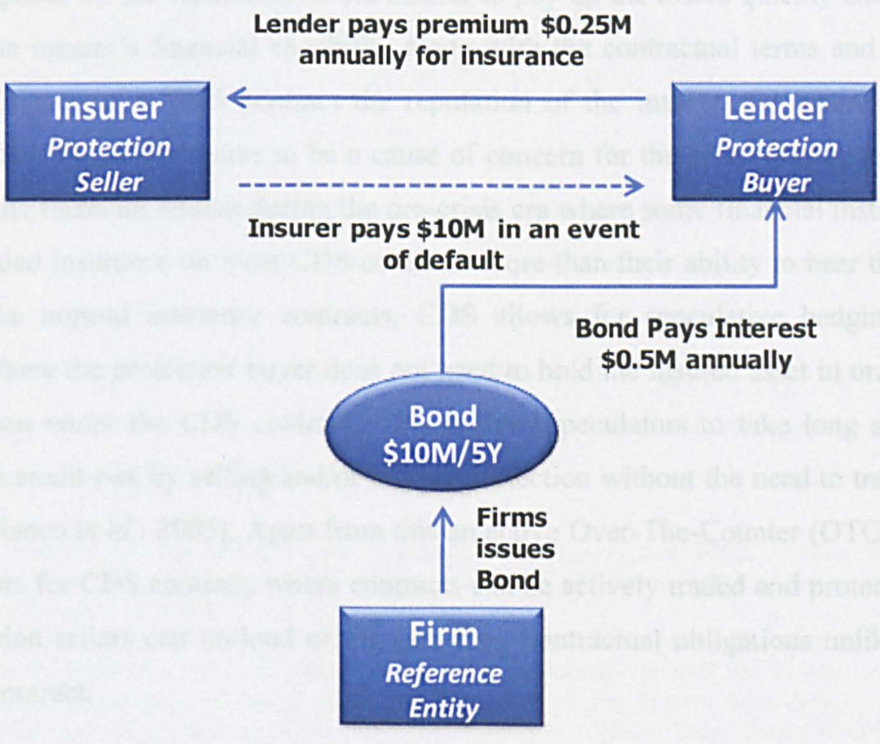
Credit Default Swap (CDS) is a contractual agreement that transfers the risk of one or more referenced entities from one party (usually a lender of credit) to another (the insurer). There are three parties involved in a typical CDS contract referred to as the protection buyer, protection seller and the referenced entity. The protection buyer pays a periodic fee (usually of semi-annually or quarterly periodicity) to the protection seller till the maturity date of the CDS contract or until the referenced entity defaults, declares bankruptcy or faces other predefined credit events[1] whichever occurs sooner. Following a credit event the protection seller is obligated to compensate the protection buyer for the loss (possibly hypothetically) incurred, as a result of the credit event and is equal to the difference between the par value of bond and its market value post credit event or post default value (typically determined using a simple auction mechanism) by means of specialised settlement procedure (either by cash or physical settlement) for a specified face value called the notional amount of the referenced entity's debt obligation (ISDA, 2015). Fig 1.1 depicts the mechanism for a typical CDS contract. The underlying referenced entity could be a corporate or a sovereign/municipal entity and in either case the cost of insurance on debt is positively related to the underlying risk of default on obligation (usually a bond) of the referenced entity. CDS contracts for varying maturity ranging from 0.5 to 30 years exist. However, 5 years maturity contracts are

[1] The major credit events as noted in ISDA framework includes, 1. Bankruptcy: relevant only for corporate entities. 2. Obligation acceleration: obligation becomes due and payable before its normal expiration date. 3. Obligation default: refers to a technical default, such as violation of a bond covenant. 4. Failure to pay: failure of the reference entity to make any due payments. 5. Repudiation/Moratorium: provides for compensation after specified actions of a government (e.g. delay in payment). 6. Restructuring: reduction and renegotiation of delinquent debts in order to improve or restore liquidity, in 2009, US contracts eliminated restructuring as a potential trigger event. (www.isda.org)

considered to be the most liquid and frequently traded. As noted in Blanco, Brenan and Marsh, (2005), 5 years CDS contract are the most liquid credit derivatives traded in the financial market and form the basic building block for more complex structured credit products[2].

There are a number of ways to change the economic exposure associated with a CDS contract, other than related to the occurrence of the credit event. 'Novation' is a mechanism whereby CDS contractual parties identify a market participant that is willing to assume the obligation of one of the original counterparties at prevailing market price. Similarly, through the 'CCP novation' mechanism, both parties in a CDS contract give up their position to the central counterparty. It is also possible to terminate a position by entering into a transaction of opposite sign called 'offsetting transaction' with other market participants. Offsetting transactions are the most common way of terminating the economic exposure related to the reference entity underlying the CDS contract (IOSCO, 2012).

Fig 1.1: Mechanism of a typical CDS contract *(Source: Author's elaboration)*



[2] Other credit derivatives products include 1) Total return Swap – where return from one asset or a group of asset is swapped for the return on another asset or group of assets and 2) Credit spread option- which is an option on the spread between the yield earned on two assets Blanco *et al.*, (2005)

1.3 Credit Default Swap – Insurance or Not?

Through a CDS contract the protection buyer pays a periodic fee to the protection seller usually denoted in spreads in exchange for compensation against the loss arising from the exposure to default of the referenced entity as a result of an unforeseen credit event. The credit event triggers the payment from the protection seller to the protection buyer to compensate the latter for his loss. Soon after the credit event the protection seller ceases to make payment to the protection buyer and is contractually bound to make up for the loss due to the credit event to the protection buyer. This makes CDS contract comparable to an insurance contract as both provide insurance against an adverse event in exchange for a periodic payment (Heise and Kühn, 2012). Similar to an insurance contract, a CDS contract also has clear specification of what constitutes a credit event and details on settlement procedure in an event of default.

Although the economic effect of the CDS is similar to an insurance contract, there are specific characteristics of a CDS contract that makes it significantly different from an insurance contract. As noted by Cummins and Doherty (2006), the value of a typical insurer's promise depends on the reputation of the insurer to pay up the losses quickly and efficiently and well the insurer's financial capability along with the contractual terms and conditions. However, in case of a CDS contract the reputation of the insurer and insurer's financial capability does not really seems to be a cause of concern for the protection buyer. This was evident in the financial market during the pre-crisis era where some financial institutions like AIG, provided insurance on most CDS contracts more than their ability to bear the risk they took. Unlike normal insurance contracts, CDS allows for speculative hedging on open positions where the protection buyer does not need to hold the insured asset in order to claim compensation under the CDS contract. This enables speculators to take long and/or short positions in credit risk by selling and/or buying protection without the need to trade the cash position (Blanco *et al.*, 2005). Apart from this an active Over-The-Counter (OTC) secondary market exists for CDS contract, where contracts can be actively traded and protection buyers and protection sellers can on-load or off-load their contractual obligations unlike a normal insurance contract.

1.4 Structure of the CDS Market

CDS market is part of the larger OTC derivative market[3] comprising of interest rate contracts (80.2%), foreign-exchange contracts (12.0%), equity linked contracts (1.3%), commodity contract (0.3%) etc. Although CDS represents only 2.6% of the OTC market, the sheer notional amount of all contracts outstanding, is comparable to the annual Gross Domestic Product (GDP) of United States[4]. The first CDS contract was created in 1994 by JP Morgan to extend lines of credit for Exxon to cover potential damages resulting from the Exxon Valdez oil spill disaster of 1989 (Linkins, 2010). JP Morgan contracted with European Bank of Reconstruction and Development (EBRD) on a $4.8 billion credit line for Exxon, where EBRD would cover for potential default by Exxon in exchange for a periodic fee (Tan and Yan 2010). By 1997, the gradual growth in market resulted in the notional open interest in CDS being in the order of $200billions (Avellaneda and Cont, 2010). Development of an active secondary market propelled the growth in the market by early 2000. Subsequently, the market for CDS grew exponentially until the financial crisis of 2008 where the total notional amount outstanding[5] was reported as close to $58.24 trillion at its peak. Following the credit crisis of 2008, the volume of CDS contracts has reduced significantly mainly due to industry level 'portfolio compression'[6] effort spurred by regulators. The total gross notional amount outstanding as of Dec 2014 was reported at $16.40 trillion[7] (BIS statistics, 2015) evenly divided between bought and sold protection.

Due to large scale use of offsetting transaction by market participants, the gross notional outstanding may largely overstate the economic exposure towards the underlying reference entity. The sum of the net position of the net buyers of protection i.e. the net notional value gives a better estimate of the net exposure as it represents the aggregate payment made in an event of default of the referenced entity[8]. As stated in IOSCO (2012), the gross notional value of outstanding contract gives an indication of the size of the CDS market in terms of

[3] The total notional amount outstanding for the OTC market was reported over $630.15 trillion as of Dec 2014 (BIS Statistics, 2015) Refer to Fig 1.2 Composition of the OTC derivatives market. Data as of Jun 2014 in trillion USD (BIS Statistics, 2015)

[4] GDP as of last quarter 2014 for United States was at $17.42 trillion (Trading Economics, 2015)

[5] Notional amount refers to the par amount of credit protection bought or sold and is used to calculate the premium payment for each payment period as well as the recovery amount in an event of default

[6] Portfolio compression mechanism has been introduced since 2007 whereby large simultaneous long and short CDS positions referencing the same underlying borrower are cancelled out. This helps reduce the unnecessary exposure to counterparties that creates no material economic benefit.

[7] Within the CDS market single name instrument comprises of $9.04 trillion and multiple name instruments accounting for $7.35 trillion measured in terms of gross notional amount outstanding as of Dec 2014. Refer to Fig 1.3 CDS – Notional amount outstanding as of Dec 2014 (BIS statistics, 2015)

[8] This assumes that the market value of the defaulting bond is zero

counterparty risk, while the net notional value is a measure of the size of the market in terms of credit risk allocation. IOSCO (2012) reports the net notional value[9] to be roughly equivalent to 10% of the gross notional outstanding. The gross market value for CDS contract represents the sum of the absolute values of all open contracts with both positive and negative replacement values evaluated at market prices prevailing on the reporting date. As of Dec 2014, BIS reports the gross market value to be $593.03 billion across all CDS instruments with single name CDS accounting for $365.73 billion (61.67%) and multi name instrument accounting for $227.3 billion (38.33%). Fig 1.4 details the gross market value as of Dec 2014 for all CDS contracts broken down as per single name and multi name contracts. Majority of the gross market value of CDS contracts is held by financial institutions representing close to 50% of the total, while non-financial firms hold less than 2% of the gross market value outstanding. Within the financial institutions majority share is held by central counterparties (24%) followed by banks (8%) and hedge funds (7%). Although the financial crisis of 2008-2009 is often quoted as the reason for reduction in CDS outstanding contract, it is rather believed that the CDS market has been stable since 2008 supported by a relatively stable outstanding notional of Equity-linked, Interest rate and Currency derivatives over the same time span (Jarrow, 2011). International Organisation for Securities Commission (IOSCO, 2012) also report a steady increase in CDS trading even after the onset of the financial crisis and a significant expansion in standardisation and risk management practises.

CDS market can be characterised by relatively high level of concentration in market participants; that act as market makers and relatively low transparency; as transactions in OTC market are typically bilateral trades between the parties involved (Augustin, Subrahmanyam, Tang and Wang, 2014). Atkeson, Eisfeldt and Weill (2014) using data from Office of Comptroller of Currency (OCC) Quarterly Report on Bank Trading and Derivative Activities, report a handful of large financial institutions including HSBC, Bank of America, Citigroup, Morgan Stanley, Goldman Sachs and JP Morgan Chase acting as market makers and medium size banks acting as customers. This is supported by Peltonen, Scheicher and Vuillemey, (2014) that test the network structure of the CDS market using Depository Trust and Clearing Corporation (DTCC) data on bilateral CDS exposures for 642 sovereign and financial reference entities in 2011. Their study finds the CDS market to be highly concentrated with around 14 dealers, suggesting a "robust but fragile" structure. As noted in

[9] Net notional with respect to any single reference entity is the sum of the net protection bought by net buyers (or equivalently net protection sold by net sellers).

Augustin, *et al.,* (2014), historically insurance companies were the main CDS protection sellers while commercial banks were the main CDS protection buyers. However, recently hedge funds and pension funds have actively started using CDS market as a part of their investment strategy. Moreover, insurance companies have started buying CDS for bond portfolio management along with selling CDS protection. As per BIS survey in December 2013, insurance companies are net protection buyers while hedge funds are net protection sellers, with an aggregate position five times that of insurance company's position. IOSCO (2012) reports low trading frequency and large average trade size in the CDS market. As per data collected from Depository Trust and Clearing Corporation (DTCC), the average daily number of trades for CDS contracts on the top 1000 single name referenced entity is about 4.3 trades per reference entity with a mean trade size of \$6.4 million as of Jun-Sept 2011.

Fig 1.2: OTC Market Gross Notional amount outstanding as of Dec 2014 *(BIS statistics, 2015)*

OTC Market - Notional Amount Outstanding as of Dec 2014

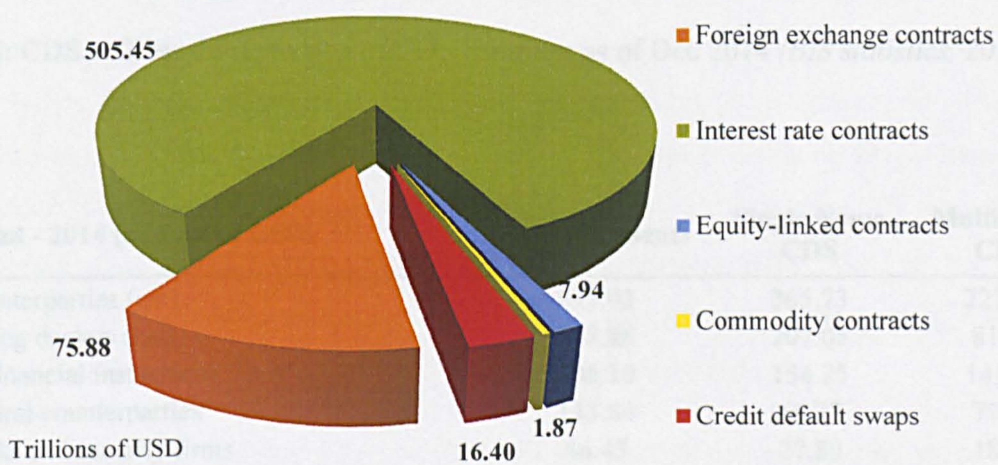


Fig 1.3: CDS – Gross Notional amount outstanding as of Dec 2014 *(BIS statistics, 2015)*

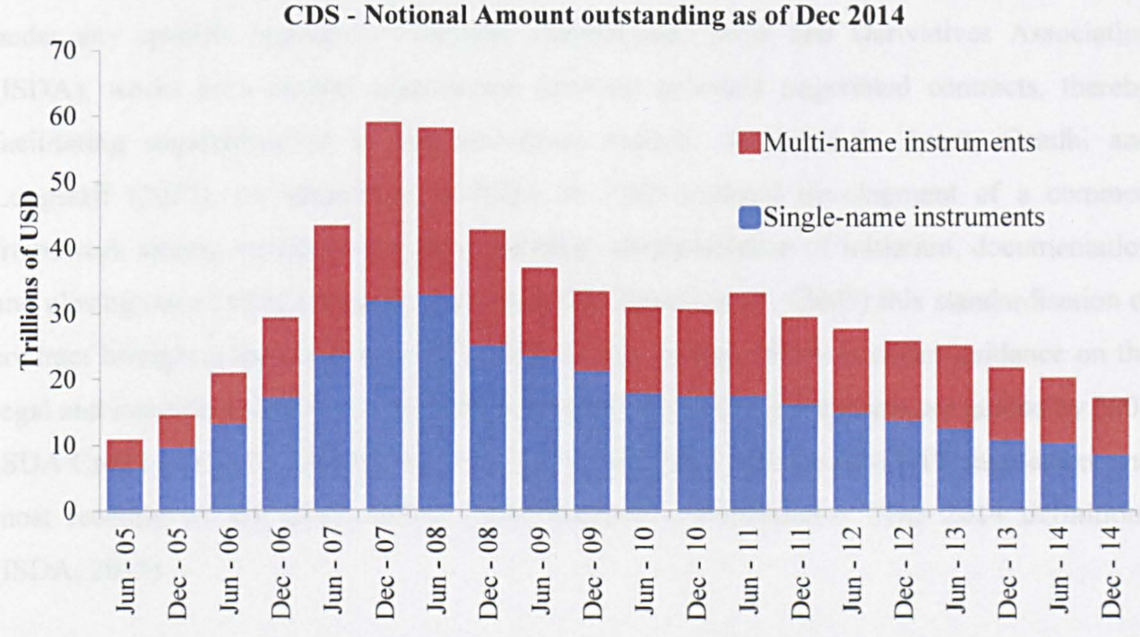


Fig 1.4: CDS – Gross market value of CDS contracts as of Dec 2014 *(BIS statistics, 2015)*

Year end - 2014 (billions of USD)	**All instruments**	**Single Name CDS**	**Multi name CDS**
All counterparties (net)	593.03	365.73	227.30
Reporting dealers (net)	288.88	207.05	81.83
Other financial institutions	296.10	154.25	141.85
Central counterparties	143.84	66.77	77.07
Banks and security firms	46.43	27.80	18.63
Insurance and financial guaranty firms	7.18	3.48	3.70
SPVs, SPCs, or SPEs	12.34	6.84	5.50
Hedge funds	42.19	24.33	17.86
Other residual financial customers	44.13	25.03	19.09
Non-financial institutions	8.05	4.42	3.62

1.5 ISDA and regulation in CDS markets

Until recently, CDS market had been largely unregulated with little transparency in market size and counterparty risk (Tan and Yan 2010). Although the CDS market was not under any specific regulatory oversight, International Swap and Derivatives Association (ISDA), works as a central organisation between privately negotiated contracts, thereby facilitating standardisation in the derivatives market. As noted in Arora, Gandhi and Longstaff (2012), the chartering of ISDA in 1985 initiated development of a common framework among market participants, enabling standardisation of initiation, documentation and closing out of CDS contracts. As detailed in Blanco *et al.*, (2005) this standardisation of contract brought a major spur to the growth of the market. ISDA provides guidance on the legal and institution details of CDS contract. Credit derivative agreements are guided by 2003 ISDA Credit Derivative Definition - "The 2003 definition" and the July 2009 supplement and most recently by the 2014 ISDA Credit Derivative Definition - "The 2014 definition" (ISDA, 2015)

In the aftermath of the global financial crisis, the United States Congress passed the Dodd-Frank Wall street reform and Consumer Protection Act, which mandates Central Counterparty Clearing (CCP) for eligible over-the-counter (OTC) derivatives. As stated in Loon and Zhong (2014) under Dodd-Frank Act, Securities and Exchange Commission (SEC) is responsible for determining which derivative contracts have to be mandatorily cleared by CCPs and the SEC has jurisdiction over security based swaps including single name CDS contracts. IOSCO (2012) claims one of the major sources of risk in the CDS market is the counterparty risk, arising from default of large protection seller, due to the highly concentrated and interconnected nature of the CDS market. The introduction of CCP is a step towards mitigating counterparty risk and preventing default contagion.

The amount of public information on CDS has increased in the recent years but regulation in the CDS market is still at its infancy stage and the CDS market is still considered quite opaque. There is a growing support for more regulation and transparency through better access to information on trade and positions. This is widely considered to increase financial stability and aid early detection of market abuse. However, similar to observations in the OTC bond market, although greater transparency is bound to reduce informational asymmetry and transaction cost, at the same time it may discourage dealers from providing liquidity. Landscape for CDS has altered with the CDS "*Big bang*" (8^{th} April 2009) and

"*Small bang*" protocols for the American and European CDS markets respectively. In the post-crisis period, the regulatory overhaul in CDS market has created further standardisation of the CDS contract, followed by temporary ban on naked CDS in Germany and ultimately Europe wide permanent ban introduced in 2011. The primary goal of the altercation[10] in the contract and trading conventions was to improve the efficiency and transparency in the CDS market.

1.6 Effects of CDS

1.6.1 Positive effects

Before the development of the CDS market, corporate credit risk had been essentially untradeable due to lack of liquidity in the bond market. In spite of tremendous growth in the secondary loan market, bank loans remained largely illiquid (Ashcraft and Santos, 2009). The introduction of CDS market provided banks and investors with a new and less expensive ways to hedge their credit risk exposure to firms. Consequently, banks and other lenders were able to transfer credit risk more effectively in order to liberate capital for further loan intermediation thereby improving the lender's credit risk transfer ability as well as conserving costly capital (Duffie, 2008). This ability to provide a unique, cost effective diversification channel for bank loans is considered the primary reason for active participation from banks and financial institution's triggering growth and development in the CDS market. The secondary market for corporate bond is mostly illiquid as majority of investors tend to hold their investment until maturity. This causes the purchase of large amount of credit risk in the secondary cash market difficult and costly for investors (Schultz, 1998). Moreover, shorting credit risk in the cash market was even more difficult exposing investor's to changes in repo rate[11]. Blanco *et al.*, (2005) confers this to the illiquid nature of the repo market for risky bonds, they further claim that even if the bond can be shorted on repo the tenor of the agreement is usually small. This exposes investors looking to short the bond for a long period of time to changes in the repo rate. Introduction of the CDS market enabled investors to short

[10] Major altercations include standardisation of the coupon payments whereby fixed coupon payment for US single name CDS were defined to be either 100 or 500 basis point and any difference to be settled through upfront payment, exclusion of restructuring as a standard credit event for North American CDS contractual clause, hardwiring the auction settlement mechanism into the standard CDS documentation (Augustin *et al.*, 2014)

[11] The rate of return earned by simultaneously selling a bond futures or forward contract and then buying an actual bond of equal amount in the cash market using the borrowed money (Investopedia, 2013).

their credit risk over long period of time at a known cost of buying protection making it easier to trade credit risk (Blanco *et al.*, 2005).

CDS market is also credited to have increased the informational content on the firm which has positively affected their cost of raising debt in the bond market (Ashcroft and Santos, 2009). The new information in the form of spreads, reduced the cost of debt by lowering the informational premium investor's demand on their bonds which in turn reduced the cost that banks extract from borrowers in connection with the informational advantage. This is an important inference since firms that have an actively traded CDS are expected to be in a better position to raise relatively more debt at a cheaper rate from the market unlike those firms that do not have an actively traded CDS. This along with the ability to take short positions on debt reduces market imperfection, facilitates access to more debt capital which in turn reduces the cost of raising debt thereby increasing the welfare of traders via optimal allocation of risk in the absence of counterparty risk (Jarrow, 2010). Moreover, as stated in Gündüz, Lüdecke and Uhrig-Homburg (2007) a CDS contract can be set up synthetically at any time, enabling transfer of credit risk in a single contract in relatively higher volumes, this along with the ability to blend market participants across different pools makes CDS market an easier place to trade credit risk. The counterparties involved in a CDS contract are dealers of major institutions with relatively high credit rating which helps to reduce the counterparty risk inherent in these OTC contracts. Blanco *et al.*, (2005) as stated in Gündüz *et al.*, (2007) claims that this structural difference makes the CDS market efficient in providing timely price information compared to the bond market.

1.6.2 Negative effects

In spite of their welfare increasing and risk diversification ability, CDS is widely seen as having exacerbated a number of corporate distress situations in the recent crisis, including the demise of Lehman Brothers and the near default of AIG and Bear Stearns. CDS trading also featured prominently during the Greek sovereign crisis of 2010 (and ongoing) raising concerns if trading in CDS could causes, rather than insure against the default of underlying entity (Tan and Yan 2010). The systemic collapse triggered by the financial crisis engulfed large corporations, insurers and financial institutions prompting increased attention in the CDS market by financial regulators worldwide (CPSS-IOSCO BIS report, 2012). Supplementary to being the main source of credit risk, studies have also shown that during period of financial distress, the interconnectedness of the network of institutions using the CDS contract amplified contagion and losses among the parties involves in the contract (Heise and Kühn, 2012). Study by Markose, Giansante, Gatkowski and Shaghaghi (2009), shows that CDS created interconnectedness in the financial network leading to severe knockout effect from default of any party involved. Finally, Duffie (2008) claims that CDS risk transfer ability bolsters stability of the entire financial system by smothering out the risk among many investors for e.g. by using a CDS mechanism, banks are able to substitute large potential exposure to borrowers with smaller and more diversified exposure. This however, can be deemed as a potential problem associated with CDS contagion effect. If banks lend money to risky firms with an intention of passing on the credit risk exposure to borrower with smaller and more diversified exposure, in exchange for a higher coupon payment then instead of improving the stability of the financial system this effect could build a systematic contagion which could cause a build-up of large scale credit risk within the entire financial system that could have a dominos effect compromising the economic stability of the Financial system.

1.7 Development of CDS market and its impact on the macroeconomy

The inter-linkage between credit risk and macroeconomy has been previously explored within the risk literature. Past studies claim default risk and credit migration probabilities to be dependent on the business cycle (Wilson, 1997) and default intensities are found to differ across different economic regimes (Bangia, Diebold, Kronimus, Schagen & Schuermann, 2002). CDS market where the spreads are driven by default expectations are thus logically bound to be effected by the state of macroeconomy. However, the growth and the development of credit derivatives market, especially CDS and its subsequent adoption and trading by market participants itself has an implication on the macroeconomy.

CDS has the potential to improve the risk allocation both within an economy as well as at the global level, and to increase the stability of banking and financial markets. CDS help banks to increase or reduce credit risks independently of the underlying transactions, to diversify risk across sectors and countries, and thus to optimise their overall risk profile. With the introduction of CDS, banks are in a better position to prevent financial difficulties and to alleviate credit problems in specific sectors or regions. This should ultimately make the banking sector more stable. At the macroeconomic level, the distribution of risk within the economy as a whole should improve with the increased adoption of CDS as credit risks can be more efficiently allocation within the economy. Economic shocks such as a slump in growth or, more especially, crises in specific sectors or companies can be better absorbed as the associated costs are lower in total and less concentrated. The use of credit derivatives can therefore improve the overall stability of the financial system.

Theoretically, the introduction of the market for credit risk should increase the ability of firm to access financing and thus should improve the broader economy. However the introduction of CDS has also given rise to negative impact on the macroeconomy, more specifically arising from the 'empty creditor' problem as elaborated by Hu and Black (2008). Danis and Gamba (2015) explain that CDS contracts allow debt holders to demand better terms in an ex-post debt renegotiation, which deters strategic default. Debt holders anticipate this leading to lower ex-ante spreads when debt is issued thereby increasing debt capacity on the positive side. However, debt holders who are hedged with CDS demand such a high payoff in re-negotiation that equity holders sometime find it optimal to file for bankruptcy, even though it would be cheaper to renegotiate.

Further empirical evidence on the effect of CDS on macroeconomy has been detailed in Subramanyam, Tang and Wang (2014), who claim that after controlling for firm specific characteristics the likelihood of rating downgrade and the likelihood of bankruptcy of the referenced firm both increases after CDS trading begins. Consequently the growth and development in the CDS market implies that the negative effect of downgrade and bankruptcy would plague the macroeconomic environment. Subramanyam, Tang and Wang (2014) further notes that the availability of CDS contracts renders more banks willing to lend because of the possibility of risk mitigation and enhances bargaining power via CDS contracts. However, the consequent expansion in the lender base also hinders debt workouts where a greater amount of lenders means that it is more likely that some lenders will become empty creditors, and thus the coordination problems will become more severe in a stressed situation in which a workout may be necessary. They conclude that this was the primary reasons why CDS is blamed to exacerbate the effect of the financial crisis. Mainstream literature on the risk of leverage caused by CDS has thus far focused on microeconomics, where increased leverage, arising out of credit derivatives including CDS, magnifies the fragility of financial institutions. Moreover leverage can fuel asset price and asset price bubbles. By linking one financial institution to another, CDS increases counterparty risk which could have serious macroeconomic implications. Further the growth and development of the CDS market, alleviates the bankruptcy risk for the firm in the economy. Subramanyam, Tang and Wang (2014) find that more creditors lend to firms after CDS contracts referencing their debt become available. Furthermore, bankruptcy risk increases with the number of lenders and with changes in the number of creditors around CDS introduction, providing another channel for the adverse effect of CDS trading on bankruptcy risk in the economy.

CDS market is also highly concentrated with very few market participants taking huge financial position. The dominance of small number of participant's means, in an event one of the major market participant drops out, it would lead to lower liquidity and higher transaction cost. This was especially evident during the financial crisis when reduced participation led to sub-optimal distribution of risk within the economy. Moreover the literature on CDS pricing has time and again pointed towards mispricing of CDS and the danger that market participants may underestimate the real risks and take on more risk than would be desirable for the overall economy. Systematic mispricing would lead to a misallocation of resources as capital would not be channelled into the most efficient uses. Price distortions would also have microeconomic implications; if prices were too high, the protection buyer would be at a disadvantage compared with the seller as he would have to pay an excessive premium. If prices were too low, the opposite would be the case. Under both conditions it would be problematic for the macroeconomy.

Credit derivatives links back to consumer and commercial credit markets and thus impacts the real economy. The bailout of AIG, due to excessive exposure to credit derivatives specifically CDS, was done to prevent the significant impact on the microeconomy. The collective microeconomic effect of credit derivative can impact the macroeconomy and this was cited as the main reason for the bailout of AIG (Bernanke, 2009). Moreover, the individual decision of financial institutions with respect to derivative contracts exerts powerful macroeconomic effects when aggregated across thousands of transactions. This not only increases the leverage of individual financial institutions, but also the leverage in entire financial markets when aggregated. Moreover as elaborated in Gerding (2011) credit derivatives and their collateral provisions causes a 'money multiplier' effect i.e. when collateral requirements are lowered along a chain of credit derivatives, credit protection sellers commit less funds to cover their obligations under the contract and deploys more capital for underwriting new derivatives or making other investments. Lowering (or raising) collateral or margin requirements geometrically increases (or decreases) the amount of credit risk that can be transferred by a chain of credit derivatives. Thus the increase in adoption of

CDS has a potential macroeconomic effect in increasing liquidity or the effective supply of money in the financial markets.

However, it is important to note that the parties to credit derivatives have less ability and incentive to factor macroeconomic consequences into their decisions to price contracts and set collateral requirements than they do with respect to counterparty risk. As argued in Gerding (2011), a party to a derivative contract has (however imperfect) incentives and mechanisms to mitigate its exposure to a counterparty's default. By contrast, the contribution of one credit derivative to aggregate monetary effects is much harder to see. Hence, counterparties may miss how macroeconomic effects mask mispricing of credit risk. Less ability and incentive for individual firms to counter cyclical macroeconomic effects opens a greater potential role for government action. Gerding (2011) further claims that regulators and central banks must consider not only counterparty risk, but also macroeconomic factors when monitoring and regulating the leverage of credit derivatives.

Overall, the positive view of the role of credit risk transfer has been extensively criticized and CDS have been blamed for part of the difficulties associated with the subprime credit crisis. (Skeel and Partnoy 2007) points out that CDS "create the risk of systemic market failure," partly because they minimize incentives to monitor the borrowers and therefore fuel credit expansion. Moreover, the role of CDS was also controversial during the sovereign default episode of Greece and Argentina. Naked CDS buyers in particular were blamed for speculating on government default thereby artificially driving up sovereign borrowing cost. As noted in Ismailescu & Phillips (2015), in May 2011, concerns over the negative effect of the sovereign bond market induced by speculative betting on sovereign CDS led German regulators to bad naked CDS position in Eurozone sovereign bonds. This was followed by European Union parliament voting in favour of a similar ban on sovereign bond CDS positions.

1.8 CDS spreads

CDS spreads denoted in basis points[12] are annual premium usually paid on a quarterly basis on the notional amount outstanding for a referenced obligation. A spread of 100 basis point on a $1 million notional amount, refers to an annual premium of (1% of $1 million)

[12] 100 basis points is equivalent to 1% point

$10,000 paid on a quarterly basis, which is the cost of insuring against the default of the underlying referenced obligation for the notional amount outstanding. Since premium is based on the market estimation of the underlying asset's credit quality, CDS spread for reference entities will be higher for firm's that possess poor credit quality and vice versa thereby providing an indication of the credit riskiness of the underlying firm's debt obligation and hence the referenced entity. The spread on a CDS contract changes over time reflecting changes in the market perception of the credit worthiness of a reference entity. Unlike corporate credit risk measures used in the past namely; bond yield spreads and credit ratings. CDS spreads provide an alternative, more reliable, cross-section and time-series indicator of corporate credit risk. Consequently, a wide range of studies have employed CDS spreads as a pure measure of corporate credit risk. Blanco *et al.*, (2005) also report that CDS spreads tends to adjust more rapidly to release of new information which in turn generates signal for the bond market that reacts with a time lag. This highlights the leading role that CDS market plays in the price discovery process. Being more liquid that the bond market, CDS market tends to be more suitable for traders with aggressive or speculative trading strategies compared to bond market which is dominate by unsophisticated buy and hold investors.

1.9 CDS spread vs. Bond yield spread

Since its introduction in early 2000, CDS have been actively used by financial market participants to hedge credit risk. Recent market trend shows that CDS occupy a major portion (96.7%) of the credit derivatives market substantiating its popularity and growth in the last decade. Consequently, a wealth of literature have advocated for CDS spreads as a better proxy for credit risk compared to bond yield. Some of these distinct advantages are detailed as follows,

CDS spreads are directly observables for a given underlying bond and hence does not require any adjustment or assumption on risk free benchmark rate whereas bond spread has to be computed using a riskless benchmark which is often difficult to ascertain (Longstaff Mithal and Neis, 2005; Blanco *et al.*, 2005). CDS spread data consist of bid and ask quotes which once made makes the dealer committed to trading a minimum principle of $10 million at the quoted price. On the contrary bond yield spread data requires no commitment from dealer to trade on the prices (Hull, Predescu and White, 2004). CDS contracts are directly written on credit event of the underlying bond and so are not distorted by embedded options, features like call and covenants unlike bond yields (Duffee, 1998). Unlike other credit risk instruments like bonds and swaps, CDS are not interest rate based instruments which ensures minimal effect of interest rate movement on spread estimation. Studies have also shown that CDS spreads react more rapidly to changes regarding the credit quality of the underlying reference entity compared to the bond market (Hull *et al.*, 2004; Blanco *et al.*, 2005; Zhu, 2006). Especially during period of financial distress, CDS market is found to dominate the information transmission process between the CDS and bond market (Delatte, Gex and López-Villavicencio, 2012).

Apart from these, as noted in Annaert, Ceuster, Roy and Vespro, (2012) the credit premium in bond spreads is driven by liquidity factors (Sarig and Warg, 1989 and Chen, Lesmond and Wei, 2007), tax effects and risk premia (Elton, Gruber, Agarwal and Mann, 2004) and various market micro-structure effects like maturity effect, coupon effect etc. which makes its an inferior measure of credit risk compared to CDS spreads. CDS also have a more pronounced liquidity relative to bonds which ensures that credit sensitive relevant information are quickly processed as such CDS provides an excellent laboratory for studying the mechanism of the credit market (Breitenfellner and Wagner, 2012). Additionally, CDS market are considered to be better than bond market due to bond market relative illiquidity and high barriers of shorting bonds which impedes the price discovery process in bond market (Blanco *et al.*, 2004). Thus, the increasingly popular CDS provides an alternative, more reliable, cross-sectional and time-series indicator of corporate credit risk. Before the growth of the secondary market for corporate bonds, corporate credit risk was mainly inferred based on credit rating. The next section highlights the use of credit rating as an indication of corporate credit risk.

1.10 Credit rating as measure of corporate credit risk

Credit ratings have been traditionally cited as the important information set highlighting a firm's capability of servicing and repaying debt obligations and hence an important source of credit risks information (Bystrom, 2006). The credit rating for an organisation represents the rating agency's opinion, on that specific date, the likelihood of future debt repayment for the rated debt obligation being paid in full and on time. Although, credit ratings do not guarantee repayment of the rated instrument, it provides a probabilistic estimate of the firm's likelihood to default thereby facilitating comparative assessment of investment options for an investor. Since credit ratings are considered to provide an estimation of the credit quality of the debt issuing firm, a closer relationship between a firm's credit rating and its credit quality is expected. Consequently, a firm's credit rating also dictates its debt pricing i.e. investors demand a higher compensation on investment for risky debt and vice versa.

A number of rationale for using Credit Rating (CR) as estimator of firm's credit risk has been explored in previous studies. CR agencies[13] are considered to have private information about the firm's past performance and its current management in addition to public information from balance sheet and company reports in arriving at a firm specific credit score (Pesaran, Schuermann, Treutler and Weiner, 2006). Moreover, in pursuit of a better rating, firm have incentive to reveal some of the private information to credit rating agencies than to debt holders, which further increases the quality of information contained in a firm's credit rating. Thus, use of credit ratings has implicit advantage over approaches that only use accounting data for estimating firm's credit risk. Unlike accounting data, credit ratings are less likely to be affected by biasness resulting from information asymmetry between company managers and shareholders. Consequently, the use of credit rating has steadily increased in recent years which can be attributed to various factors including globalisation of the financial market, the growing complexity of financial products and use of credit rating in financial regulation and contracting (Frost, 2007). Credit ratings have also become a key input in the credit risk models employed by banks and insurance companies for managing portfolio credit risk. Accordingly, a large number of studies (including Altman and Saunders, 2001; Falkenstein, Boral and Carty, 2000; Sobehart, Keenan and Stein, 2000; Cantor, Hamilton and Tennant, 2007 among others) have analysed the use of credit rating in accessing default probability of a firm. These studies have provided diverse views on the effectiveness of credit rating as a predictor of financial distress. Studies by Abid and Naifar (2006), finds a strong significant relationship between CDS spreads and credit rating and claim that the information efficiency of credit rating could be attributed to the fact that rating agencies evaluates company financial along with other criteria like management quality, industry perspective and competitiveness of the market into account while estimating

[13] Standard and Poor's Group, Moody's Group, and Fitch Group are considered to be the three biggest credit rating agencies, collectively occupying 87.44% of the global market share (ESMA, 2014)

corporate credit risk and hence are better estimators of firm's credit risk. Consequently, some theoretical credit risk models including Jarrow, Lando and Turnbull (1997) use rating and rating transition as an input in their models. Studies by Aunon-Nerin, Cossin, Hricko and Huang (2002) also highlights credit rating as the most important predictor in their credit risk model. However, their research also emphasize that the effect of credit rating is lower in high-rated and higher in low-rated corporate hinting towards a possibility of difference in the effect of credit rating on credit risk across investment grade and high yield corporate.

However, from a Credit Rating Agency's (CRA) point of view; there exist a mutual tension between stability and accuracy of credit rating (Cantor, Hamilton and Tennant, 2007). This can be interpreted as follows, in an attempt to provide stability in ratings, CRA's may not be able to aptly reflect the minor changes in credit quality of the firms making it less accurate. Whereas, trying to accurately map the credit quality of a firm over a period of time tend to make CR constantly varying compromising its stability. Therefore credit rating agency may endeavour to avoid rating changes if it has to be subsequently reversed compromising its credit risk estimation capability. Credit ratings which were perceived as an early warning system, had also come under immense criticism during the financial crisis of 2008-2009 where they failed to provide a true estimation of a firm's credit risk and provided a 'reactive' rather than a 'proactive' assessment of a firm's credit quality. Previous studies also indicate that a firm's rating could be positively related to its business cycle and hence could be cyclical in nature. Studies by Cantor and Mann (2003) support this claim by finding a positive correlation between rating changes in Moody's credit rating and cyclical indicators. However, they also indicate that credit rating is less cyclic than credit spreads and equity based measures of credit risk. CRA's can also be biased in their assessment of credit worthiness for a region, thereby producing ratings that may not be a true reflection of the credit quality. Moreover, the anticipation of rating upgrade and rating downgrade have an asymmetric effect on CDS spreads i.e. anticipation of rating downgrade has a higher effect of CDS spreads compared to an equivalent rating upgrade. Studies by Norden (2011) finds evidence that the anticipation for negative rating changes being stronger among firms with higher number of major bank lenders in syndicated loan markets highlighting differences in CDS spreads changes based on firm type for a similar rating revision. Furthermore, earlier studies (including Katz, 1974; Hettenhouse and Sartoris, 1976; Weinstein, 1977 and Pinches and Singleton, 1978 among others) on credit rating and rating transition by major credit rating agencies as noted in Aunon-Nerin *et al.*, (2002) concluded a lag between the arrival of new information and rating changes thereby inferring, ratings do not necessarily provide much new information, except for small not very frequently trading firms. Credit ratings cannot be easily operationalized to measure and compare the credit quality of different debt issuer on a time-series and cross-sectional basis, hampering the credit risk estimation process. Moreover, as all firms within a rating range are treated as encompassing the same credit risk, credit rating can be viewed as a highly generalised measure of corporate credit risk. As firms operating within different industry sector differ from each other grouping them within a single credit rating category dilutes the credit risk measure.

Although CR's are an indicator of a firm credit quality, it may also have a direct influence on the credit risk of the firm. It is well known that a firm's share price head south following a rating downgrade announcement further hampering the firm's ability to counter credit risk shocks. Similarly corporate credit risk which manifests itself through credit rating and accounting information could have a direct or indirect influence on CDS spreads. Based on these arguments it can be inferred that although credit rating provides a fair amount of estimation of a firm's credit risk, it does not provide an accurate representation of the firm's credit quality nor can it be easily operationalized to undertake a comparative assessment based on its generalising nature.

Collectively, credit rating, bond yield spreads and CDS spreads represent the evolution in the measure of corporate credit risk that have been used in past studies. Recently, studies on corporate credit risk, consider the limitations associated with credit rating and bond yield spreads and hence emphasise the value relevance of using CDS spreads as a more robust measures of corporate credit risk.

1.11 Contribution of the Thesis

The thesis presented herein; consist of five main chapters, with each subsequent chapters building on and drawing from the previous chapter and focusing on a specific research aim and objectives within the overall thesis. Overall the structure of the thesis can be seen as a collection of parts making up an overall coherent piece of work.

Chapter One; provides a brief introduction to the Credit Default swap instrument and highlights its growing popularity in the last decade. As noted earlier, the market for CDS contracts have grown exponentially since the start of 2003, peaking at the advent of the financial crisis of 2007-2008. The gradual reduction in the market for CDS contract, measured in terms of gross notional amount outstanding, draws an inaccurate picture of the breadth and scope of the CDS market in the aftermath of the global financial crisis. Specifically, the 'portfolio compression' effort spurred by regulators in early 2007, cancelled out large simultaneous long and short CDS positions for the same underlying firm, in the estimation of notional amount outstanding. This tends to underrepresent the exposure to credit risk that counterparties in a CDS contract are exposed to during a credit event. CDS market participants are mainly big and systematically important financial institutions (SIFIs) including banks, pension funds, hedge funds and insurance companies globally who mostly hold uncovered (naked) positions in the CDS market. Thereby, in the lure of income from the default insuring mechanism these institutions expose themselves to large payout or adverse credit risk in an event of the underlying reference entity's credit event. Moreover, the global interconnected of the financial system exposes financial institutions to contagion effect; especially during period of economic downturn as witnessed during the global financial crisis. Chapter One; also highlights that the effect of CDS introduction to the financial market is highly debated both in industry as well as in academia, particularly during the 2007-2008 credit crises. On one hand, CDS is heavily criticised for the creation of Mortgage Based Securities (MBS) as well as implicated during the sovereign default episode of Greece (ongoing) and Argentina (July 2014). Opponents of CDS and OTC market in general denounce them as "poisonous", "toxic", "time bombs", "financial hydrogen bombs", "speculative bets that influence ... defaults", "weapons of mass destruction" etc. (Wall Street Journal, 2009). However, the role of CDS as a risk management tool and as a means of allocating credit risk more efficiently should not be forgotten. Moreover, the dynamic nature of CDS spreads that presents a new source of real time information on the corporate credit risk, which as rationalised in previous studies to be better than both; credit ratings as a well as the bond yield spreads lends further support to the importance of the CDS market.

Chapter Two provides a contribution to the literature on pricing of CDS. This study contributes to the existing literature in the following ways. Firstly, it examines the behaviour of corporate CDS spreads before, during and after the financial crisis to assess the impact of the financial crisis on the three developed economies. US, UK and European Union (EU) are also the biggest markets for corporate CDS contracts globally. Consequently, a comparative evaluation of the corporate credit risk dynamics will provide fascinating insights into the corporate CDS market. This is a first study that explores such a wider sample domain and is more comprehensive in terms of the geographical coverage and period of analysis. Secondly, this Chapter documents the changing nature of spread predictor variables across different markets and for different period of analysis. This study follow Das, Hanouna and Sarin (2009) and incorporate accounting and market variables to model the dynamics of CDS spread before, during and after the Financial crisis across all Global Industry Classification Standard (GICS) sectors (excluding Government) for the US, UK and EU. This Chapter provide a comparative evaluation of accounting and market based variables in explaining the variation in quarterly CDS spreads emphasizing the changing nature of the spreads predictor variable sets. Thirdly, this study challenges the notion of CDS spreads being a pure measure of credit risk. This study ascertains, just like any other market measure; CDS spreads could also be plagued by noise and hence their use as pure measures of risk could lead to wrong estimation of corporate credit risk dynamics. In doing so, this study also test the effect of CDS market liquidity on spreads and find a significant effect of non-default drivers on spreads to further substantiate the research claim.

The central theme of this chapter is testing the determinants of CDS spreads with a focus on pricing across different period of analysis. Past studies on CDS pricing, either focusses on credit indices or use small samples particularly focussing on a specific sector, economy or a period of analysis. The existence of large number of studies that note different and at times contradictory findings by using too restrictive samples which are mostly biased towards US corporate, provides an interesting scope of inquiry. This chapter dwell into the behaviour of CDS spreads across a wider sample domain encompassing US, UK and EU corporate CDS for which data is available on Bloomberg. The timeline of analysis covers the three major economic conditions namely, pre-crisis, crisis and post-crisis period and CDS spreads are modelled using firm specific accounting fundamental, theory driven market variables and macroeconomic indicators across all GICS sectors. Past studies, validate accounting and market variables to capture important credit risk information but their comparative evaluation across different sub-periods has not be undertaken before. Individually each set of predictor variables and their extent of variability in explaining CDS spreads dynamics is expected to provide glimpse into reliability of these information set in CDS pricing. Chapter Two, evaluates each variable set individually as well as in a combined model to ascertain the improvement in CDS pricing across the sub-periods of analysis. Understanding what drives CDS spreads and the basis of CDS pricing is crucial as CDS spreads are still considered pure measures of credit risk. In an event CDS pricing are haphazard and spreads plagued by financial market dynamics, their use as pure measure of credit risk would lead to wrong estimates. Consequently, the signals from CDS market may not entirely reflect the credit risk within the financial system prompting regulators to draw policy implications that may not be effective in stabilising the CDS market and the financial system as a whole. Recently, few studies have also provided evidence on the notion that CDS spreads may not be reflecting the true credit risk inherent in the CDS market. However, none of these studies have explored such a wider sample domain across such a longer timeline as this study and so the findings from this study provide strong evidence of CDS spreads being plagued by non-default elements.

Chapter Two, also examines the dynamics of corporate bond yield spreads for those corporate that have active CDS contract trading in the market. One of the earliest studies on CDS pricing by Longstaff *et al.,* (2005), provides a unique way of splitting bond yield spreads into default and non-default components by attributing CDS spreads for the referenced entity as the measure of default component of bond yield spreads for the same referenced entity. The estimation of the monthly bond yield spreads for all CDS that have spreads data available for the sample and timeline under consideration although is a laborious process, but is bound to provide crucial data on the percentage split of default and non-default component of bond yield spreads that has important implications for both the CDS and bond pricing literature. Past studies have well documented bond yield spreads to be plagued by non-default elements; specifically bond market liquidity and a similar effect could be tested for CDS spreads. Chapter Two, regresses bond liquidity variables on bond yields spreads as a whole, as well as default and non-default component of yields spreads individually to access whether spreads are driven by bond liquidity dynamics and to what extend across each sub-period of analysis. Moreover, the effect of liquidity dynamics in the CDS market is also tested on CDS pricing, to note if these are driving spreads more than the credit risk of the underlying reference entity. Chapter Two, draws some important observations which have value relevance for policy implications that have been discussed later on in Section 2.6 as well as in Chapter Five.

Chapter Three, focusses on the policy interventions during the financial crisis initiated by Government and Central banks in US and UK to stabilise the financial markets. The start of the financial crisis in United States could be traced back[14] to the bankruptcy of American

[14] Timeline of crisis in United States is available at https://www.stlouisfed.org/financial-crisis/full-timeline

Home Mortgage Corporation in Aug 2007, followed by Fitch rating downgrade of Countrywide Financial Corporation leading to Federal Open market Committee (FOMC) reducing fed fund rate and issuing statement claiming "the downside risk to growth has increased appreciably". This was subsequently followed by the diminishing liquidity in the interbank funding market, creation of Term Auction Facility (TAF), Term Security Lending Facility (TSLF), Troubled Asset Relief Programme (TARP), collapse of Lehman brothers, takeover of Merrill lynch by Bank of America, Bear Stearns by JP Morgan and Federal Reserve stepping in to save AIG. In the United Kingdom, the unfolding of the financial crisis mirrors the events in United States, with Northern Rock facing liquidity crisis and being supported by Bank of England (BOE) in Sept 2007 and government bailing out Royal Bank of Scotland (RBS), Lloyds TSB and Halifax Bank of Scotland (HBOS). Since the advent of the financial crisis, the Federal Reserve (in US) and the BOE (in UK) have taken a number of steps to contain the ongoing financial crisis and to limit its impact on the broader economy. Central banks in US and UK reduced key rates to unprecedented levels to offset the risk in the private sector risk premia as well as employed unconventional measures in the form of quantitative easing to stabilise the financial markets. An expansionary policy intervention, as seen during the financial crisis, should ideally stimulates the economic environment and hence should impact firm's from certain sectors (especially financial sectors) as well as the economy providing breathing space and by lowering the credit risk perception among investors. This chapter questions whether these measures taken to normalise the financial markets were effective in reducing the credit risk within the financial system. From the scope of analysis, the study is limited to major announcements pertaining interest rate, quantitative easing and fiscal policy announcements in US and UK. Moreover, the scope of inquiry spans across corporates in all sectors and those that are registered in US and UK. This chapter notes the effect in the CDS market following these announcements, which is a better avenue to measure system wide credit risk unlike equity markets which are considered less informative. Specifically, if the policy interventions were effective in reducing the stress in the CDS market, a reduction in credit risk could be noted following these announcements. This study also tests if these announcements collectively grouped based on interest rate, quantitative easing and fiscal policy had similar effect or if market participants react more favourably to a certain type of policy announcement over others.

Chapter Three provides a contribution to the literature on the effectiveness of policy announcements on aggregate level corporate credit risk. Without taking a view at priori on the effectiveness of the policy actions, this study intends to provide an empirical justification of the effectiveness of macroeconomic policies announcements in US and UK during the recently financial crisis. Using the well-established event study methodology this study tests if the interventions were effective in lowering system wide corporate credit risk measured using individual firm level daily CDS return. Thus the most important contribution of this study is testing the effect of policy announcement on corporate CDS market using a better credit risk measure i.e. CDS returns. This Chapter builds on the work by Greatrex and Rengifo (2010) and aims to investigate the relative effectiveness of the monetary and fiscal policy announcement on aggregate credit risk dynamics of corporates. Government and Central Bank's unprecedented intervention to stem the systematic effect of the credit shock during the financial crisis provides the motivation for this study. This study specifically investigates; if the series of monetary and fiscal policy announcements achieved the intended goal of reducing corporate credit risk in US and UK. Secondly, unlike most studies in the past that considers a single effect across all types of firm following a policy announcement, this study break down the effect based on sector - financial and non-financial, credit quality - investment grade and speculative grade, firm size - small, medium and large and CDS liquidity – low, medium and high, to test the effect across the samples for both US and UK. Furthermore, this study tests if a particular policy announcement had a significant effect on firms with certain characteristics operating within the economy, thereby providing an important contribution towards the firm specific heterogeneity in credit risk following policy announcement during the crisis period.

To quantify the effect in the CDS market following the policy announcement, previous studies including Greatrex and Rengifo (2010) access the impact in CDS index that are driven by CDS spreads collated based on quality (high grade and investment yield) and sectors (financial and non-financial). As CDS spreads are at-market spreads for newly issued default swap contracts with constant maturity, the changes in spreads do not accurately indicate the change in credit riskiness over time. Hence, using spreads to estimating the change in credit risk will lead to an incorrect estimation of underlying firm's credit dynamics. This study estimates daily CDS returns from CDS spreads as detailed in Brendt and Obreja (2010), which gives the flexibility of aggregating CDS returns over sectors, quality, firm size and liquidity. CDS returns estimated on a daily basis is the return for the insuring party in a CDS contract given the change in the value of the risky and risk-free bonds long and short portfolio position. A fall in CDS return following the announcement would thus indicate the losses arising to the insuring party resulting from credit deterioration of the underlying firm. An event study methodology is used to access the change in the CDS abnormal returns following the policy announcements and a battery of parametric and non-parametric test statistics are used to ascertain the significance of the cumulative abnormal returns. This study uses very narrow event windows to capture the effect immediately following the policy announcements. Moreover, apart from checking the effect following the announcements across the full sample of firms, this study splits firms into quality – investment grade and speculative grade, sector – financial and non-financial, firm size – big and small and CDS liquidity – low and high to check the variable effect of a particular policy announcement on underlying reference entity with the above characteristics.

Chapter Three, tests the cumulative average abnormal returns following each of the interest rate, quantitative easing and fiscal policy announcements across a range of narrow event windows and the finding from this study provides useful insights into the variable effect of policy announcement across the two countries namely; US and UK. The effects following the announcements are also tested across the policies types and for underlying firms with specific characteristics. Such a detailed analysis as undertaken in this study has not been attempted before in previous literature. The findings will provides a glimpse into the effect on aggregate corporate CDS returns following the type of policy announcements and if one policy type had a higher effect on the corporate CDS return than the other. Similarly, for the type of policy announcement and the subsequently effect in aggregate CDS returns for firms with specific characteristics could provide an indication to policy makers on the type of firms that would benefit the most in terms of credit risk reduction following certain announcements.

Since event study methodology does not lend itself to causality i.e. the effect on CDS returns following the announcement could not be attributed to the effect of the announcement and is a design specific challenge that event study methodology is unable to address. Chapter Three, attempts to infer the abnormal return following the announcement on firm specific characteristics by regressing firm specific variables on abnormal returns following the policy announcements. Next, the process is reversed and abnormal returns following the policy announcements are categorised into low and high returns and the characteristics of firms are analysed to note if they are statistically difference across the two groups. This study will provide useful insights to policy makers on the kind of effect a particular type of policy announcement had on CDS returns thus making them more aware and prepared to handle a similar crisis situation in future with a more informed policy intervention i.e. 'using the right tool for the right job'. Evaluating the aggregate level effect as well as the differential effect based on firm specific characteristics challenges previous studies that have attempted to attribute an overall effect across all firms types irrespective of the sector, quality, size and firm specific dynamics. The underlying theme of this chapter is the differential effect across the policy initiative, firm characteristics and economy under considerations, and so when it comes to policy intervention during the crisis period one size does not fit all.

Chapter Four, makes a contribution to the asset pricing literature by attempting to generalize the Fama and French (FF) asset pricing model through its application to the CDS market. Although the asset pricing literature for the equity market is well developed with an evolution of asset pricing models ranging from CAPM, FF three factor (3F) and five factor (5F) models and the various augmented versions of CAPM and FF models, there is no previous study that have attempted to generalise these models to explain the dynamics of the CDS market. Chapter Three, details the estimation procedure used in Brendt and Obreja (2010) to obtain daily CDS returns. These returns are driven by the change in the value of the risky and risk-free bond long and short portfolio position and represent important information set from the perspective of corporate credit risk. The growth in the market for CDS and the existence of large amount of daily spread data provides an interesting field of exploration into the generalizability of asset pricing model using CDS returns. This study expects the FF model estimated for the CDS market, to be able to explain the cross section of CDS returns just like FF model is able to explain for the equity returns. If the FF model could be applied and generalised to the CDS market, it will lend important supporting evidence on the value relevance of the FF asset pricing model, which is although widely accepted but still a hugely debated topic in the asset pricing literature. Moreover, by using the Fama French model to explain variation in cross-section of CDS returns, this study aims to identify if the model works for the CDS market.

Chapter Four provides a contribution to the literature of asset pricing by testing the external validity of the FF three-factor (3F) and the five-factor (5F) models and its application to the CDS market. No other study has attempted to test the application of FF factor models to explain CDS return dynamics. This Chapter will thus aim to provide useful insights on the generalizability of the FF models with an attempt to identify whether the model 'works' for the CDS market. To identify if the model works, this study examines if the FF model explains the daily CDS returns for the US firms that has active CDS trading data available in Markit database. Further to investigation of asset pricing application on the CDS market, this Chapter also accesses the external validity of the default risk hypothesis. This study tests whether default risk is priced in the cross-section of CDS returns and whether the SMB and HML factors are proxying for default risk in the CDS market. The lack of clarity on the type of risk captured by *SMB* and *HML* factors along with the availability of CDS returns where spreads are driven primarily by changes in underlying firms' credit quality provides an interesting avenue to explore in the context of the CDS returns. This Chapter evaluates the economic relevance of *SMB* and *HML* factors using the CDS returns, and aims to provide clarification on whether *SMB* and *HML* actually captures the default risk. CDS returns drawn from spreads which are used as a measure of firm default risk provides an ideal testing ground for evaluating this research question. This will provide useful contribution and insight on the debate on the kind of risk captured by *SMB* and *HML*. Finally, this Chapter provides further tests on asset pricing by augmenting the FF model (1993, 2015) with a default risk factor estimated using distance-to-default (DTD) measure, thus providing important contribution towards the preferred model for asset pricing test for the CDS market

Apart from testing the external validity of the FF model, this study also aims to access the external validity of the default risk hypothesis, by testing if the default risk is priced in the cross section of CDS returns and if the FF factors; *SMB* and *HML* factors are proxying for default risk in the CDS returns. Past studies on stock returns, have widely debated about the type of risk captured by the FF factors, while some attribute *SMB* and *HML* to capture firm distress risk other studies attributed these factor to proxy for investor's bias in earning growth, market risk, risk associated with future GDP growth among others. The CDS returns derived from spreads which in turn captures market expectation of firm default risk provides an ideal testing ground for the default risk hypothesis. The findings from this study will provide a clear outcome for this widely debated topic lending some clarity and insight into the kind of risk dynamic captured by the *SMB* and *HML* factors.

Recently, Fama and French (2015) augment their original 3F model with two additional factors; profitability and investment and propose a 5F asset pricing model. They claim the 5F model to be a better asset pricing model as it successfully addresses the limitation of the 3F model. This study tests this claims by building both the 3F and the 5F model for the CDS market and testing the improvement provided by the 5F model over and above the 3F model. The portfolio construction logic used in this study is similar to as elaborated in FF with some minor adjustments to ensure the portfolio returns are not plagued by missing observation bias. Next, this study augmented the 3F and the 5F model with default risk variable; distance-to default to access the improvement in the model across the range of portfolios. This is done with an attempt to firstly; understand the nature of risk captured by the *HML* factor and secondly to check if a pure measure of default risk provides improvement to the original 3F and 5F model proposed by FF. This is a first study to apply FF models to the CDS market and is expected to generate avenue for further research in the CDS market pricing literature with a goal of improving the proposed model and the asset pricing model literature in general.

CHAPTER 2

WHAT DRIVES CORPORATE CDS SPREADS: COMPARISON ACROSS US, UK AND EU MARKETS

CHAPTER 2 - WHAT DRIVES CORPORATE CDS SPREADS? - COMPARISON ACROSS US, UK AND EU MARKETS

Abstract

This paper investigates the behaviour of CDS spreads to assess the impact of US financial crisis on corporate credit risk for US, UK and EU firms. This paper is the first to provide a comparative evaluation by exploring a wider sample domain both in terms of geographical coverage and period of analysis. CDS spreads are regressed against both accounting as well as market-based variables; jointly they provide a better fit for the data. The analysis reveals accounting and market-based variables are more significant predictors of CDS spreads during periods of financial distress than at other times, although the significance of the variables and their spread prediction power varies considerably across each period of analysis and across each market. A substantial portion of spreads that cannot be accounted for especially in the post-crisis period can be noted across the three markets even after controlling for CDS market liquidity. To explore this puzzle, the characteristics of the default and non-default components of yield spreads before, during and after the crisis are studied. This study notes, default risk only partially explains the movement in yield spreads and non-default component is a key driver of yield spreads more so in the crisis and post-crisis era. By regressing the non-default component of yield spreads against liquidity proxies, this study finds a significant effect of liquidity for both the crisis and post-crisis period for the three markets. The result indicates; CDS spreads may have overreacted as such should not be considered as a pure measure of credit risk unlike claimed in previous studies.

Keywords: CDS spreads, financial crisis, default, non-default, liquidity, and panel data.

JEL Classification: C33, G01, G13, G15, G23

2.1 Introduction

Corporate credit risk is a subject of growing concern among academics and practitioners since the number of corporate defaults have peaked globally following the financial crisis. The cost of corporate default has skyrocketed with large scale corporate failure causing tremendous strain on the global economy. S&P reports the global corporate defaults in 2008-2009 peaked at 391 with total debt outstanding of 1057.33 billion USD (S&P, 2012). Consequently, understanding what drives corporate credit risk is crucial for evaluating firm's financial strength in light of the changing economic conditions.

Previous studies have focused on various competing measures for estimating corporate credit risk dynamics including credit rating, bond yields spreads and Credit Default Swap (CDS) spreads. CDS spreads are considered a better proxy for credit risk compared to bond yield, due to various reasons; 1) CDS spreads are directly observables for a given underlying bond and hence does not require any adjustment or assumption on risk free benchmark rate whereas bond spread has to be computed using a riskless benchmark which is often difficult to ascertain (Longstaff, Mithal and Neis, 2005; Blanco, Brenan and Marsh, 2005). 2) CDS spread data consist of Bid and Ask quotes which once made makes the dealer committed to trading a minimum principle of $10 million at the quoted price. On the contrary bond yield spread data requires no commitment from dealer to trade on the prices (Hull, Predescu and White, 2004). 3) CDS contracts are directly written on credit event of the underlying bond and so are not distorted by embedded options, features like call options and covenants unlike bond yields (Duffie, 1998). 4) Unlike other credit risk instruments like bonds and swaps, CDS are not interest rate based instruments which ensures minimal effect of interest rate movement on spread estimation. 5) Studies have also shown that CDS spreads react more rapidly to changes regarding the credit quality of the underlying reference entity compared to the bond market (Hull *et al.*, 2004; Blanco *et al.*, 2005; Zhu, 2006). Especially during period of financial distress CDS market is found to dominate the information transmission process between the CDS and bond market (Delatte, Gex and Lopez-Villavicencio, 2012).

Apart from these, as noted in Annaert, Ceuster, Roy and Vespro, (2012) the credit premium in bond spreads is driven by liquidity factors (Sarig and Warg, 1989 and Chen, Lesmond and Wei, 2007), tax effects and risk premia (Elton, Gruber, Agarwal and Mann, 2004) and various market micro-structure effects like maturity effect, coupon effect etc. which makes it an inferior measure of credit risk compared to CDS spreads. CDS also have a more pronounced liquidity relative to bonds which ensures that credit sensitive relevant information are quickly processed as such CDS provides an excellent laboratory for studying the mechanism of the credit market (Breitenfellner and Wagner, 2012). Additionally, CDS market are considered to be better than bond market due to the bond market relative illiquidity and high barriers to shorting bonds which impedes the price discovery process in bond market (Blanco *et al.*, 2005). Thus, the increasingly popular CDS provides an alternative, more reliable, cross-section and time-series indicator of corporate credit risk. Consequently, a wide range of studies have employed CDS spreads as a pure measure of corporate credit risk. These coupled with the existence of large amount of CDS data, have yielded a number of studies that have attempted to determine firstly; the factors that drive the CDS spreads and secondly the impact of CDS spreads on the wider market as a whole. However there are very few studies that aim to investigate the dynamics of CDS spreads movement across different period of analysis.

One of the earliest studies in this area was by Longstaff *et al.*, (2005) who used CDS spreads to obtain direct measures of the size of both the default and non-default component of bond yield spreads. Later studies include those by Kunt and Huizing (2013), Becchetti, Carpentieri and Hasan (2012), Calice, Chen and Williams (2012), Annaert Ceuster Roy and Vespro (2012); Demirgüç-Kunt and Huizinga (2013); Hart and Zingales (2011); Norden and Weber (2010); Huang Zhou and Zhu (2009); Raunig and Scheicher (2009); Sarno, Eichengreen, Mody and Nedeljkovic (2009) amongst others. Majority of these studies have focused on credit indices or used small samples particularly focussing on a specific sector, economy or a period of analysis. Studies by Becchetti *et al.*, (2012) use option-adjusted credit spread index with very basic spread predictor variables. Study by Tan and Yan (2010) is limited to North American CDS contracts from 2002-2009 and does not measure the effect post-crisis. Annaert *et al.*, (2012) is limited to financial sector firms specific to 32 listed Euro area banks. Svec and Maurice (2010) research is specific to the investment grade Australian companies. Other similar studies including Cossin and Hricko (2001) and Aunon-Nerin, Cossin, Hricko and Huang (2002) use either too restrictive samples or are highly biased towards US corporate.

This paper contributes to the existing literature in the following ways. Firstly, it examines the behaviour of corporate CDS spreads before, during and after the financial crisis to assess the impact of the financial crisis on the three developed economies. US, UK and European Union (EU) are also the biggest markets for corporate CDS contracts globally. Consequently, a comparative evaluation of the corporate credit risk dynamics will provide fascinating insights into the corporate CDS market. This is a first paper that explores such a wider sample domain and is more comprehensive in terms of the geographical coverage and period of analysis.

Secondly, this paper documents the changing nature of spread predictor variables across different markets and for different period of analysis. It follow Das, Hanouna and Sarin (2009) and incorporate accounting and market variables to model the dynamics of CDS spread before, during and after the Financial crisis across all Global Industry Classification Standard (GICS) sectors (excluding Government) for the US, UK and EU[15]. This paper provide a comparative evaluation of accounting and market based variables in explaining the variation in quarterly CDS spreads emphasizing the changing nature of the spreads predictor variable sets.

Thirdly, this paper challenges the notion of CDS spreads being a pure measure of credit risk. This paper ascertains, just like any other market measure; CDS spreads could also be plagued by noise and hence their use as pure measures of risk could lead to wrong estimation of corporate credit risk dynamics. This paper also test the effect of CDS market liquidity on spreads and find a significant effect of non-default drivers on spreads to further substantiate the research claim.

The remainder of this paper is as follows. Section 2.2 introduces CDS spreads descriptive for the three markets, Section 2.3 introduces the independent variables that determine the credit spread used in this study. Section 2.4 presents the empirical results for the panel data regression. Section 2.5 carries out a series of robustness checks to validate the research findings. Section 2.6 discusses the policy implications and Section 2.7 concludes.

2.2 US, UK and EU CDS Spreads

For US, UK and EU samples, 5 year constant maturity quarterly CDS spreads[16] belonging to the senior debt type are used. The observations are sub-divided into three separate period of analysis, as in Breitenfelner and Wagner (2012). More specifically, pre-crisis period is defined as 1st Jan 05 to 30th Jun 07; crisis period from 1st Jul 07 to 30th Jun 09 and post-crisis period from 1st Jul 09 to 31st Dec 12. The crisis period for both US and UK are closely

[15] EU henceforth; includes Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal and Spain. The availability of corporate CDS spreads data in Bloomberg drives our choice of selecting the 12 EU countries

[16] Data collected for all CDS contracts that have spreads data available from CBGN database in Bloomberg

linked. However for EU the sovereign credit crisis started late in Q2-09 and is still ongoing. This study aims to test the effect of the Global Financial Crisis (GFC) on US, UK and EU corporates and this drives our choice of selecting a standard period of analysis across the three samples. This study rationalizes that credit risk dynamic of listed firms will not only be a function of the economic condition for the national boundary but likely to be influenced by global economic condition as financial markets are global and interconnected. Similar to Kahle and Stulz (2013) other studies propose a modified version of the period of analysis further splitting the crisis period. However, the choice of periods is based on the ease of comparing corporate credit risk dynamics across the economic conditions and the need to have enough number of observations in each period to draw statistically significant inferences.

Fig. 2.1 displays the median, 10th and 90th percentile CDS spread on a quarterly basis. For US and UK, median spread increased dramatically from Q3-07 reaching its peak in Q4-08. After the crisis period, spreads declined for both US and UK, where the decline starts effectively from Q1-09. For EU, median spreads increased during crisis period but peaks during post-crisis period evidencing the effect of the EU sovereign credit crisis.

To examine the broad statistics, let's turn to Table 2.1. Panel A presents spreads on an annual basis for the whole period of analysis, i.e. from 1st Jan 05 to 31st Dec 12. It can be noticed, though there is an overall decline in spreads from 2009 onwards, the median spread has remained stubbornly high for both US and UK, indicating that for certain firms at least the CDS spread has decreased whilst for other it has not. However, the spreads are nowhere comparable to the pre-crisis level. For EU median spreads reduced following the financial crisis but again rose sharply in the post-crisis period, indicating the turmoil caused by the ongoing sovereign debt crisis. Panel B, breaks down spreads by issuing country of the underlying firm. Huge variations in EU median spread across crisis and post-crisis period can be noticed. Median spreads for Germany and Netherlands are lower than US and UK, however those for Greece, Portugal and Ireland are much higher in the post-crisis period highlighting the variable effect of Eurozone crisis on corporate credit risk. In Panel C, a similar trend can be observed across most GICS sectors for the three markets. Of all sectors, 'Financial' and 'Consumer Cyclical' sectors have consistently higher median spreads in the crisis and post-crisis period across the three markets.

Fig 2.1: US, UK and EU CDS spread (level in basis points) from Q1-05 till Q4-12. Graph contains observations on a quarterly basis. The median spreads along with 10th and 90th percentiles are plotted across each sub periods. The pre-crisis period is defined as 1st Jan 2005 to 30th Jun 2007; crisis period from 1st Jul 2007 to 30th Jun 2009 and post-crisis period from 1st Jul 2009 to 31st Dec 2012.

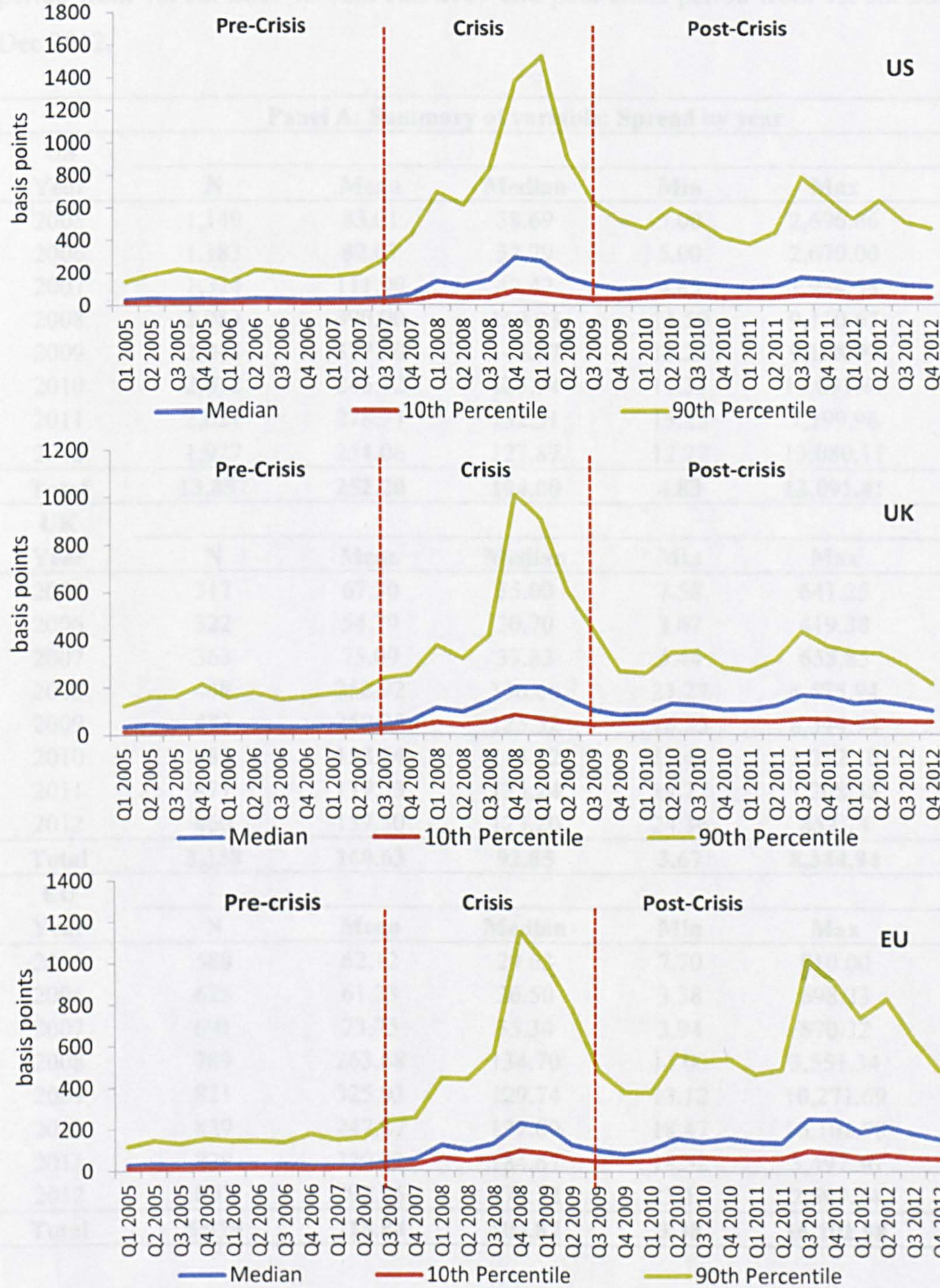


Table 2.1: Descriptive statistics of Credit Default Swap (CDS) spreads.

Descriptive statistics of credit default swap spreads (in basis points) from 1st Jan 05 to 31st Dec 12, for US, UK and EU broken down by year in Panel A and by country in Panel B. N is the number of quarterly CDS spread observations available across each year, across GICS sector and country. The pre-crisis period is defined as 1st Jan 2005 to 30th Jun 2007; crisis period from 1st Jul 2007 to 30th Jun 2009 and post-crisis period from 1st Jul 2009 to 31st Dec 2012.

Panel A: Summary of variable: Spread by year						
US						
Year	**N**	**Mean**	**Median**	**Min**	**Max**	**Std dev.**
2005	1,149	83.01	38.69	5.00	2,696.86	153.77
2006	1,183	82.67	32.79	5.00	2,670.00	177.13
2007	1,374	111.90	42.42	4.83	1,954.58	182.58
2008	2,083	390.90	159.93	11.50	9,110.67	698.77
2009	2,048	377.30	145.87	17.25	9,108.99	730.09
2010	2,072	245.12	125.94	17.31	13,091.41	567.86
2011	2,021	278.77	132.51	15.22	7,199.96	579.93
2012	1,927	254.06	127.87	12.77	13,080.11	532.29
Total	**13,857**	**252.20**	**104.00**	**4.83**	**13,091.41**	**555.66**
UK						
Year	**N**	**Mean**	**Median**	**Min**	**Max**	**Std dev.**
2005	317	67.30	35.00	7.58	641.25	98.04
2006	322	54.79	30.70	3.67	419.38	71.25
2007	363	75.09	37.83	4.44	655.85	100.68
2008	448	252.92	136.66	21.27	4,575.94	366.48
2009	472	260.25	125.32	16.25	8,344.94	531.03
2010	485	158.54	114.22	17.44	1,212.10	150.03
2011	471	179.33	135.24	19.72	1,208.55	168.83
2012	460	157.50	123.20	24.36	857.74	134.41
Total	**3,338**	**160.63**	**92.85**	**3.67**	**8,344.94**	**274.51**
EU						
Year	**N**	**Mean**	**Median**	**Min**	**Max**	**Std dev.**
2005	588	62.12	29.63	7.70	810.00	101.37
2006	625	61.23	26.50	3.38	698.33	99.42
2007	691	73.75	35.34	3.94	870.32	114.30
2008	789	263.68	134.70	14.00	3,551.34	361.06
2009	821	325.03	129.74	13.12	10,271.69	697.25
2010	829	247.87	137.60	18.47	16,102.98	627.66
2011	829	320.93	184.67	18.52	3,497.36	413.18
2012	807	292.76	179.12	23.15	2,597.74	318.62
Total	**5,979**	**218.84**	**104.87**	**3.38**	**16,102.98**	**436.90**

Panel B: Summary of variables: Spread by Country									
	Pre-crisis			Crisis			Post-crisis		
Country	**N**	**Mean**	**Median**	**N**	**Mean**	**Median**	**N**	**Mean**	**Median**
US	**2,909**	**80.56**	**35.00**	**3,918**	**371.08**	**144.39**	**7,030**	**256.97**	**125.51**
UK	**806**	**60.25**	**32.72**	**882**	**240.40**	**118.17**	**1,650**	**167.02**	**118.38**
EU[1]	**1,542**	**59.99**	**26.14**	**1,561**	**266.40**	**119.57**	**2,876**	**278.19**	**154.14**
France	456	56.84	30.91	426	222.35	118.05	748	207.53	136.76
Germany	360	67.94	26.41	385	261.83	115.00	745	175.09	110.94
Netherlands	152	41.13	23.94	173	243.85	88.33	334	173.69	103.43
Italy	180	64.26	19.79	165	243.52	118.46	303	372.10	242.34
Spain	147	32.50	18.31	135	339.24	150.00	228	384.40	279.26
Finland	66	89.46	43.04	56	468.12	180.49	98	282.65	233.46
Ireland	50	91.74	30.64	56	311.36	235.68	91	697.57	394.96
Portugal	45	31.77	16.21	41	104.80	108.15	73	529.57	469.61
Belgium	34	41.66	20.46	45	437.01	107.11	76	528.54	97.11
Luxembourg	16	322.60	345.39	32	503.99	454.00	79	381.97	312.06
Austria	26	23.04	18.75	35	180.48	130.83	61	183.63	164.02
Greece	10	43.06	44.16	12	175.86	126.45	40	1115.40	978.56

Note: (1) No quarterly CDS spread data available for EU countries; Cyprus, Estonia, Malta, Slovakia and Slovenia.

Panel C: Summary of variable: Spread by GICS Industry classification									
US	**Pre-crisis**			**Crisis**			**Post-crisis**		
GICS sector	**N**	**Mean**	**Median**	**N**	**Mean**	**Median**	**N**	**Mean**	**Median**
Basic Materials	215	110.90	56.26	298	441.14	165.82	461	181.15	123.91
Cons, Non-cyclical	390	67.68	28.85	642	235.09	88.94	1,266	172.93	88.46
Financial	654	42.49	25.98	742	517.51	208.00	1,325	368.80	169.10
Utilities	201	48.43	39.17	345	226.47	128.35	616	288.06	116.13
Industrial	376	55.91	29.93	470	194.22	96.79	849	220.37	87.44
Energy	229	41.48	30.25	349	174.97	115.39	648	143.70	113.05
Technology	93	56.71	50.05	153	396.01	106.66	304	243.09	128.43
Consumer, Cyclical	487	186.04	73.88	542	637.64	275.68	943	382.62	189.91
Communications	264	76.53	44.25	375	401.69	194.52	606	201.60	114.59
Diversified	-	-	-	2	102.47	102.47	12	69.62	65.25
Total	**2,909**	**80.56**	**35.00**	**3,918**	**371.08**	**144.39**	**7,030**	**256.97**	**125.51**

UK	**Pre-crisis**			**Crisis**			**Post-crisis**		
GICS sector[2]	**N**	**Mean**	**Median**	**N**	**Mean**	**Median**	**N**	**Mean**	**Median**
Basic Materials	44	93.84	35.00	69	570.93	179.80	128	236.42	119.10
Cons, Non-cyclical	160	36.53	34.97	144	112.02	74.65	253	79.06	68.24
Financial	147	14.55	10.44	216	268.09	153.34	420	180.01	159.15
Utilities	100	40.96	20.88	125	112.90	73.67	246	136.14	88.11
Industrial	114	73.71	38.68	96	221.29	130.83	177	121.38	106.65
Energy	10	6.93	6.35	8	45.66	45.17	14	124.69	88.71
Consumer, Cyclical	98	110.22	91.56	88	377.76	295.63	153	298.35	211.76
Communications	123	104.33	42.42	120	228.23	140.75	231	197.04	135.09
Diversified	10	24.72	23.66	16	140.76	84.02	28	65.57	62.86
Total	**806**	**60.25**	**32.72**	**882**	**240.40**	**118.17**	**1,650**	**167.02**	**118.38**

EU	**Pre-crisis**			**Crisis**			**Post-crisis**		
GICS sector	**N**	**Mean**	**Median**	**N**	**Mean**	**Median**	**N**	**Mean**	**Median**
Basic Materials	164	104.07	42.81	142	364.89	145.48	258	191.93	119.12
Cons, Non-cyclical	162	43.68	27.04	154	119.17	86.69	294	128.90	86.70
Financial	402	14.94	12.00	474	187.29	120.63	940	302.18	189.72
Utilities	177	20.85	20.50	157	86.57	63.77	274	131.64	87.16
Industrial	178	74.92	27.83	164	259.10	112.77	316	195.34	133.51
Energy	40	20.02	16.79	40	90.91	62.68	69	109.27	90.58
Technology	19	177.35	134.00	24	1,105.98	422.50	35	404.72	252.39
Consumer, Cyclical	183	86.31	56.74	164	393.93	219.49	291	378.15	223.84
Communications	207	116.92	54.00	226	437.00	164.35	373	498.87	228.75
Diversified	10	115.80	88.08	16	455.02	444.69	26	499.81	462.42
Total	**1,542**	**59.99**	**26.14**	**1,561**	**266.40**	**119.57**	**2,876**	**278.19**	**154.14**

Note: (2) No quarterly CDS spread data available for Technology GICS sector for the UK sample.

Following Gorton and Metrick (2010), the difference between LIBOR[17] and OIS[18] is used as proxy for counterparty risk. Table 2.2, provides breakdown of counterparty risk across each sub-period of analysis. Across the three markets (mean) counterparty risk increased ten folds in the crisis period and are still more than double the level in post-crisis period (compared to pre-crisis levels). Fig. 2.2 plots counterparty risk across US, UK and EU indicating despite the decline in market turmoil, there is still significant counterparty risk in all three markets. Furthermore, a strong positive correlation between spread and counterparty risk is found for all three markets.

Table 2.2: Descriptive statistics of Counterparty risk

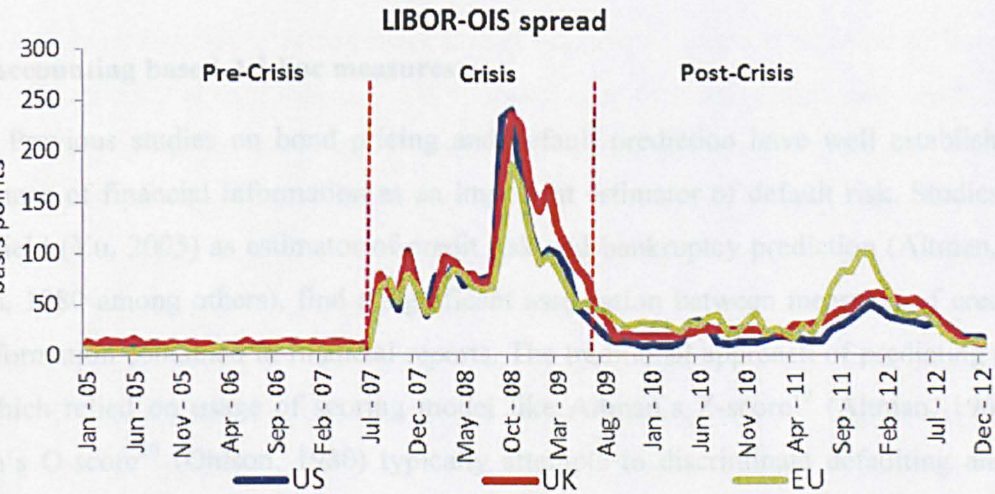
Descriptive statistics of counterparty risk in % age, defined as the difference between LIBOR and OIS starting from 1st Jan 05 till 31st Dec 12. Observations are on monthly frequency and periods as defined in Table 2.1. For US sample: Libor (BB code: US0003M Index) and OIS (BB code: USSOC Curncy), UK sample: Libor (BB code: BP0003M Index) and OIS (BB code: BPSWSC Curncy) and for EU sample: Libor (BB code: EUR003M Index) and OIS (BB code: EUSWEC Curncy)

	US			UK			EU		
	Mean	**Med.**	**Stdev**	**Mean**	**Med.**	**Stdev**	**Mean**	**Med.**	**Stdev**
				Whole period					
LIBOR	2.33	1.34	2.08	3.08	2.47	2.28	2.27	2.10	1.52
OIS	1.99	0.26	2.12	2.66	0.94	2.28	1.89	1.54	1.48
LIBOR - OIS	0.34	0.15	0.43	0.42	0.23	0.46	0.37	0.29	0.36
				Pre-crisis					
LIBOR	4.62	5.07	0.91	4.99	4.87	0.42	2.93	2.83	0.73
OIS	4.53	4.99	0.91	4.89	4.75	0.42	2.87	2.77	0.73
LIBOR - OIS	0.09	0.08	0.02	0.11	0.11	0.02	0.06	0.06	0.01
				Crisis					
LIBOR	2.93	2.80	1.58	4.71	5.81	2.00	3.83	4.64	1.44
OIS	2.03	1.99	1.71	3.70	5.03	2.23	3.05	4.01	1.47
LIBOR - OIS	0.90	0.75	0.55	1.01	0.82	0.55	0.78	0.69	0.38
				Post-crisis					
LIBOR	0.36	0.31	0.10	0.78	0.74	0.16	0.90	0.85	0.41
OIS	0.15	0.15	0.04	0.47	0.49	0.06	0.53	0.43	0.34
LIBOR - OIS	0.21	0.17	0.11	0.30	0.24	0.15	0.37	0.31	0.22

[17] Libor is the rate paid on unsecured interbank loans, cash loans where the borrower receives an agreed amount of money either at call or for a given period of time at an agreed interest rate. These loans are not traded and can be expressed as the interest rate at which banks are willing to lend to other Financial Institutions

[18] OIS is a fixed to floating interest rate swap that ties the floating leg of a contract to a daily overnight reference rate. The floating rate of the swap is a geometric average of the overnight index over every day of the payment period

Fig 2.2: Monthly counterparty risk, defined as the difference between LIBOR and OIS starting from 1st Jan 05 to 31st Dec 12. Observations are on monthly basis and periods as defined in Table 2.1.



2.3 Explanatory variables driving CDS spreads

Although there has been a number of studies using CDS spreads as measures of default risk, very little is known about what exactly drives corporate credit spreads in general (Annaert *et al.,* 2012) which necessitates the need for exploration into the determinants of CDS spreads. Since CDS spreads are considered to be pure measures of corporate default risk, the drivers of CDS spreads are bound to be similar to those that drive the credit risk of a firm. This necessitates the need to explore into various drivers of a corporate credit risk. Due to sparse research examining the drivers of corporate credit risk, this research draws from wealth of literature on credit risk modelling that studies the effect of various firm-level, market-level and macro-economic proxies that are used to infer credit risk dynamics of a firm. A bulk of these variables used to extract credit risk information can be classified into; Intrinsic - firm-level variables and Extrinsic - macro-economic variable. Few credit risk forecasting models propose the use of these variables as supplementary in understanding credit risk rather than their use in isolation. A brief review of the major category of variables used to study variations in corporate credit risk in the past literature is detailed as follows;

Firm level variables can be categorised into further two types; Accounting based ad-hoc estimators which are measures drawn from company financial statement that provide indication of firm level credit risk and Market based theoretical measures that draw from information in company financial statement along with stock trading data.

2.3.1 Accounting based Ad-hoc measures

Previous studies on bond pricing and default prediction have well established the importance of financial information as an important estimator of default risk. Studies using bond yield (Yu, 2005) as estimator of credit risk and bankruptcy prediction (Altman, 1968; Ohlson, 1980 among others), find a significant association between measures of credit risk and information contained in financial reports. The traditional approach of predicting default risk which relied on usage of scoring model like Altman's Z-score[19] (Altman, 1968) and Ohlson's O-score[20] (Ohlson, 1980) typically attempts to discriminate defaulting and non-defaulting firms using accounting information. These models use the information contained in the financial statements of the company to provide an adequate assessment of the financial distress risk and classifies a company as sound or financially distressed based on some predefined benchmarks. Apart from using default forecasting models powered by accounting variables, later studies have employed the direct use of accounting variables in estimation of CDS spread and found a significant spread predictive power of accounting variables. Studies by Callen, Livnat and Segal (2009), support this by finding a significant effect of credit relevant accounting information especially earning announcement on short-term maturity CDS prices, indicating accounting information could be employed to estimate firm's short-term credit risk. The usefulness of accounting information for credit risk estimation is further supported by Das *et al.*, (2009) who find that, accounting based information explains nearly two-third of the variation in CDS spreads and have comparable estimation power than market-based variables. Also as detailed in Batta (2011), accounting information contained in accounting reports can provide a direct effects on corporate credit risk as well as provides an indirect effect through security prices and credit rating. This is supported by Ahmed, Billing,

[19] Z-score is based on a statistical technique of Multivariate Discriminant Analysis (MDA) which has been widely adopted to identify potential insolvent companies. The solvency profile is represented as a single index score and is a linear combination of variables with an aim to provide distinction between a solvent and insolvent firm (Mason and Harris, 1979).
[20] Ohlson's O-score uses an econometric technique based on logistic transformation (Logit model) to assign a score that forecasts the probability of default for a firm (Ohlson, 1980)

Morton and Stamford-Harris (2002) who affirms the key role of accounting information in credit rating assessment process. Batta (2011) argues that the indirect role of accounting information on credit ratings implies that models which fail to account for accounting information in conjunction with credit rating miss a crucial channel for interpreting and disseminating credit relevant information derived from firm's financial reports.

Although accounting based models uses variables[21] that are believed to have some degree of financial distress prediction ability their use in estimating corporate credit risk can be challenged on various grounds; 1) There is no theoretical basis for the use of specific accounting variables in default prediction models. 2) Accounting variables are considered to be 'backward looking' as it relies on historical information rather than market's assessment of the future (Bystorm, 2006), hence the information on basis of which these models are built cast doubts on the validity and reliability front. 3) Accounting measures are updated with a rather low frequency, are released with a time lag as well as suffer from possible accounting manipulations[22] (Bystorm, 2006). 4) Accounting variables are sample-specific, as the accounting ratios and ratio weights are estimations drawn from the sample. Therefore a change in these ratios over time necessitates a re-development of the models on a periodic basis. 5) Moreover, accounting variables are prone to conservatism as they are subject to historical cost accounting, which substantially alters the book value from the true asset value and by doing so reduces its default predicting power (Agarwal and Taffler, 2008). 6) Additionally these variables are by design of limited utility in predicting defaults as accounting data are prepared on 'going-concern'[23] basis (Hillegiest, Keating, Cram and Lundstedt, 2004).

Acknowledging, there is no theoretical rationale for use of ad-hoc accounting information; these variables are found to provide good indication of the financial health of the company and hence cannot be ignored. If information from company operation and management are an indication of the company's financial strength, these measures can help understand company's credit risk dynamics and hence could prove to be an important driver of corporate credit risk and simultaneously help in understanding CDS spread behaviour.

---

[21] Z-score and O-Score is calculated using accounting variables like total assets, total liabilities, market value of equity, retained earnings, working capital etc.

[22] The most well know example is the case of Enron during the years leading up to its eventual default and chapter 11 bankruptcy filing in December 2001, where manipulated accounting information led to an incorrect estimation of Enron's credit risk

[23] The going-concern concept directs accountants to prepare financial statement with an assumption that business will remain in existence for an indefinite period.

Following Das *et al.*, (2009), this study use 10 accounting based variables to proxy for (1) firm size, (2) profitability, (3) financial liquidity, (4) trading account activity, (5) sales growth and (6) capital structure. These variables are listed below:

1. *Firm size (ln_size)*: We use the natural log value of total assets divided by the Consumer Price Index.
2. *Three ratios that gauge profitability*: They are return on assets *(ROA)*, Net income growth *(incgrowth)* and interest coverage *(c)*. ROA is calculated using net income divided by total assets. Further Net income growth is calculated as net income minus previous quarter's net income divided by total assets. Interest coverage is calculated as pre-tax income plus interest expense divided by interest expense.
3. *Financial liquidity*: The quick ratio *(quick)* and cash to asset ratio *(cash)* is used. The quick ratio is calculated as current assets minus inventories over current liabilities and the cash to asset ratio is cash and equivalents over total assets.
4. *Trading account activity (trade)*: The ratio of inventories to cost of goods sold.
5. *Quarterly sales growth (salesgrowth)*: Sales divided by the previous quarter sales minus one.
6. *Capital structure*: The ratio of total liabilities to total assets *(booklev)* and the ratio of retained earnings to total assets *(retained)*.

2.3.2 Market based measures

The literature of credit risk modelling using market based measures suggest two competing paradigms for modelling credit risk namely; the structural-form that uses option pricing theory to evaluate corporate credit risk and the reduced-form approach using term structure theory to explain credit spread behaviour. The following section provides a brief review of the two approaches for estimating corporate credit risk.

2.3.2.1 Structural approach

Structural model for credit risk also referred to as contingent claims modelling was first introduced by Merton (1974) and was later developed and extended by Leland (1994), Leland and Toft (1996), Anderson and Sundaresan (1996) among others. It is governed by 'symmetric information' assumption whereby a firm's credit risk information is considered to be consistent across different stakeholder. Thus the model hypothesizes, the firm's asset value process to be known by both firm's management and market alike and the market to have complete information of the firm's liability structure. The model assumes complete knowledge of very detailed information set, akin to that held by the firm's managers (Jarrow, 2011). Moreover, this informational assumption implies that the firm's default time can be predicted (Jarrow and Protter, 2004). Structural model uses both the market-based information and accounting-based information to calculate credit risk and default probability of a firm. Option pricing model based on the seminal work by Black and Scholes (1973) and Merton (1974) is considered to be a natural fit for the structural model as it uses both these sets of information within their model specification. Structural form treats default as an Endogenous process i.e. default risk can be explained in terms of a firm's fundamental specifically its balance sheet. The basic assumption underlying the structural model considers the company's equity as an option with a strike price equal to the book value of its liabilities and the market price equal to the market value of its assets at maturity. Thus as stated in Andreou and Ghysels (2008), the structural approach makes explicit assumptions about the dynamics of the firm's assets, capital structure, debt and share-holders and assumes default if the assets of a firm are insufficient according to some pre-defined benchmark.

Structural model presumes a 'redundancy assumption' which assumes that the default risk is principally driven by leverage and asset volatility. Hence, it assumes that, CDS trading does not affect the probability of bankruptcy or the possibility of credit downgrade. However Subrahmanyam, Tang and Wang (2014), argues that buyers of CDS contracts can potentially influence the financial decision of the reference entity and hence indirectly influence the credit risk of the claims that they issue. Their observation on the introduction of CDS in a firm increases the likelihood of both downgrade and bankruptcy is in contrast to the 'redundancy assumption' of the structural model. Moreover, due to 'symmetric assumption' in the Structural model, there is no adverse selection or moral hazard issue as both the market and management has same information regarding firm asset value process. This assumption is inconsistent with both the theory and evidence of credit market equilibrium (Jarrow, 2011; Jarrow and Protter, 2006). Also as stated in Jarrow (2011), since the firm's asset value process is neither traded nor observed, these parameters have to be tested implicitly to validate the model. Moreover the results are strongly dependent on the estimation procedure used and does not perform well in forecasting defaults (Bharath and Shumway, 2008; Patel and Pereira, 2007). Also, as stated in Tan and Yan (2010), the structural models based on seminal work of Merton (1974) ignores the interaction between credit and market risk, due to which it does not always match the level of observed credit spreads as the original model fails to capture the effect of these interactions. Consequently, the structural model is not considered as an ideal measure for inferring default probabilities for pricing, hedging or risk management (Jarrow, 2011) which led to subsequent development of the reduced form approach for credit risk modelling as detailed under.

2.3.2.2 Reduced form approach

The reduced-form approach for credit risk analysis was pioneered by Jarrow and Turnbull (1992) and subsequently studied by Jarrow and Turnbull (1995), Duffie and Singleton (1999) Duffie and Garleanu (2001), Jarrow and Yu (2001), Yu (2007), Guo, Jarrow and Zeng (2009) and Leung and Kwok (2009) among others. This flexible modelling approach considers default as a random event controlled by an exogenous intensity process and assumes that credit event occurs by surprise i.e. at a totally inaccessible time. The exogenous process is usually defined by a Poisson process and the default intensity is extracted from credit/debt market securities. The presence of default intensity implies that default time for a firm cannot be anticipated by the market as the market does not have full information similar to one that the manager of a firm possesses, but only a subset generated by default process and several other related state variable (Campi and Cetin, 2007)

As stated in Figlewski, Frydman and Liang (2012) the basic reduced form model, considers a credit event to correspond with the first jump time of a Poisson process with a constant hazard rate. Due to which unlike the structural form, credit event in reduced-form approach can be flexibly defined as default as well as upgrade / downgrade from one bond rating category to another or any well-defined change of state. Moreover, the limited information assumption underlying the reduced-form approach which considers the modeller to have the same amount of information as the market makes this approach more realistic (Jarrow and Protter, 2006). However, reduced-form modelling approach has its own set of limitations. Lack of clear economic rationale for defining the nature of default process, along with the flexibility of the model in its functional form resulting in strong in-sample fitting properties but poor out-of-sample predictive ability renders the diagnosis of model improvement a daunting task and interpretation of result a challenging exercise (Arora, Bohn and Zhu, 2005).

Structural and reduced-form approach has been extensively studied within the credit risk management literature with contrasting opinions on the effectiveness of the model in predicting a true value of the firm's default risk. Apart from the basic assumption regarding the nature of default, the other primary differences between these two approaches is the assumption relating debt and default (Hilscher, Jarrow and Van Deventer, 2008). Reduced-form approach considers default risk associated with an issuer even in the absence of debt. However in a structural model, firms with no debt are assumed as having no default risk. Although this is a major limitation of the structural models, majority of the firms listed in the stock exchange employ some or the other form of debt financing within their capital structure (which is our sample of analysis). Hence, the use of structural approach as a market-based measure in evaluating default risk can be justified. Hilscher *et al.*, (2008) also claims that reduced form approach is better than structural approach as it includes more variables and thus can never be less accurate than the structural approach, however the selection of variables in Reduced-form approach is estimated based on the relative importance in fitting historical default. It can be argued that since the choice of variables are based on historical default fitting approach; it cannot guarantee to provide a better prediction due to its dependency on backward looking approach to selection of predictor variables. On the contrary, structural model only considers variables related to firm value and volatility which are crucial in predicting default risk so could be considered a sufficient enough market-based default risk estimation measure. Apart from this, studies by Chen and Sopranzetti (2003), support the use of structural approach claiming that structural approach of credit risk modelling are mainly used for default prediction or capital structure analysis while reduced form approach are more suitable for Investment banks to price credit derivatives, this could be attributed primarily to the fundamental difference of model's reliance on equity pricing in case of structural approach and debt pricing in case of reduced form approach. Moreover, as states in Arora *et al.*, (2005), reduced form approaches are difficult to calibrate due to the differing quality of bond pricing information on the reference entity which makes it tedious to implement. All these along with the widely used nature of structural approach (distance to default) as a measure of market-based credit risk metric forms the basis of using structural approach as a market based measure of corporate credit risk.

To estimate default risk, this study employs Merton (1974) model based on the assumption that the firm has a simple capital structure comprising of just debt and equity. Merton interprets the equity of the firm as a call option on the firm's asset and debt as strike price of that call option. The starting point of the Merton model is the assumption that the total value of firm V follows a geometric Brownian motion;

$$dV = \mu_v V dt + \sigma_v dW \tag{2.1}$$

Where μ_V is the expected return on V, σ_V is the volatility of the firm value V and W is the standard Wiener process. Let X be the book value of the debt at time t, with maturity of duration T. The market value of equity E based on the Black-Scholes-Merton (BSM) model is then;

$$E = VN(d_1) - Xe^{-rt}N(d_2) \tag{2.2}$$

where,

$$d_1 = {ln\left(\frac{V}{X}\right) + \left(r + \frac{1}{2}\sigma_v^2\right)T} \Big/ {\sigma_v^2\sqrt{T}} \tag{2.3}$$

$$d_2 = d_1 - \sigma_v\sqrt{T} \tag{2.4}$$

r is risk-free interest rate and N is the cumulative density function of standard normal distribution.

This study uses "distance to default" (*DTD*) in the Merton model as a measure of credit risk. The key to estimating *DTD* is the estimation of V and σ_V in the BSM model. To estimate these two variables, this paper follows the approach as detailed in Vassalou and Xing (2004). Assuming a forecasting horizon of 1 year, i.e. (T = 1) or 250 trading days in a year, firstly σ_V and μ_V are estimated iteratively using the estimated equity volatility from the past year as a starting value. Using BSM and for each trading day, V is computed using E as the market value of equity for that day. The estimation procedure is repeated for the remaining 250 trading days in that year. The standard deviation of the return in V during that period becomes the new starting value for σ_V for the next iteration. If the difference in σ_V between two successive iterations is less that 10^{-4}, the iteration procedure is discontinued and the values are inserted in the BSM equation to obtain V. The resulting values of V, σ_V and μ_V are then used to calculate the firm-specific *DTD* over a horizon T as,

$$DTD = \frac{\ln\left(\frac{V}{X}\right) + \left(\mu_v - \frac{1}{2}\sigma_v^2\right)T}{\sigma_v^2\sqrt{T}} \tag{2.5}$$

Default occurs when the ratio of the value of assets to debt is less than one, (i.e. its log is negative). The exogenous default boundary is set as book value of short term liabilities plus one half of the long term liability and is similar to the one used by *KMV CreditMonitor*^{TM} and considered to be relatively more realistic. The *DTD* measures the number of standard deviation this ratio needs to deviate from its mean for default to occur. The probability of default is then simply *N* (*-DTD*). Average annualised equity return (*ret)* is estimated using the last 250 trading day market capitalization value of the equity, a negative relationship between equity return and CDS spreads is expected as better market performance indicates a lower credit risk. As volatility is a measure of market uncertainty, it may proxy for market strains that limits capital mobility across different market segments or the investor's risk aversion (Pan and Singleton, 2008) and thus increase in volatility should lead to an increase in credit spread. This study uses volatility *(σret)* as the annualized standard deviation estimated from prior 250 trading days daily stock price return.

2.3.3 Extrinsic Macro-economy level drivers

In theory, the risk of default for an entity is depended on the underlying entity's ability to circumvent a credit event - which is internal to the firm and the macro-economy in which it operates and its effect - which is external to the firm. Similarly as identified in credit risk literature, credit risk for a firm could be driven both by idiosyncratic factors (which are firm specific) as well as systematic factors (that affects the macro-economy as a whole). This warrants an exploration into macro-economic factors that could facilitate in explaining the evolution of credit risk over time.

Previous studies have shown that a negative effect on macro-economic variables increases the yield on corporate bond (Fama and French, 1989). Consequently, CDS spread which is considered as a proxy for credit risk, is bound to have an equivalent effect resulting from the movement in macro-economic variables. Studies by Jonsson and Fridson (1996), Chava and Jarrow (2004) and Duffie, Saita and Wang (2007) amongst others, have demonstrated a countercyclical relationship between default risk and economic activity, further supporting the importance of using macro-economic factors in explaining corporate credit risk. As detailed in Dionne, Gauthier, Hammami, Maurice and Simonato (2011) the motivation for studying macro-economic variables as drivers of credit spread behaviour stems from the strong inter-linkage between interest rates and output from firms and the macro economy. The macro-economic fundamentals are postulated to influence yield spreads and fluctuate over the business cycle which rationalises their fundamental role in explaining spread behaviour through time.

Pesaran, Schuermann, Treutler and Weiner (2006) used a Merton type credit risk model and studied both domestics and foreign macro-economic variables to understand the impact of global macro-economic variables on 10 major global economies in the default prediction models. The variables used in the model namely; GDP, Inflation, equity prices, real exchange rates, short term interest rates, real money balances and oil price were proxies used for estimate the state of the economy. Although, this study notes that the macro-economic variables are highly correlated, causing the results to be influenced by multi collinearity within the model estimates. Nonetheless, evidence point towards an asymmetric and a non-proportional impact of macro-economic shocks on credit risk. This implies that during periods of financial distress particularly shocks in the macro-economy certain macro-economic variables could have a variable impact on CDS spreads. Macro-economic variables used in the model could be estimated for the country or wider on a global perspective providing indication of the health of the local and global economies accordingly. Later studies by Albertus, Van Eyden and Gupta (2009) uses additional proxies for macro-economic condition of the economy to include country specific variables like Household debt to income ratio and House price index in the context of evaluating the South African economy. Although, recognising the fact that, these credit-market related variables may serve as an overlapping proxy for the macro-economic condition, the study rationalises that the extent of variables ensures the coverage of all possible proxies for specific local, national and international economic activity. Similarly, studies by Svec and Maurice (2010) employed the use of domestic corporate funding cost (three month and six month bank bill rate used as a measure of short term funding cost), domestic and international equity index returns and index volatility to measure the impact of market and economy wide variables on CDS spreads. Their study find strong evidence of movement in Australian investment grade CDS spreads as driven mostly by International equity return and volatility. Their study provides indication of the effect of the global economy on local corporate credit risk highlighting the dependence of economies across the financial arena.

Although a majority of studies have argued for a significant effect of macro-economic variables on credit risk, some research on credit risk modelling using macro-economic variables have rendered dissimilar results. The relationship between default risk and macro-economic variables are at times found to be highly dependent on the macro economic variables explored in the model, how the variables were entered in the specification (as contemporaneous, time lagged or averaged over time), other variables used in the specification and time period used for analysing the effect (Figlewski *et al.*, 2012). Moreover, certain macro-economic variable tend to have a lagging effect and at times have to be de-trended to analyse the influence of these variables across CDS spreads. Given the well noted limitations of macro-economic variables, the substantial effect of the economy on firm stability and hence its credit risk management ability could not be ignored. This warrants a closer examination of corporate credit risk in light of the macro-economic environment in which the firm is operating to deduce a comprehensive view of factors influencing corporate credit risk.

This study include a variety of macroeconomic variables that are firm invariant but time variant in our model and act as a time dummies accounting for time clustering in our dataset. For the risk-free rate, 3-month US-Libor for US, 3-month UK-Libor for UK and 3 month Euribor for EU are used[24]. As periods of low interest rates are normally associated to period of economic downturn, we expect a negative relationship between the risk-free rate (*r*) and CDS spreads. We include the prior year i.e. 12 months stock index (*index*) return namely; S&P500 index for the US, FTSE100 index for UK, and EUROSTOXX 50 Index for EU. The prior year return on the respective index GICS sector (*rgics*) provides sector return. As periods of low market/sector returns are normally related to period of economic downturn, we expect a negative relationship between the index/sector return and spread. Alternatively, improvement in the business environment should lessen firm's chances of default and thus increase their default recovery rates. Duffie (1998), Collin-Dufresne, Goldstein and Spencer-Martin (2001) and Bharath and Shumway (2008) find a similar negative relationship between changes in interest rates and firm default risk. Thus following Collin- Dufresne *et al.*, (2001), Ericsson, Jacobs and Ovieda (2009) among others, we use the market wide stock index as measure of the business environment, GICS return as measure of sector performance and risk-free rate as measure of economic activity. All these variables act as time dummies and are firm invariant for the dataset.

[24] This study acknowledges that these risk free rate proxies rose sharply is the crisis period, partly due to lack of liquidity in the market. However, these also represent the best available proxy for risk free rate in the context of our study.

2.4 Empirical Results

2.4.1 Descriptive Statistics

Table 2.3, presents summary statistics of the predictor variables used in this study for the US (Panel A), UK (Panel B) and EU (Panel C) market. In general the calculated average value of the explanatory variables used is much smaller than their corresponding standard deviation. The Skewness-Kurtosis Test reported in Prob>Chi[25] column of Table 2.3, rejects normality in all cases due to high kurtosis and skewness values in all three sample sets. The fact that the variables change over time leads to high kurtosis coefficient which in turn leads to rejection of normality across all three sub-periods.

Table 2.3: Descriptive statistics of explanatory variables

'Size' is the log of value of total assets divided by the consumer price index (CPI) with 2005 as the base, *'ROA'* is the net income divided by total assets, *'incgrowth'* is the net income minus the previous quarter's net income dived by total assets, *'c'* is calculated as pre-tax income plus interest expense divided by interest expense, *'quick'* is current assets minus inventories over current liabilities, *'cash'* is cash and equivalents over total assets, *'trade'* is inventories to cost of goods sold ratio, *'salesgrowth'* is sale growth estimated as Sales divided by the previous quarter sales minus one, *'booklev'* is total liabilities to total assets, *'retained'* is retained earnings to total assets, *'ret'* is annualised prior 250-trading day equity return, *'σret'* is annualised prior 250-trading day equity volatility, *'DTD'* is distance to default (bounded between +20 and -20), *'r'* is the 3 month interbank offer rate taken from Bloomberg, *'index'* is prior year return in the S&P500 index for the US, FTSE100 index for the UK and EUROSTOXX 50 index for EU, *'rgics'* is prior-year GICS industry return for the respective indexes, *'Cpn'* is coupon on corporate bond in percentage terms, *'Pri_amt'* is principal amount outstanding in billions of USD, GBP and EUR for US, UK and EU respectively, *'Age_Y'* is age of bonds in years, *'Mat_Y'* is time to maturity of bonds in years, *'IQR'* is the interquartile range and is a proxy for the bid-ask spread. *'abs_bidask'* is difference between bid and ask quotes and *'pro_bidask'* is estimated as the ratio of the spread between bid and ask quotes and average of bid and ask quotes. The data covers a period from 1st Jan 2005 to 31st Dec 2012.

[25] The result where "." is reported is interpreted as an absurdly large number indicating the variables are most certainly not normal.

Panel A - US				Descriptive Statistics				
Variables	Mean	Median	Min.	Max.	Std. Dev.	Skew.	Kurt.	Prob>chi
ln_size	5.202	5.095	-0.002	10.062	1.415	0.802	3.995	0.00
ROA	0.013	0.014	-8.941	0.984	0.087	-85.820	8,840.729	.
incgrowth	-0.001	0.000	-8.454	0.981	0.086	-75.848	7,467.961	.
C	-145.741	3.992	$-18*10^{-5}$	10,799.0	16,952.3	-109.11	11,906.83	.
quick	0.922	0.780	0.018	8.781	0.661	3.105	20.500	.
cash	0.064	0.042	0.000	0.668	0.066	2.065	9.564	.
trade	1.403	0.693	0.020	160.630	5.933	15.455	293.817	.
salesgrowth	9.716	4.017	-98.812	8,500.561	141.956	51.656	3,021.159	.
booklev	0.678	0.661	0.062	6.159	0.216	5.942	134.960	.
retained	0.073	0.099	-51.118	0.721	0.566	-58.719	5,193.152	.
ret	0.915	0.091	-1.000	1,312.857	18.696	60.391	4,044.626	.
σret	0.317	0.253	0.001	3.707	0.227	3.214	20.706	.
DTD	9.800	9.242	-20.000	20.000	6.462	-0.189	3.181	0.00
R	0.019	0.006	0.002	0.055	0.020	0.717	1.815	.
index	0.033	0.066	-0.397	0.466	0.196	-0.460	3.240	0.00
rgics	0.023	0.038	-0.340	0.416	0.124	-0.330	3.895	0.00
Cpn	4.907	4.950	0.420	16.750	1.835	0.253	4.431	.
Pri_Amt	$76.2x10^{6}$	$27.4x10^{6}$	30,000	$16x10^{10}$	$44.4x10^{7}$	22	627	.
Age	5.590	4.839	0.000	26.958	4.049	1.160	4.619	.
Mat_Y	5.066	4.625	0.003	30.375	3.444	1.242	6.931	.
IQR	0.926	0.513	0.000	41.393	1.394	6.289	84.115	.
abs_bidask	15.091	7.500	-1,452.99	682.513	33.089	0.219	368.184	.
pro_bidask	0.093	0.076	-0.354	0.720	0.063	2.463	12.297	.

Panel B - UK	Mean	Median	Min.	Max.	Std. Dev.	Skew.	Kurt.	Prob>Chi
ln_size	5.136	4.937	1.376	9.993	1.799	0.652	2.943	0.00
ROA	0.022	0.017	-0.369	0.942	0.073	5.868	80.315	.
incgrowth	0.002	0.000	-0.610	0.939	0.062	2.076	58.688	0.00
c	5.687	3.725	-107.191	278.667	11.962	10.550	225.115	.
quick	0.445	0.395	0.000	7.565	0.507	4.829	51.825	.
cash	0.065	0.048	-0.057	0.535	0.062	2.122	10.098	0.00
trade	0.626	0.359	0.003	4.659	0.761	2.040	7.565	0.00
salesgrowth	6.206	0.000	-91.804	539.758	33.050	8.041	99.040	.
booklev	0.747	0.740	0.236	1.875	0.217	0.745	5.917	0.00
retained	0.092	0.109	-3.706	0.962	0.326	-4.475	39.012	.
ret	0.555	0.139	-0.998	278.734	5.771	40.383	1,883.251	.
σret	0.276	0.229	0.026	1.339	0.159	2.440	11.765	.
DTD	10.216	10.798	-20.000	20.000	7.158	-0.777	4.391	0.00
r	0.028	0.012	0.005	0.063	0.023	0.398	1.347	.
index	0.035	0.058	-0.313	0.447	0.171	-0.288	3.148	0.00
rgics	0.024	0.031	-0.341	0.363	0.107	-0.125	3.772	0.00
Cpn	3.693	3.375	0.250	20.000	1.912	1.571	9.749	.
Pri_Amt	41.2×10^7	18.5×10^5	35,000	65.8×10^7	78×10^7	3.008	15.205	.
Age	6.494	6.392	0.003	29.958	3.027	0.599	5.297	.
Mat_Y	3.899	2.358	0.000	24.550	3.989	1.550	5.294	.
IQR	0.934	0.443	0.000	4941.154	32.533	151.698	23,036.48	.
abs_bidask	11.517	7.012	0.000	242.119	13.881	5.761	64.343	.
pro_bidask	0.104	0.079	0.000	0.827	0.081	3.090	15.372	.

Panel C - EU	Mean	Median	Min.	Max.	Std. Dev.	Skew.	Kurt.	Prob>Chi
ln_size	5.852	5.722	2.589	9.810	1.512	0.442	2.767	0.00
ROA	0.008	0.006	-1.180	0.489	0.044	-13.436	431.874	.
incgrowth	0.000	0.000	-1.307	1.662	0.045	5.977	649.823	.
c	6.875	3.981	-137.368	1,631.00	41.539	34.802	1,352.294	.
quick	0.658	0.620	0.004	15.214	0.523	12.518	308.721	.
cash	0.051	0.038	0.001	0.385	0.046	1.909	8.710	.
trade	0.753	0.606	0.001	3.728	0.659	1.637	5.525	0.00
salesgrowth	8.030	4.526	-97.993	1,843.75	50.682	17.657	507.636	.
booklev	0.765	0.763	0.034	1.908	0.177	0.699	6.791	0.00
retained	0.110	0.088	-1.473	0.800	0.193	-1.508	11.410	.
ret	55.432	-0.005	-1.000	151,268.7	2,773.637	54.146	2,950.750	.
σret	0.347	0.292	0.053	2.904	0.202	3.105	21.622	.
DTD	7.016	6.817	-20.000	20.000	8.441	-0.787	4.431	0.00
r	0.022	0.015	0.002	0.050	0.015	0.593	1.942	.
index	-0.007	0.032	-0.268	0.179	0.106	-0.764	2.976	0.00
rgics	-0.004	0.007	-0.394	0.287	0.127	-0.584	3.883	0.00
Cpn	4.053	4.000	0.100	20.000	1.620	1.724	12.589	.
Pri_Amt	$37.9\text{x}10^6$	$10.4\text{x}10^6$	5,000	$50\text{x}10^8$	$57.8\text{x}10^6$	2.712	13.334	.
Age	3.523	2.783	0.000	19.639	2.840	1.105	3.994	.
Mat_Y	5.424	5.228	0.000	15.875	2.580	0.318	2.671	.
IQR	0.659	0.406	0.005	60.102	0.943	10.584	343.504	.
abs_bidask	14.042	7.447	-467.500	1,483.097	31.517	21.997	911.525	.
pro_bidask	0.051	0.037	-0.256	0.533	0.041	2.887	16.221	.

2.4.2 Regression Analysis

This study follow Aunon-Nerin *et al.*, (2002) who find the use of logarithm of spreads provide a better fit than their direct use in regression. Further the study follows Das *et al.*, (2009), who find the inclusion of accounting variables improves the overall fit of the model. Thus for each firm *i* and quarter *t*, the following panel data fixed-effect regression function is estimated, where:

$$\begin{aligned} ln(CS_{it}) = \alpha_i + \beta_{1i}size_{it} + \beta_{2i}ROA_{it} + \beta_{3i}incgrowth_{it} + \beta_{4i}c_{it} + \beta_{5i}quick_{it} + \beta_{6i}cash_{it} \\ + \beta_{7i}trade_{it} + \beta_{8i}salesgrowth_{it} + \beta_{9i}booklev_{it} + \beta_{10i}retained_{it} + \beta_{11i}DTD_{it} \\ + \beta_{12i}ret_{it} + \beta_{13i}\sigma ret_{it} + \beta_{14i}r_t + \beta_{15i}Index_t^{-1yr} + \beta_{16i}rgics_t + \varepsilon_{it} \qquad (2.6) \end{aligned}$$

The model assumes correlation (clustering) over time for a given firm, with independence over firms. Fixed-effect panel data regression is used due to the following reasons. Firstly, the OLS pooled regression model is too restrictive as it considers the coefficients to be constant across each firm in the sample and thus does not explain the full richness of the panel dataset. Moreover, as the true model of the dataset is fixed-effect, the pooled OLS regression is bound to provide inconsistent estimate[26]. Secondly, the study assumes the individual-specific effect i.e. unobserved heterogeneity αi in the model are correlated with the regressors[27], which further substantiates the choice of using fixed-effect regression. Finally, the model consists of regressors that are both firm and time variant and well as those that are time-variant but firm-invariant and act as time dummies in the model. Fixed-effect regression is better equipped to handle both types of regressors in one single regression model. A test on stationarity of the independent variables in the regression model is undertaken using the fisher-type[28] unit root test statistics. The results reported in Table 2.5 indicate absence of non-stationarity as most series across the sub-periods display stationarity behaviour.

---

26 This is tested using the Breusch-Pagan Langrage multiplier test (Table 2.4 – Panel A) and found to be significant at 95% level and thus does not support the use of pooled OLS regression.

27 This is tested with the random-effect model using the Hausman statistics (Table 2.4 – Panel B). We find that the Hausman test is significant at 95% level

28 Among all the unit root test available in Stata only the Fisher-type tests can be applied on the regression model used in this study. The choice of Fisher-type test is based on the unbalanced nature of the panel which other unit root test statistics like Levin–Lin–Chu, Harris–Tzavalis test, Breitung test, Im–Pesaran–Shin test and Hadri Lagrange multiplier stationarity test cannot address.

Table 2.4: Breusch-Pagan Langrage multiplier test and Hausman test statistics

Panel A - The Breusch Pagan Lagrange Multiplier test

Prob > Chi	**US**	**UK**	**EU**
Whole Period	0.00	0.00	0.00
Pre-Crisis Period	0.00	0.00	0.00
Crisis Period	0.00	0.00	0.00
Post-Crisis Period	0.00	0.00	0.00

The Breusch Pagan Lagrange Multiplier test helps in deciding between the random effect regression and the simple OLS regression. The null hypothesis in the LM test is that the variance across firms is zero. There is no significant difference across firms (i.e. there is no panel effect). If the value Prob>Chi is less than critical value 0.05, we reject the null hypothesis and conclude that the panel effect is present and the use of OLS regression would lead to incorrect estimates.

Panel B - Hausman Test Statistics

Prob > Chi	**US**	**UK**	**EU**
Whole Period	0.00	0.00	0.04
Pre-Crisis Period	NA	0.00	0.02
Crisis Period	0.00	0.78	0.03
Post-Crisis Period	NA	0.00	0.25

The Hausman tests helps in deciding between the fixed effect and random effect regressions. The null hypothesis is the preferred model is the random effect vs. the alternative the fixed effect. The Hausman statistics tests if the unique errors are correlated with the regressors, the null hypothesis being they are not correlated with the regressors. If the value for Prob>Chi is less than the critical value 0.05, the fixed effect is the preferred model for evaluating the panel data regression function. NA indicates the model fitted on these data fails to meet the asymptotic assumptions of the Hausman test. Note: The Hausman test is significant for the whole period across all the three samples. However is EU sample the Hausman test statistics is not significant across some individual sub-period. We however proceed with the fixed effect regression across all samples and sub-periods for reasons stated earlier.

Table 2.5: Test for stationarity of explanatory variables.

Table shows the p-value for the inverse chi - square statistics which requires panels to be finite in order to undertake the unit root test for stationarity. The test specifications are based on Augmented Dickey Fuller (ADF) test with 0 lags and including panel means and time trend wherever applicable. "-" denotes insufficient observations to carry out unit-root test as per the specifications provided. H0: All panels contain unit roots, Ha: At least one panel is stationary.

p-value for inverse	US			UK			EU		
chi-square test	Pre-Crisis	Crisis	Post-Crisis	Pre-Crisis	Crisis	Post-Crisis	Pre-Crisis	Crisis	Post-Crisis
ln_size	0.00	0.00	0.00	-	0.00	0.00	0.00	-	0.00
ROA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-	0.00
incgrowth	0.00	0.00	0.00	-	-	-	-	-	-
c	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
quick	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
cash	0.00	0.00	0.00	-	0.00	0.00	0.00	-	0.00
trade	0.00	0.00	0.00	-	0.00	0.00	0.00	0.00	0.00
salesgrowth	0.00	0.00	0.00	-	0.00	0.00	0.00	0.00	0.00
booklev	0.00	0.00	0.00	-	0.00	0.00	0.00	-	0.00
retained	0.00	0.00	0.00	-	0.00	0.00	0.00	-	0.00
ret	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
σret	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00
DTD	0.00	0.00	0.00	0.03	0.00	0.00	0.00	-	0.00
r	0.00	0.00	0.00	1.00	1.00	0.00	0.00	1.00	1.00
index	0.00	0.00	0.00	0.01	0.02	0.00	0.00	0.00	0.00
rgics	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 2.6: Fixed effect panel data regression

Panel data fixed effect regression (with robust standard errors) of the log of CDS spreads to accounting and market-based variables. The sample is based on CDS spreads from Q1 2005 to Q4 2012 on a quarterly basis. (R^2 reported is the fixed effect within regression values)

	US				UK				EU			
Variables	**Whole Period**	**Pre-Crisis**	**Crisis**	**Post-Crisis**	**Whole Period**	**Pre-Crisis**	**Crisis**	**Post-Crisis**	**Whole Period**	**Pre-Crisis**	**Crisis**	**Post-Crisis**
Intercept	4.532***	3.374***	4.728***	4.237***	1.318	4.997***	-0.453	2.094	3.318***	5.058***	5.468**	6.662***
ln_size	-0.065	0.018	-0.057	-0.082	0.336	-0.455	0.885*	0.272	0.204	0.217	-0.119	-0.649
ROA	-2.05***	-2.079**	-0.928**	-2.48***	0.377	-0.073	-2.041	-0.851	-2.062	-0.07	-0.212	-5.197
incgrowth	1.218***	1.149**	0.662***	0.849**	-0.068	0.556	1.015	0.997	0.712	-0.487*	0.011	2.5
c	0.001***	-0.001	-0.001	0.001***	-0.01***	-0.002	0.007	-0.01***	-0.005	0.004	-0.001	-0.003
quick	-0.03	-0.104	-0.15***	0.095**	0.035	-0.096	0.218*	0.149*	0.057	0.063	-0.093	0.007
cash	0.259	0.623	0.437	-1.25***	0.325	-0.304	-2.77**	0.384	-1.757**	-1.153	-0.675	0.558
trade	0.008**	-0.012	0.003	0.006	-0.187	0.42	-1.09***	-0.131	0.111	-0.11***	0.137	0.037
salesgrowth	-0.001	-0.001	-0.001	-0.001	0.001	0.002	-0.003	0.003	-0.001	-0.003***	-0.002	-0.001
booklev	1.085***	1.078***	0.385	1.254***	2.817***	2.161**	1.48	0.447	-0.051	-2.592*	-0.942	1.687
retained	0.327*	-0.495**	0.222	0.098	0.982	1.215	0.388	0.531	-0.44	-0.131	-0.067	-0.49
ret	-0.002	-0.002	-0.005	-0.002***	0.021	0.245	0.066***	-0.009	0.001	-0.012	0.073	-0.003**
σret	0.99***	1.68***	0.778***	0.655***	0.351	-0.486	1.033*	1.794***	2.37***	0.684	2.149***	2.401***
DTD	-0.03***	-0.01***	-0.02***	-0.01***	-0.025**	-0.038	-0.053**	0.013*	-0.03***	0.015	-0.03	-0.012*
r	-15.9***	-5.42***	-7.79***	48.7***	-13.5***	-14.299	1.767	28.059**	-10.9***	-29.0***	-3.066	-3.584
index	-0.141*	-1.37***	-1.21***	0.027	-0.69***	0.345	-0.384	-0.38***	-1.68***	0.008	-1.91***	-1.556**
rgics	-0.97***	0.198	-0.69***	-0.71***	-0.89***	-0.034	-0.125	-0.84***	-0.169	-0.297	0.199	-0.25
N	6,393	1,256	1,778	3,359	578	129	146	303	590	135	211	244
R^2	62.07%	25.11%	75.13%	27.77%	57.07%	27.24%	65.59%	37.19%	64.07%	52.26%	66.66%	44.00%
Adj. R^2	61.97%	24.14%	74.90%	27.42%	55.85%	16.85%	61.32%	33.68%	63.07%	45.79%	63.91%	40.05%

Table 2.6 provides the regression output for US, UK and EU over whole and sub-periods of analysis. Due to missing firm-level data, the number of quarterly observation drops substantially across the three markets[29]. However across the three samples and for each sub-period there are enough quarterly observations to draw consistent estimates[30]. Across the three samples, size of firm *(ln_size)* does not have a bearing on the CDS spreads except for a weak relation (at 10% level) for UK in crisis period. For US, there is a statistically significant negative relationship between spread and ROA. Firm with higher profitability have more cash and cash surplus to absorb shocks in its business operations and are better immune against unexpected financial shocks. This implies firms with higher ROE would have lower probability of default and hence a negative relationship between ROE and CDS spreads is expected. The results indicate it is true across all sub-periods. However, in case of UK and EU, for all sub-periods this relationship is negative but not significant. Net Income growth provides an indication of the rate of growth of the firms. Firms with net income growing at a faster rate would ideally indicate a better revenue model and/or business opportunity and hence should be in a better position to counter default related risk. Accordingly a negative relationship between net income growth and CDS spreads is expected. However, contrary to expectation, the net income growth *(incgrowth)* is positive and significant across all sub-periods for US indicating faster growing firms have more credit risk. The positive relationship may be as a result of firms' growing at a faster rate due to reasons not associated with better business opportunity or revenue model and maybe pointing towards a highly leveraged firm. However, this relationship does not hold and is not significant for UK and EU. Firms that are better able to manage their debt/interest obligations tend to be more immune to credit risk and so a negative relationship between interest coverage ratio and CDS spreads is expected. Similar to Das *et al.*, (2009), we find a significant negative relationship between interest coverage ratio *(c)* and spreads for the whole period and post-crisis period for UK, but this relationship is not significant for EU, while it is positive and significant in the whole period and post-crisis period for the US sample. Das *et al.*, (2009), takes the trailing four quarter average of interest coverage ratio in their model to account for seasonality. The differences in our result could be attributed to the way in which we assimilate interest coverage ratio directly in our model rather than transforming them as specified in Blume *et*

[29] Some ratios specifically Trading account activity and Sale growth are not specifically relevant to firms in the banking sector and this leads to a loss of observations for firms in the financial sector

[30] Kahle and Stulz (2013) provide an alternative definition of periods breaking down the crisis period into first year (Q3 2007 – Q2 2008), post Lehman (Q3 2008 – Q1 2009) and last year (Q2 2009 – Q1 2010). However breaking down our sample into further divisions would leads to lower observations per period of analysis due to the quarterly nature of our dataset

al. (1998). Variables measuring financial liquidity (quick ratio and cash to asset ratio) provide an indication of the level of liquid asset the firm has to meet any short term liquidity shocks. Accordingly firms with higher financial leverage would be in a better position to handle credit risk shocks and we expect a negative relationship between CDS spreads financial liquidity variables. Similar to Das *et al.*, (2009), we find the quick ratio *(quick)* is positive and significant in post-crisis period for US and for crisis and post-crisis period for UK. However, this relationship is not significant for EU while it turns negative and significant for the crisis period in US. Cash to asset ratio *(cash)* is negative and significant as expected but only for post crisis period in US, crisis period in UK and whole period in EU. Corporates with significant amount of debt on its balance sheet are considered to be highly leveraged. Higher leverage hinders firms' stability as interest payments have to be made to debt holders before any profit can be realised by the firm. The unstable nature of business and hence revenue combined with the requirement to pay interest on debt periodically makes a firm susceptible to fluctuations in revenue due to changes in business operations. Thus higher leverage is associated with higher expected default risk and we expect a positive relationship between leverage and CDS spreads. We find the book value of leverage *(booklev)* to be positive and significant for whole period across both US and UK indicating leverage increases firm's credit risk. However, this relationship becomes insignificant for all other periods across the samples. For the remaining accounting variables the results are mixed with the significance of each parameter changing for each sub-period and across the three markets.

With regard to market-based variables, the volatility of the underlying asset reflects the uncertainty of the firms' security value, thus higher equity volatility indicates higher default risk and we expect a positive relationship between equity volatility and CDS spreads. A significant positive relationship can be found between the spread and volatility of returns *(σret)* as expected for US. For UK and EU, we find a similar relationship indicating higher volatility drives up credit risk but the results are not significant for pre-crisis period. Higher equity returns provides indication of market expectation of firm assets and greater demand for firm stocks is driven by positive market expectation in terms of both risk and returns. We expect a positive relationship between annualised equity return and CDS spreads. Annualised equity return *(ret)* for the post-crisis period is negative and significant for US and EU as expected. However it turns positive and significant for the UK sample during the crisis period and non-significant for other sub periods. Turning now to distance to default *(DTD)* coefficient for US, DTD indicate the number of standard deviation the firm is away from theoretical default and as expected. We find a significant negative relationship for whole period and each sub-period. However, this relationship is not significant during the pre-crisis period for UK and pre-crisis and crisis period for EU. We note that, most market-based variables are significant across all periods (with some exceptions) in US, whereas all market-based variables become significant during the crisis period for UK and during post-crisis period for EU. The overall R^2 for the model varies across each sub-period and is characterised by low R^2 during pre-crisis period, higher R^2 during crisis period and reduction in model's explanatory power in post-crisis period. This indicates that accounting and market-based variables are more significant predictors of spreads during crisis period than at other times. Overall, spread explanatory power of the predictor variables in our model changes significantly based on the period of analysis. The model has a good overall fit with closer R^2 and *Adj.* R^2 values across each sub-period of analysis. We also undertake a multi-collinearity diagnostic test (Table 2.7) and the results indicate absence of biasness resulting from multi-collinearity effect. The observations across the period of analysis and the three samples analysed in effect contradicts to that of Das *et al.*, (2009). We find that majority of the accounting variables are not consistently significant predictors of CDS spreads and their significance and sign changes based on the period and the sample of analysis.

Das *et al.*, (2009) further claims that accounting variables are better predictors of CDS spreads than market based variables. This paper investigates if this is true across the periods and for the three samples of analysis and tests if the effect of adding each block of predictor variables i.e. accounting and market-based variables are consistent over each sub-periods. A hierarchical fixed-effect regression is run using block of predictor variables across each sub-period of analysis. Table 2.8 provides the result for the model *Adj.* R^2 firstly, by using only accounting variables and then by adding market-based variables to obtain the change in model's explanatory power across each sub-period. The model *Adj.* R^2 and change in *Adj.* R^2 for US, UK and EU sample is reported in Panel A, Panel B and Panel C respectively. Across US and UK markets there is a substantial increase in model's explanatory power when the market-based variables are included (Block 1) in the post-crisis period. The effect size[31] estimates the magnitude of difference between the *Adj.* R^2 values and we find the effect of adding market-based variables is mostly small (< 0.1) for pre-crisis and post-crisis whereas the effect is medium in crisis period for US (0.14) and UK (0.17) samples. For EU, the

[31] Effect size of less than 0.1 indicates a small effect, effect size between 0.1 and 0.3 indicates a medium effect and effect size larger than 0.3 indicates a large effect (Cohen, 1988)

increase in model's *Adj.* R^2 over and above the accounting variables indicates a large effect size for the whole period, small effect size in the pre-crisis and crisis and large effect size in the post-crisis period. This confirms that market-based variables have significant explanatory power in determining spreads across each sub-period of analysis although their incremental explanatory power is different across each sub-period and sample.

Table 2.7: Test for multi-collinearity among predictor variables

	US		UK		EU	
Variables	**VIF**	**Tolerance**	**VIF**	**Tolerance**	**VIF**	**Tolerance**
ln_size	1.14	0.88	1.51	0.66	1.41	0.71
ROA	2.05	0.49	2.04	0.49	2.45	0.41
incgrowth	1.79	0.56	1.71	0.58	1.99	0.50
c	1.00	1.00	1.39	0.72	1.40	0.72
quick	1.66	0.60	1.42	0.71	1.44	0.70
cash	1.52	0.66	1.53	0.66	1.43	0.70
trade	1.01	0.99	1.20	0.83	1.25	0.80
salesgrowth	1.05	0.95	1.14	0.88	1.14	0.88
booklev	1.65	0.61	1.49	0.67	1.59	0.63
retained	1.44	0.69	1.41	0.71	1.87	0.54
ret	1.12	0.89	1.71	0.59	1.27	0.79
σret	2.33	0.43	2.45	0.41	2.06	0.49
DTD	1.83	0.55	3.13	0.32	2.19	0.46
r	1.15	0.87	1.14	0.88	1.19	0.84
index	1.83	0.55	1.91	0.52	3.57	0.28
rgics	1.16	0.86	1.42	0.70	3.54	0.28
Mean VIF	**1.48**		**1.66**		**1.86**	

The collinearity among predictor variables are tested across the whole period and for the three sub - samples of analysis namely; US, UK and EU. The VIF (Variance Inflated Factor) score across each set of predictor variables (including the mean VIF) is less than the standard rule of thumb (less than 10). Tolerance defined as 1/VIF checks the degree of multi-collinearity and is higher than the threshold 0.1. The results indicate that across the three samples, absence of multi-collinearity effect and hence the estimates of the coefficient are stable for the analysis undertaken.

Table 2.8: Hierarchical fixed effect regression

Hierarchical fixed effect (within) regression (with robust standard errors) using block of predictor variables in the regression model. The accounting variables (AC) block consists of a set of 10 predictor variables (*size, ROA, incgrowth, c, quick, cash, trade, salesgrowth, booklev, retained*). Market-based variables (MB) block consist of 3 predictor variables (*ret, σret, DTD*). Variables (*r, index, rgics*) act as a time-dummy variables accounting for the time clustering in our datasets. The values for time dummy variables are same across all firms in the same period in the regression model. Change represents the change in *Adj.* R^2 value by adding a block of predictor variables in the regression model.

Panel A	**US**							
	Whole period		**Pre-crisis**		**Crisis**		**Post-crisis**	
Block 1	**Adj. R²**	**Change**	**Adj. R²**	**Change**	**Adj. R²**	**Change**	**Adj. R²**	**Change**
AC	54.98%	-	17.84%	-	71.36%	-	21.78%	-
AC + MB	61.97%	6.99%	24.14%	6.30%	74.90%	3.54%	27.43%	5.66%
Effect size	0.18		0.08		0.14		0.08	
Block 2	**Adj. R²**	**Change**	**Adj. R²**	**Change**	**Adj. R²**	**Change**	**Adj. R²**	**Change**
MB	61.42%	-	21.48%	-	69.31%	-	23.28%	-
MB + AC	61.97%	0.55%	24.14%	2.66%	74.90%	5.60%	27.42%	4.15%
Effect size	0.01		0.04		0.22		0.06	

Panel B	**UK**							
	Whole period		**Pre-crisis**		**Crisis**		**Post-crisis**	
Block 1	**Adj. R²**	**Change**	**Adj. R²**	**Change**	**Adj. R²**	**Change**	**Adj. R²**	**Change**
AC	53.61%	-	12.92%	-	54.61%	-	27.25%	-
AC + MB	55.85%	2.24%	16.85%	3.93%	61.32%	6.71%	33.68%	6.43%
Effect size	0.05		0.05		0.17		0.10	
Block 2	**Adj. R²**	**Change**	**Adj. R²**	**Change**	**Adj. R²**	**Change**	**Adj. R²**	**Change**
MB	57.83%	-	15.90%	-	66.20%	-	27.26%	-
MB + AC	55.85%	-1.98%	16.85%	0.94%	61.32%	-4.88%	33.68%	6.41%
Effect size	-0.04		0.01		-0.13		0.10	

Panel C	EU							
	Whole period		Pre-crisis		Crisis		Post-crisis	
Block 1	**Adj. R^2**	**Change**	**Adj. R^2**	**Change**	**Adj. R^2**	**Change**	**Adj. R^2**	**Change**
AC	40.33%	-	44.31%	-	63.10%	-	15.87%	-
AC + MB	63.07%	22.74%	45.79%	1.48%	63.91%	0.81%	40.05%	24.18%
Effect size	0.62		0.03		0.02		0.40	
Block 2	**Adj. R^2**	**Change**	**Adj. R^2**	**Change**	**Adj. R^2**	**Change**	**Adj. R^2**	**Change**
MB	65.90%	-	36.83%	-	58.31%	-	49.54%	-
MB + AC	63.07%	-2.84%	45.79%	8.96%	63.91%	5.60%	40.05%	-9.49%
Effect size	-0.08		0.17		0.16		-0.16	

Considering the estimates could be biased on the order of entering the block of explanatory variables used to explain spreads. The regression model is re-rum, this time by entering market-based variables first and estimating model's *Adj.* R^2 and then adding the accounting variables to re-estimate models *Adj.* R^2 and change in *Adj.* R^2 value (Block 2). The observations indicate that adding accounting variables increases noise reducing model's explanatory power. However, it is important to note that these changes in *Adj.* R^2 value are very small. For US, we find that adding accounting variables increases the model's *Adj.* R^2 (small effect size) across each sub-period. Moreover, there is increment in model's *Adj.* R^2 for pre-crisis and post-crisis period for UK and in pre-crisis and crisis period for EU. This indicates accounting variables may have some incremental explanatory power although not as much as the market-based variables. Based on these observations, it can be concluded that, although market-based variables provide a better explanation of the variance in spreads, the use of accounting variables further enhances model's explanatory power. However, combination of both type of variables perform better than each of them individually. Moreover, even by adding both set of predictor variables along with macroeconomic indicators there is still a substantial portion of spreads that cannot be accounted for especially in the post-crisis period for all the three markets.

2.4.3 Default and Non-default components

For firms analysed in the previous section, monthly corporate bond yield spread is estimated based on bracketing procedure as detailed in Longstaff *et al.*, (2005). This study uses SEC registered, fixed rate, senior, unsecured bonds with no embedded options and with maturity bracketing the horizon of CDS spread observations in our dataset. Moreover, each firm needs to have at least two bonds to be included in the bracketing set. Monthly bond yields are estimated for 294 firms in US, 50 firms in UK and 95 firms in EU. The bracketing set procedure uses 3894, 1089 and 2715 individual bonds (for US, UK and EU respectively) to draw bond yield estimates from Jan 2005 till Dec 2012. To estimate the standard benchmark risk free rate, treasury curve is used to interpolate yield on a riskless bond with same maturity and coupon using standard cubic spline algorithm. This estimated risk free rate is subtracted from bond yield to obtain monthly bond yield spreads for each CDS contract. In order to obtain five year yield spreads, yield spreads for individual bonds in the bracketing set are regressed on their respective maturities. The fitted value of regression at 5 years horizon is used to estimate the corporate yield spreads for the firm. In total 15745, 3034 and 6283 monthly bond yield spreads are estimated for US, UK and EU respectively. The monthly median CDS spread[32] are used as estimate of default component of monthly bond yield spread. The difference between the two gives the non-default component of bond yield spreads.

For US and UK, the median bond yield spread increases across all sectors during the crisis period with a subsequent decline in the post-crisis period. However, for both US and UK, the median post-crisis spread is much higher than the pre-crisis level. Contrary to US and UK, median bond yield spreads for EU peaks in the post-crisis period. Tables 2.9 Panel B provides the median default component, non-default component and ratio of median default component to median bond yield spread across firms in US, UK and EU respectively. For US, default component to yield spread represents about 25%, escalating to 30% and 50% of the bond yield spreads for pre-crisis, crisis and post-crisis period. Similarly, the UK and EU samples follow a similar trend with default ratio at 20%, 32% and 53% and 19%, 47% and 66% in pre-crisis, crisis and post-crisis period respectively. From Panel C, it can be noted that default ratio varies widely across the GICS sector and for each sub-period. Across the three samples 'Financial' GICS sector shows the highest escalation in default component, highlighting the stress in the financial sector observed since the GFC of 2008-2009.

---

[32] Table 2.9 uses the median values of CDS spreads as the Default component of median bond yield spreads for a specific sample set. These values are different from those in Table 2.1 due to loss of observations resulting from no corresponding bracketing set or bond yield spreads available for those corporates across the period of analysis. Also Table 2.1 report data collated on quarterly basis while data in Table 2.9 is estimated and collated on a monthly basis.

Table 2.9: Ratio of default component to bond yield spread

The sample is based on monthly corporate bond yield spread estimated based on the bracketing approach of Longstaff *et al.*, (2005) from Jan 2005 to Dec 2012. *Dflt* is median default component, *Ndflt* is the median non-default component, *Spread* is the average yield spread over the benchmark 3 month interbank offer rate, *Ratio* is the default component divided by the yield spread. *Ratios* denoted by asterisk are significantly different from 1 at 5% level. N^B is the number of monthly bond yield spreads in the bracketing set. Panel A-1 and Panel B-1- is for US sample, Panel A-2 and Panel B-2 is for UK sample and Panel A-3 and Panel B-3 is for EU sample. Panel A-4 and Panel B-4 shows collectively for all countries in our sample. Periods are as defined in Table 2.1.

Panel A-1: Median yield spread for US across each sub-period								
	Whole period		Pre-crisis		Crisis		Post-crisis	
GICS sector	N^B	Spread	N^B	Spread	N^B	Spread	N^B	Spread
Basic Material	978	214.32	269	132.68	262	326.86	447	212.35
Consumer, non-cyclic	3,303	154.81	817	103.75	820	268.97	1,666	141.84
Financial	4,308	225.80	1,432	95.88	1,140	385.03	1,736	283.10
Utilities	1,116	201.81	235	110.05	288	332.19	593	197.55
Industrial	1,853	175.85	486	121.13	454	282.81	913	168.62
Energy	851	219.87	175	107.84	223	315.60	453	223.81
Technology	495	149.84	106	70.35	128	256.92	261	134.50
Consumer, cyclic	1491	243.00	484	191.45	378	478.12	629	226.40
Communication	1350	232.81	470	149.47	345	439.99	535	257.88
Total	**15,745**	**197.78**	**4,474**	**113.31**	**4,038**	**330.42**	**7,233**	**203.29**

Panel B-1: Median default and non-default component of yield spread across each sub-period												
	Whole period			Pre-crisis			Crisis			Post-crisis		
GICS sector	Dflt	Ndflt	Ratio	Dflt	Ndflt	Ratio	Dflt	Ndflt	Ratio	Dflt	Ndflt	Ratio
Basic Material	86.66	101.12	0.40*	30.25	78.77	0.23*	105.70	179.22	0.32*	118.56	80.36	0.56*
Consumer, non-cyclic	57.38	93.53	0.37*	28.50	80.24	0.27*	62.96	189.07	0.23*	66.27	71.34	0.47*
Financial	122.50	98.52	0.54*	23.50	66.27	0.25*	176.52	171.44	0.46*	165.60	98.92	0.58*
Utilities	83.65	108.99	0.41*	34.38	75.08	0.31*	99.59	195.74	0.30*	104.26	94.86	0.53*
Industrial	56.79	108.02	0.32*	24.88	85.52	0.21*	76.83	195.47	0.27*	72.45	94.61	0.43*
Energy	75.63	102.33	0.34*	31.30	49.24	0.29*	91.03	192.17	0.29*	110.99	93.64	0.50*
Technology	50.01	66.04	0.33*	25.30	35.12	0.36*	59.80	179.00	0.23*	49.65	56.12	0.37*
Consumer, cyclic	114.06	105.59	0.47*	44.00	86.97	0.23*	163.68	163.00	0.34*	137.05	95.74	0.61*
Communication	92.55	128.13	0.40*	51.35	69.95	0.34*	171.81	229.67	0.39*	101.86	132.66	0.39*
Median	**77.58**	**101.36**	**0.39***	**28.50**	**72.40**	**0.25***	**98.99**	**186.97**	**0.30***	**102.03**	**88.94**	**0.50***

Panel A-2: median yield spread for UK across each sub-period								
	Whole period		Pre-crisis		Crisis		Post-crisis	
GICS sector[1]	N^B	**Spread**	N^B	**Spread**	N^B	**Spread**	N^B	**Spread**
Basic Material	92	274.00	30	184.11	21	424.93	41	262.46
Consumer, non-cyclic	258	153.60	106	233.32	64	221.45	88	8.22
Financial	1,390	232.55	387	49.04	349	358.74	654	273.81
Utilities	694	80.48	245	65.18	202	231.85	247	-28.15
Industrial	87	169.56	30	-46.06	27	315.46	30	253.87
Energy	.	.	.	.	.	.	.	.
Technology	.	.	.	.	.	.	.	.
Consumer, cyclic	130	244.76	57	158.89	48	361.59	25	216.21
Communication	383	331.22	143	131.47	108	333.25	132	545.97
Total	**3,034**	**203.48**	**998**	**91.86**	**819**	**313.79**	**1,217**	**220.78**

Panel B-2: Median default and non-default component of yield spread across each sub-period												
	Whole period			Pre-crisis			Crisis			Post-crisis		
GICS sector[1]	**Dflt**	**Ndflt**	**Ratio**	**Dflt**	**Ndflt**	**Ratio**	**Dflt**	**Ndflt**	**Ratio**	**Dflt**	**Ndflt**	**Ratio**
Basic Material	90.91	192.39	0.33*	.	.	.	276.32	408.79	0.65*	86.34	168.57	0.33*
Consumer, non-cyclic	63.27	87.41	0.41*	40.92	56.61	0.18*	67.30	180.00	0.30*	80.08	62.71	9.74*
Financial	141.53	104.48	0.61*	9.69	39.73	0.20*	149.00	161.70	0.42*	162.02	109.90	0.59*
Utilities	70.00	130.92	0.87*	19.00	85.16	0.29*	66.86	175.63	0.29*	81.61	132.13	-2.90
Industrial	89.13	129.91	0.53*	.	.	.	315.00	267.61	1.00	83.98	116.82	0.33*
Energy	.	.	.	.	.	.	.	.	.	.	.	.
Technology	.	.	.	.	.	.	.	.	.	.	.	.
Consumer Cyclic	55.09	130.68	0.23*	50.11	104.21	0.32*	56.27	253.11	0.16*	55.01	85.41	0.25*
Communication	73.52	135.07	0.22*	36.65	124.84	0.28*	100.59	175.49	0.30*	93.43	122.21	0.17*
Median	**87.60**	**117.85**	**0.43***	**18.70**	**68.29**	**0.20***	**100.16**	**179.53**	**0.32***	**116.51**	**114.74**	**0.53***

Note: (1) No monthly bond yield spread data exist for Energy and Technology GICS sector for UK sample.

Panel A-3: Median yield spread for EU across each sub-period								
	Whole period		Pre-crisis		Crisis		Post-crisis	
GICS sector[2]	N^B	Spread	N^B	Spread	N^B	Spread	N^B	Spread
Basic Material	306	194.24	120	107.39	87	310.10	99	297.55
Consumer, non-cyclic	591	156.62	136	108.31	164	188.78	291	176.20
Financial	3,371	187.65	847	86.44	877	198.97	1,647	245.17
Utilities	592	127.82	193	66.07	168	155.41	231	156.54
Industrial	555	175.79	180	119.84	134	243.35	241	207.63
Energy	.	.	.	.	.	.	.	.
Technology	.	.	.	.	.	.	.	.
Consumer, cyclic	331	190.88	121	119.57	86	224.12	124	282.98
Communication	450	189.14	140	123.13	141	244.79	169	217.24
Diversified	87	434.78	30	110.05	24	619.16	33	547.64
Total	**6,283**	**176.11**	**1,767**	**98.34**	**1,681**	**205.95**	**2,835**	**224.25**

Panel B-3: Median default and non-default component of yield spread across each sub-period												
	Whole period			Pre-crisis			Crisis			Post-crisis		
GICS sector[2]	Dflt	Ndflt	Ratio	Dflt	Ndflt	Ratio	Dflt	Ndflt	Ratio	Dflt	Ndflt	Ratio
Basic Material	80.03	113.23	0.41*	33.48	71.05	0.31*	119.77	129.76	0.39*	198.21	161.14	0.67*
Consumer, non-cyclic	62.69	90.03	0.40*	18.35	89.61	0.17*	64.24	129.54	0.34*	83.28	77.01	0.47*
Financial	119.57	73.67	0.64*	11.75	76.95	0.14*	104.23	97.87	0.52*	188.23	62.92	0.77*
Utilities	58.23	72.27	0.46*	17.41	51.50	0.26*	57.08	101.39	0.37*	79.69	75.18	0.51*
Industrial	90.19	101.96	0.51*	31.37	91.79	0.26*	105.00	147.51	0.43*	120.23	97.73	0.58*
Energy	.	.	.	.	.	.	.	.	.	.	.	.
Technology	.	.	.	.	.	.	.	.	.	.	.	.
Consumer Cyclic	134.77	74.89	0.71*	47.75	55.29	0.40*	176.81	40.31	0.79*	179.69	102.48	0.63*
Communication	72.90	119.39	0.39*	42.33	82.10	0.34*	86.49	149.93	0.35*	87.24	135.91	0.40*
Diversified	427.90	128.72	0.98*	.	.	.	446.65	149.18	0.72*	420.26	120.23	0.77*
Median	**90.60**	**85.54**	**0.51***	**18.67**	**76.16**	**0.19***	**96.07**	**110.55**	**0.47***	**146.96**	**81.79**	**0.66***

Note: (2) No monthly bond yield spread data exist for Energy and Technology GICS sector for EU sample.

Panel A-4: Median yield spread across each sub-period								
	Whole period		Pre-crisis		Crisis		Post-crisis	
Sample	N^B	Spread	N^B	Spread	N^B	Spread	N^B	Spread
US	15,745	197.78	4,474	113.31	4,038	330.42	7,233	203.29
UK	3,034	203.48	998	91.86	819	313.79	1,217	220.78
EU	6,283	176.11	1,767	98.34	1,681	205.95	2,835	224.25

Panel B-4: Median default and non-default component of yield spread across each sub-period												
	Whole period			Pre-crisis			Crisis			Post-crisis		
Country	Dflt	Ndflt	Ratio	Dflt	Ndflt	Ratio	Dflt	Ndflt	Ratio	Dflt	Ndflt	Ratio
US	77.58	101.36	0.39*	28.50	72.40	0.25*	98.99	186.97	0.30*	102.03	88.94	0.50*
UK	87.60	117.85	0.43*	18.70	68.29	0.20*	100.16	179.53	0.32*	116.51	114.74	0.53*
EU[3]	90.60	85.54	0.51*	18.67	76.16	0.19*	96.07	110.55	0.47*	146.96	81.79	0.66*
Spain	150.39	36.04	0.71*	10.80	32.97	0.25*	128.99	31.53	0.67*	281.98	45.84	0.81*
France	89.76	87.28	0.55*	27.83	72.28	0.26*	102.24	125.93	0.45*	133.26	86.45	0.67*
Italy	88.12	96.90	0.41*	14.51	86.63	0.15*	80.04	126.44	0.37*	192.10	88.12	0.73*
Germany	112.50	50.26	0.76*	14.19	96.61	0.15*	96.68	79.26	0.60*	142.97	28.78	0.83*
Portugal	116.56	83.12	0.35*	12.11	.	.	91.50	92.77	0.53*	591.15	82.40	1.06
Finland	90.31	125.44	0.43*	38.76	73.08	0.34*	118.24	129.04	0.37*	145.20	149.94	0.41*
Ireland	156.38	167.44	0.31*	8.58	.	.	138.34	.	.	616.68	167.44	1.22
Netherlands	70.86	107.16	0.41*	21.63	104.13	0.19*	79.53	131.14	0.37*	100.18	98.07	0.47*
Austria	141.65	54.39	0.70*	14.25	36.15	0.43*	140.02	53.11	0.90	188.58	65.67	0.69*
Belgium	70.69	109.57	0.38*	21.67	61.30	0.24*	75.84	136.72	0.37*	84.56	123.33	0.36*
Luxembourg	78.56	140.76	0.41*	.	.	.	121.53	139.90	0.55*	76.91	140.76	0.38*

Note: (3) No Dflt and Ndflt data available for EU countries; Cyprus, Estonia, Greece, Malta, Slovakia and Slovenia

Table 2.9, also shows that default risk only partially explains bond yield spread and non-default component is a key additional explanatory factor. Fig. 2.3 plots the aggregate time-series variation in the median non-default component of yield spreads for the three markets. The plots show a similar trend across the three markets i.e. considerable increase in non-default component during crisis period and comparably higher non-default component in post-crisis period than pre-crisis era. For EU, although the non-default component tends to move below zero, it merely indicates that default proportion of yield spread has increased tremendously which is causing the median non-default element to go negative. Collectively, a significantly higher ratio of default component to bond yield spreads in the post-crisis period may be further highlighting that CDS spreads that make up the default component could be plagued by noise and may not be truly representing higher risk of default in the post crisis era. Fig. 2.4 plots the histogram of non-default component for US, UK and EU across the whole period. We notice a considerable cross-sectional variation in non-default components of yield spreads. Moreover, non-default frequency peaks at around 90bp for US and EU whereas the peak is higher at around 130-150bp for UK. These results together indicate that default component represents more than 50% of the total bond yield spreads in the post-crisis era and the presence of a significant amount of non-default component in yield spreads across the three markets. This also highlights that although the bond markets have stabilized, there is still fear in the market of the possibility of default which is still significant even in the post-crisis period. Moreover, these results are more prominent during crisis period and holds true in post-crisis period across the three markets; irrespective of the type of firm. Longstaff *et al.*, (2005) drew similar inferences but their study argued this effect to be true for only high-rated investment grade US firms. Our observations extend this inference across all types of firms, across all period of analysis and across the three samples.

Fig 2.3: Time-series plot of the median non-default component across US, UK and EU. The plot shows the time series of the median non-default (*Ndflt*) component in basis points across the US, UK and EU for the period 1st Jan 05 to 31st Dec 12. Observations are on monthly basis and periods as defined in Table 2.1.

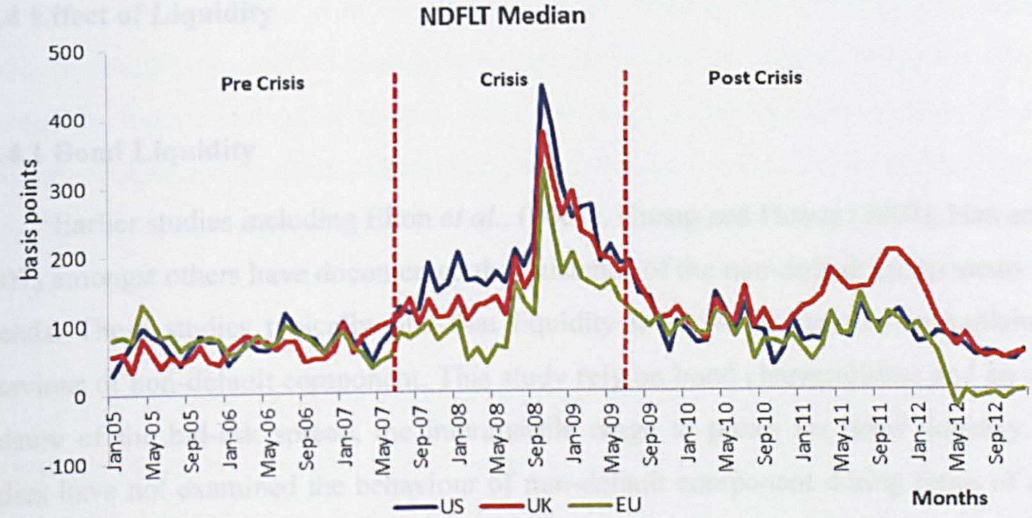
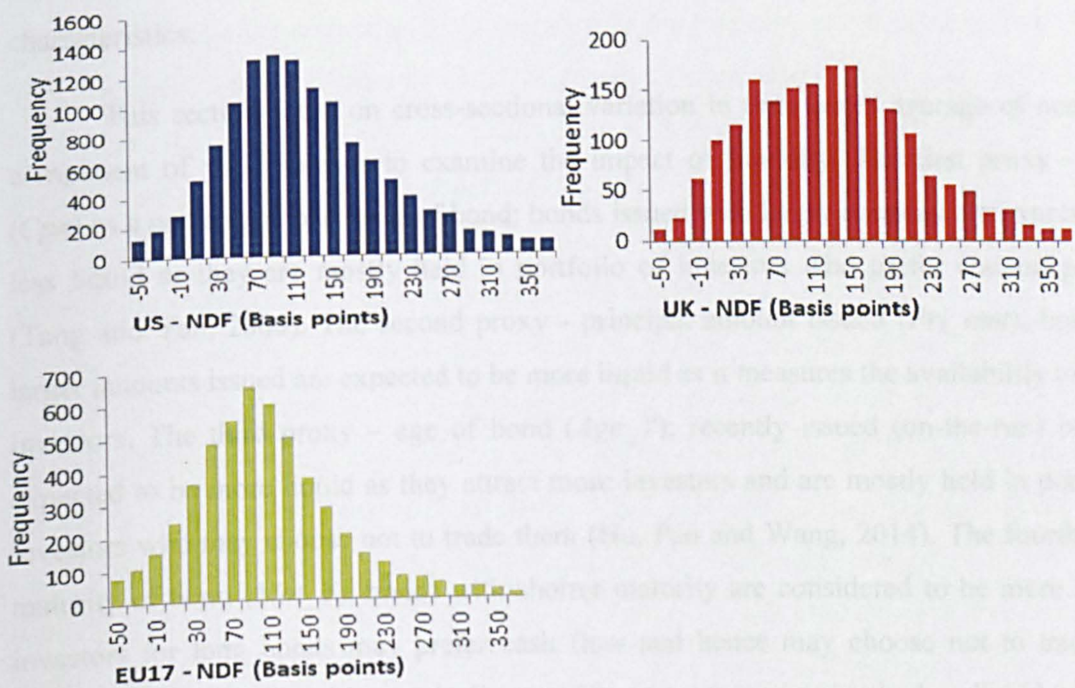


Fig 2.4: Distribution of non-default components for the US, UK and EU sample The plots show the distribution of non-default component of yield spread for the period 1st Jan 05 to 31st Dec 12.



2.4.4 Effect of Liquidity

2.4.4.1 Bond Liquidity

Earlier studies including Elton *et al.*, (2001), Huang and Huang (2003), Han and Zhou (2007) amongst others have documented the existence of the non-default components in yield spreads. These studies typically find that liquidity is a crucial variable in explaining the behaviour of non-default component. This study rely on bond characteristics and an adjusted measure of the bid-ask spread, the interquartile range to proxy for bond liquidity. Earlier studies have not examined the behaviour of non-default component during times of crisis or the impact of liquidity on non-default component during crisis period. A recent study by Friewald, Jankowitsch and Subrahmanyam (2012) examines the impact of liquidity on the bond spread during times of financial crisis and concludes liquidity became more pronounced during the financial crisis. Friewald *et al.*, (2012) restrict their study only to bond market and hence only to corporate spread. This study extends their analysis to non-default component and across pre-crisis, crisis and post-crisis period. However, where their analysis included a wide range of liquidity measures and bond characteristics, this study due to monthly observations are restricted (with the exception of the interquartile range) to bond characteristics.

This section focus on cross-sectional variation in time series average of non-default component of yield spreads to examine the impact of liquidity. The first proxy - coupon (*Cpn*) as a percentage par value of bond; bonds issued with larger coupons are expected to be less liquid as they are mostly held in portfolio of investors who prefer coupon payments (Tang and Yan, 2006). The second proxy - principal amount issued (*Pri_amt*); bonds with larger amounts issued are expected to be more liquid as it measures the availability of bond to investors. The third proxy – age of bond (*Age_Y*); recently issued (on-the-run) bonds are expected to be more liquid as they attract more investors and are mostly held in portfolio of investors who may choose not to trade them (Hu, Pan and Wang, 2014). The fourth proxy - maturity of bond (*Mat_Y*), bonds with shorter maturity are considered to be more liquid as investors for long bonds may prefer cash flow and hence may choose not to trade them. Bonds with longer maturities, typically over 10 years are assumed to be less liquid as they are purchased by buy and hold investors who trade infrequently. The final proxy - interquartile range (*IQR*), is an indirect measure of bid-ask spread, defined as the difference between the

75th percentile and 25th percentile of daily price observations and captures inter-period volatility. Bonds with more volatility are expected to be less liquid indicating risk-averse investor's preference for stable returns. Although, most of the liquidity variables used in this study are either constant across bonds or change linearly over time and could be considered a crude liquidity proxies. However, their use makes intuitive sense and have been found to be widely used in studies including Edward, Harris and Piwowar (2007), Tan and Yan (2010) among others.

Panel A, of Table 2.10 provides the regression output (between-effect panel data regression) log of yield spread against liquidity proxies for US, UK and EU. We use the between-effect estimator as most of the liquidity proxies are firm variant but time invariant (except *IQR*). The between-effect estimator uses the between variations across firms by using the time average across the variables in our regression model. The between-effect regression function is,

$$ln(BYS_i) = \alpha + \beta_{1i}Cpn_i + \beta_{2i}Pri\_Amt_i + \beta_{3i}Age\_Y_i + \beta_{4i}Mat\_Y_i + \beta_{5i}IQR_i + \varepsilon_t \qquad (2.7)$$

It can be noted that most of the liquidity proxies are significant across sample. The *(Cpn)* coefficient is positive and significant across all sub-periods. Similarly, as expected the coefficient *(Pri_amt)* and *(Age_Y)* is negative and significant across all sub-periods for all three samples. The coefficient of *(Mat_Y)* is negative and significant across all sub-periods for US and EU. However, for UK *(Mat_Y)* is negative and significant only for the crisis period whereas it is positive and significant for whole and post-crisis period. *(IQR)* is positive and significant for all sub-periods in US and EU (except in pre-crisis period), while this relationship only hold true during crisis period for UK and is not significant for other sub-periods in UK sample. Across the three markets, liquidity proxies collectively explain about 45-48% of the variation in bond yield spreads for the whole period. However the *Adj.* R^2 value varies across each sub-period for each sample. The higher *adj.* R^2 value in crisis period for UK sample is in agreement to Friewald *et al.*, (2012) who find liquidity effect becomes more pronounced during crisis period when capital constraints become binding and inventory holding cost and search cost rises dramatically. However, it is interesting to note that liquidity effect is more pronounced for the US and UK during post-crisis period contrary to popular belief in bond market.

Panel B of Table 2.10 provides regression output (between-effect panel data regression) log of non-default component of yield spread against the liquidity proxies across the samples. The coefficient sign and significance of variables are mostly similar to observations in Panel A. Overall, bond liquidity proxies explain about 38% of the variation in the non-default component of yield spreads in whole period for the three samples. The model explanatory power remains mostly stable across sub-periods for US and UK. However, for EU liquidity proxies explain higher variation in pre-crisis period, explanatory power drops in crisis period and further declines in post-crisis period. Further Panel C provides regression output for log of default component i.e. CDS spreads to bond liquidity proxies across the sample. Bond liquidity proxies explain about 25-27% of the variation in CDS spreads for the whole period, while the model explanatory power changes based on the period of analysis. Overall for US sample, liquidity proxy explains higher variation of CDS spreads in the pre-crisis period, for UK in the crisis period and for EU in the post crisis. Furthermore, studies by Tan and Yan (2006) and Erickson and Renault (2006) claims liquidity effect may interact with credit risk and may be more pronounced for bonds with lower credit risk and vice versa. We test whether the effect of liquidity on yield spreads is a function of credit risk. Results (Table 2.10 – Panel D) indicate *Adj.* R^2 trend remains almost similar for each sub-period and across the three samples indicating, after controlling for credit risk the effect of bond liquidity on yield spreads is still significant across each sub-period of analysis.

In summary Table 2.10 illustrates, bond market liquidity plays an important role in both explaining the corporate yield spread and non-default component of yield spread. Furthermore, liquidity proxies that are significant predictors for the yield spread may not be equally significant for non-default component. Liquidity proxies explain about 45% of the variation on bond yield spreads for whole period and about 38% of the variation in non-default component of yield spreads which is significantly high. Liquidity effect varies across sub-periods and become more pronounced during crisis period for UK whereas for the US and EU, bond liquidity is still a significant factor influencing non-default component of yield spreads especially in post-crisis period. An explanation of the increase in liquidity effect for UK during crisis period could be risk-averse nature of investors who choose to move their portfolio from illiquid to liquid assets. Higher liquidity effect during post-crisis period also indicates investor's scepticism even in post-crisis period thereby increasing the gap between liquid and illiquid bonds and tendency for 'flight to quality' effect during crisis and post-crisis period.

Table 2.10: US, UK and EU: Between-effect regressions

Regressing log of corporate yield spread (Panel A), log of non-default component (Panel B) and log of default component (Panel C) against bond liquidity proxies. Panel D is robustness test showing the effect by adding default risk measures using ln_spread.

Panel A	Log of Corporate Yield Spread - US				Log of Corporate Yield Spread – UK				Log of Corporate Yield Spread – EU			
	Whole Period	Pre-crisis	Crisis	Post-crisis	Whole Period	Pre-crisis	Crisis	Post-crisis	Whole Period	Pre-crisis	Crisis	Post-crisis
Intercept	4.97***	4.09***	5.3***	6.05***	5.70***	9.42***	5.72***	5.50***	5.48***	4.61***	4.77***	5.11***
Cpn	0.21***	0.36***	0.187***	0.21***	0.23***	0.47***	0.24***	0.25***	0.24***	0.37***	0.28***	0.24***
Pri_amt	-0.05***	-0.1***	-0.03***	-0.10***	-0.1***	-0.4***	-0.1***	-0.1***	-0.06***	-0.1***	-0.03***	-0.04***
Age_Y	-0.03***	-0.03***	-0.01***	-0.03***	-0.1***	-0.09**	-0.03***	-0.1***	-0.09***	-0.06***	-0.04***	-0.06***
Mat_Y	-0.05***	-0.1***	-0.04***	-0.05***	0.05***	-0.002	-0.03**	0.07***	-0.05***	-0.1***	-0.1***	-0.02*
IQR	0.49***	0.40***	0.164***	0.518***	0.001	-0.238	0.13***	-0.001	0.3***	0.174	0.23***	0.28***
N	76,506	23,935	20,748	31,823	15,937	2,138	2,791	11,008	46,365	5,860	9,980	30,525
R^2	48.53%	44.73%	33.72%	47.29%	46.00%	39.23%	49.40%	43.56%	44.08%	59.19%	48.63%	38.51%
Adj. R^2	48.53%	44.72%	33.70%	47.28%	45.98%	39.09%	49.31%	43.53%	44.07%	59.16%	48.60%	38.50%

Panel B	Log of Non-default component - US				Log of Non-default component – UK				Log of Non-default component – EU			
	Whole Period	Pre-crisis	Crisis	Post-crisis	Whole Period	Pre-crisis	Crisis	Post-crisis	Whole Period	Pre-crisis	Crisis	Post-crisis
Intercept	4.11***	3.84***	4. 7***	3.99***	3.17***	8.11***	5.25***	3.15***	3.438***	4.82***	2.32***	3.83***
Cpn	0.30***	0.34***	0.209***	0.34***	0.38***	0.43***	0.27***	0.40***	0.425***	0.41***	0.4***	0.41***
Pri_amt	-0.06***	-0.1***	-0.03***	-0.07***	-0.03*	-0.3**	-0.08**	-0.04**	-0.03**	-0.1***	0.05***	-0.1***
Age_Y	-0.006	-0.02***	-0.009*	-0.008	-0.04***	-0.08*	-0.02*	-0.04**	-0.03***	-0.05**	-0.02*	-0.1***
Mat_Y	-0.04***	-0.02**	-0.03***	-0.03**	0.009	0.006	-0.026*	0.04**	-0.18***	-0.05**	-0.2***	-0.1***
IQR	0.184***	-0.001	0.03**	0.20***	-0.001	-0.331	0.059*	-0.001	0.305***	-0.02	0.24***	0.35***
N	62,230	19,510	17,723	24,997	12,372	2,023	2,400	7,949	30,795	4,694	7,558	18,543
R^2	38.30%	33.87%	23.99%	38.09%	37.52%	32.09%	37.24%	34.19%	39.11%	66.08%	44.33%	31.40%
Adj. R^2	38.30%	33.85%	23.97%	38.08%	37.49%	31.92%	37.11%	34.15%	39.10%	66.04%	44.29%	31.38%

Panel C	Log of default component - US				Log of default component – UK				Log of default component – EU			
	Whole Period	Pre-crisis	Crisis	Post-crisis	Whole Period	Pre-crisis	Crisis	Post-crisis	Whole Period	Pre-crisis	Crisis	Post-crisis
Intercept	3.78***	2.99***	3.8***	5.62***	5.79***	-0.34	4.94***	5.62***	5.78***	-0.88	5.63***	5.07***
Cpn	0.04***	0.11***	0.05***	0.04***	-0.03**	0.19***	-0.02	0.01	-0.09***	-0.02	-0.03***	-0.05***
Pri_amt	0.02***	-0.02**	0.04***	-0.05***	-0.04***	0.13**	-0.01	-0.03***	-0.03***	0.19***	-0.05***	0.01
Age_Y	-0.04***	0.02***	-0.03***	-0.02***	-0.09***	-0.06**	-0.06***	-0.03***	-0.07***	0.03	-0.04***	-0.02***
Mat_Y	-0.09***	-0.1***	-0.05***	-0.14***	0.02	0.01	-0.01	-0.02***	-0.06***	-0.07***	-0.01	-0.04***
IQR	0.84***	0.97***	0.31***	0.72***	0.01	-0.17	0.25***	-0.01	0.59***	0.55**	0.2***	0.47***
N	93,799	24,223	22,549	47,027	20,539	1,876	2,484	16,179	70,502	5,282	10,335	54,885
R^2	28.66%	24.43%	18.72%	22.99%	25.13%	14.60%	25.29%	9.62%	27.10%	11.04%	17.99%	20.39%
Adj. R^2	28.65%	24.38%	18.66%	22.96%	25.07%	13.86%	24.81%	9.53%	27.08%	10.77%	17.86%	20.37%

Panel D	Log of Corporate yield spreads - US				Log of Corporate yield spreads – UK				Log of Corporate yield spreads – EU			
	Whole Period	Pre-crisis	Crisis	Post-crisis	Whole Period	Pre-crisis	Crisis	Post-crisis	Whole Period	Pre-crisis	Crisis	Post-crisis
Intercept	3.38***	3.21***	4.09***	2.771***	3.45***	7.93***	3.81***	3.1***	3.14***	4.54***	3.02***	2.60***
Cpn	0.22***	0.32***	0.18**	0.188***	0.25***	0.32***	0.25***	0.25***	0.28***	0.37***	0.30***	0.26***
Pri_amt	-0.05***	-0.06***	-.05***	-0.07***	-0.07***	-0.33**	-0.05**	-0.07***	-0.04***	-0.11***	-0.01*	-0.05***
Age_Y	-0.02***	-0.03***	-0.01*	-0.02***	-0.05***	-0.04	-0.02	-0.05***	-0.06***	-0.06***	-.02***	-0.05***
Mat_Y	-0.02***	-0.04***	-.03***	0.02***	0.04***	-0.01	-0.02	0.08***	-0.04***	-0.05**	-0.09**	-0.01*
IQR	0.14***	0.16***	0.07***	0.15***	-0.01	-0.35	0.08*	-0.01	0.19***	0.16	0.16***	0.18***
Ln_CDS	0.4***	0.32***	0.34***	0.58***	0.39***	0.48***	0.29***	0.43***	0.38***	0.23***	0.3***	0.5***
N	70,171	20,610	19,257	30,304	14,042	1,227	2,171	10,644	42,958	4,818	9,202	28,938
R^2	67.04%	55.21%	56.58%	66.01%	49.90%	38.83%	49.45%	49.33%	53.04%	65.32%	52.45%	48.42%
Adj. R^2	67.04%	55.20%	56.57%	66.00%	49.88%	38.58%	49.33%	49.31%	53.03%	65.28%	52.42%	48.41%

Notes: (1) ***, **, * Indicates rejection of the null hypothesis at 1%, 5% and 10% respectively based on *t* statistics.

Earlier studies including Tan and Yan (2006) have indicated illiquidity in bond market can affect dealer's hedging capabilities and hence increase the premium embedded in CDS spreads. Accordingly, when an underlying bond has poor liquidity *ceretis paribus* the corresponding CDS spreads is higher. Our observation in Panel C of Table 2.10, point towards a significant effect of bond illiquidity during crisis period which is still higher in the post-crisis period. Based on liquidity spillover effect from bond to CDS market, higher CDS spreads during crisis and post-crisis period may not be necessarily due to the higher risk of default but may imply a larger component of illiquidity effect driving CDS spreads especially for US and EU. Likewise, liquidity dynamics of CDS market could also affect CDS spreads for firms in our sample. We proceed to test the liquidity dynamics of CDS market and its effect on CDS spreads in the following section.

2.4.4.2 CDS liquidity

Lesplingart, Majois and Petitjean (2012) considers CDS market as being rather illiquid compared to equity market, evident from higher bid-ask spreads and non-continuous nature of trades which relies heavily on the degree of confidence between counterparties. This causes liquidity to dry up quickly especially during crisis period and could take a long time to recover. Until recently, CDS market liquidity has been sparsely studied (see Tan and Yan, 2006 and Lesplingart *et al.*, 2012) We follow Lesplingart *et al.*, (2012) and use absolute quoted bid-ask spread *(abs_bidask)* and proportionally quoted bid-ask spread *(pro_bidask)* as proxies for CDS market liquidity. Bid–ask spread represents the cost a trader needs to pay to unwind a position. Higher bid ask spread indicate greater divergence of opinion or information asymmetry and hence lower liquidity (Tan and Yan, 2006). *(pro_bidask)* is estimated as the difference between bid-ask spread divided by mean bid-ask spread. *(abs_bidask)* is an indicator of CDS market illiquidity, lower values in the pre-crisis period points towards higher liquidity in CDS market. Similarly, *(pro_bidask)* is a measure of CDS market liquidity. The time series aggregate of these variables collectively indicate, liquidity dried up in crisis period and the CDS market is still very illiquid in the post-crisis era across the three markets.

Next fixed-effect panel data regression is run using issuer-clustered standard errors to account for possible correlations within CDS issuer cluster. Two specifications using each of the CDS liquidity proxies *(abs_bidask and pro_bidask)* is considered individually in the regression model and results are analysed across each sub-period. The main focus of this section is to estimate the effect of CDS market liquidity on CDS spreads. Hence, we control for credit risk and use the same 16 independent variables as detailed in section 2.3.1. From the regression outputs, it can be noted that spread explanatory power of the model changes based on the period of analysis and sample under consideration. Under specification 1, *(abs_bidask)* is positive and significant across all sub-period for all three markets except in the pre-crisis period for UK and EU. For specification 2, *(pro_bidask)* is negative and significant across all sub-periods and markets (except for crisis period in EU). Table 2.11 provides the *Adj.* R^2 and the incremental *Adj.* R^2 value (change) under each of the two specifications for US, UK and EU. From Table 2.11, for Specification 1 the effect size is mostly small. However, under Specification 2, the increase in *Adj.* R^2 corresponds to effect size mostly in the medium to large range. Coefficient for *(abs_bidask)* is positive and significant, indicating if bid-ask spread widens (i.e. liquidity decreases) spread increases. Specification 2, using *(pro_bidask)* provides the highest increment in model's R^2 value across all period. The results above collectively signify, CDS liquidity has a significant effect on CDS spreads across all sub-periods which cannot be ignored when studying the dynamics of CDS spreads as such CDS spreads may not be a true measure of pure credit risk.

Table 2.11: Effect of CDS liquidity variable in the spread prediction model

The table compares the change in *Adj.* R^2 value for the regression model by adding the CDS liquidity variables. Specification 1 uses absolute bid ask spreads (*abs_bidask*) calculated as the difference between ask and bid quote, whereas Specification 2 using proportional bid ask quote (pro_*bidask*) calculated as difference between ask and bid quotes divided by mid bid-ask spread.

	US				UK				EU			
	Whole Period	**Pre-crisis**	**Crisis**	**Post-crisis**	**Whole Period**	**Pre-crisis**	**Crisis**	**Post-crisis**	**Whole Period**	**Pre-crisis**	**Crisis**	**Post-crisis**
						Original Sample						
N	6,393	1,256	1,778	3,359	578	129	146	303	590	135	211	244
R^2	62.07%	25.11%	75.13%	27.77%	57.07%	27.24%	65.59%	37.19%	64.07%	52.26%	66.66%	44.00%
Adj. R^2	61.97%	24.14%	74.90%	27.42%	55.85%	16.85%	61.32%	33.68%	63.07%	45.79%	63.91%	40.05%
						Specification 1 : Absolute bid-ask spreads						
N	6,191	1,224	1,678	3,289	565	126	140	299	427	50	207	170
R^2	64.19%	26.13%	77.52%	44.05%	62.22%	28.12%	77.54%	45.24%	65.50%	66.80%	73.17%	56.45%
Adj. R^2	64.09%	25.09%	77.29%	43.76%	61.05%	16.81%	74.41%	41.93%	64.07%	49.16%	70.76%	51.58%
Change	2.12%	0.95%	2.39%	16.34%	5.20%	-0.04%	13.09%	8.25%	1.00%	3.38%	6.85%	11.53%
Effect size	0.06	0.01	0.11	0.29	0.13	0.00	0.51	0.14	0.03	0.07	0.23	0.24
						Specification 2 : Proportional bid-ask spreads						
N	6,191	1,224	1,678	3,289	565	126	140	299	427	50	207	170
R^2	73.06%	61.95%	80.44%	45.56%	76.00%	53.13%	70.74%	46.72%	73.33%	79.82%	68.31%	62.83%
Adj. R^2	72.99%	61.41%	80.24%	45.28%	75.25%	45.75%	66.66%	43.50%	72.22%	69.10%	65.46%	58.67%
Change	11.01%	37.27%	5.34%	17.85%	19.41%	28.91%	5.34%	9.82%	9.15%	23.31%	1.55%	18.62%
Effect size	0.41	0.97	0.27	0.33	0.78	0.53	0.16	0.17	0.33	0.75	0.04	0.45

2.5 Robustness tests

As indicates in Das *et al.*, (2009) most accounting data may not be actually known at the end of quarter instead reported at some subsequent time. Furthermore Sengupta (2004) suggest the delay to be on an average around 40 days. Consequently, lag of one quarter on accounting variables is taken and regression models are re-run. Results (reported in Table 2.12) indicates that *Adj.* R^2 trends remains consistent and robust even after using lagged accounting variables in the regression model. Considering not all firms in our sample publish accounting data on quarterly basis, we check if the regression results change on using only Q2 and Q4 observations i.e. excluding observations from Q1 and Q3. Overall, *Adj.* R^2 shows a similar trend across all sub-periods, denoting stability and robustness of our regression estimates. Most of the studies in this field consider financial sector separately when analysing spread prediction models (Das *et al.*, 2009). Most firms in financial sector act as counterparties to CDS insurance contracts. Hence, the relationship between the accounting variables and CDS spreads for firm belonging to financial sector may not be hold true as with other sectors. The results are compared to see if they vary when excluding observations from financial GICS sector. These results collectively indicate that our estimates are not driven or affected by observations from firms belonging to financial GICS sector pointing towards consistency and reliability of our model estimates.

Table 2.12: Robustness test - Panel data fixed effect regression of the log of CDS spreads to accounting and market based measures under different specifications

Panel data fixed effect regression of the log of CDS spreads to accounting and market based measures. The sample is based on quarterly CDS spreads from Q1 2005 to Q4 2012. Periods are as defined in Table 2.1. The R^2 and Adj. R^2 are reported firstly, for the original sample, secondly using 1 quarter lag of accounting variables, thirdly excluding Q1 and Q3 observations and lastly excluding all observations from firms belonging to Financial GICS sector for the US, UK and EU. Change in *Adj.* R^2 is the difference in *Adj.* R^2 compared to the original sample and effect size estimates the magnitude of effect between the *Adj.* R^2 *values*. *NA* denotes insufficient observations

	US				UK				EU			
	Whole Period	**Pre-crisis**	**Crisis**	**Post-crisis**	**Whole Period**	**Pre-crisis**	**Crisis**	**Post-crisis**	**Whole Period**	**Pre-crisis**	**Crisis**	**Post-crisis**
					Original Sample							
N	6,393	1,256	1,778	3,359	578	129	146	303	590	135	211	244
R^2	62.07%	25.11%	75.13%	27.77%	57.07%	27.24%	65.59%	37.19%	64.07%	52.26%	66.66%	44.00%
Adj. R^2	61.97%	24.14%	74.90%	27.42%	55.85%	16.85%	61.32%	33.68%	63.07%	45.79%	63.91%	40.05%
					Using 1 quarter lag of accounting variables							
N	5,992	1,100	1,592	3,300	563	124	140	299	566	123	201	242
R^2	61.80%	29.09%	73.44%	25.44%	56.92%	44.45%	74.17%	35.75%	64.83%	58.09%	69.21%	41.59%
Adj. R^2	61.70%	28.04%	73.17%	25.08%	55.66%	36.14%	70.81%	32.10%	63.81%	51.76%	66.53%	37.44%
Change	-0.28%	3.90%	-1.73%	-2.35%	-0.19%	19.30%	9.49%	-1.57%	0.74%	5.98%	2.62%	-2.62%
Effect size	0.00	0.16	-0.02	-0.09	0.00	1.15	0.15	-0.05	0.01	0.13	0.04	-0.07
					Excluding Q1 and Q3 observations							
N	3,240	621	949	1,670	101	22	29	50	267	58	112	97
R^2	63.91%	36.91%	76.32%	31.90%	74.56%	*NA*	*NA*	*NA*	66.92%	*NA*	76.86%	61.86%
Adj. R^2	63.73%	35.24%	75.91%	31.24%	69.71%	*NA*	*NA*	*NA*	64.80%	*NA*	72.96%	54.23%
Change	1.76%	11.10%	1.01%	3.82%	13.87%	*NA*	*NA*	*NA*	1.74%	*NA*	9.05%	14.18%
Effect size	0.03	0.46	0.01	0.14	0.25	*NA*	*NA*	*NA*	0.03	*NA*	0.14	0.35
					Excluding Financial GICS Sector							
N	6,179	1,197	1,722	3,260	550	129	140	281	590	135	211	244
R^2	61.76%	25.31%	75.38%	27.30%	57.86%	27.24%	65.56%	38.61%	64.07%	52.26%	66.66%	44.00%
Adj. R^2	61.66%	24.30%	75.15%	26.94%	56.60%	16.85%	61.08%	34.89%	63.07%	45.79%	63.91%	40.05%
Change	-0.31%	0.15%	0.24%	-0.48%	0.75%	0.00%	-0.24%	1.21%	0.00%	0.00%	0.00%	0.00%
Effect size	-0.01	0.01	0.00	-0.02	0.01	0.00	0.00	0.04	0.00	0.00	0.00	0.00

2.6 Policy Recommendations

This chapter examined the extent to which CDS spreads are sensitive to both accounting and financial market variables in US, UK and EU before, during and after the financial crisis. It also explored, how the parameters behave during crisis period, and notice a rapid increase in the CDS spreads during the financial crisis. By splitting bond spread into the default component and the non-default component, this study has been able to isolate and show that; during the financial crisis, the non-default component of yield spread has decreased. However, overall bond spread is not only driven by credit risk but also by liquidity and underlying bond characteristics such as coupon, age and maturity of bonds etc. Given the explosion in the use of CDS contracts by market participants, the findings from this section have a number of implications for policy makers.

Firstly, the variables driving the CDS spreads change over time. This is consistent with studies for bond yield spreads. The results thus imply that policy makers need to be aware of the period and context in which estimates are made and that if the context changes or estimation period is long, then they need to re-estimate the model. Second, given the changing nature of the CDS spread during the crisis, it is possible that CDS spreads have overreacted to the prevailing market conditions. Thus relying on CDS spreads alone as an estimate of market signalling may be inaccurate. In such circumstances policy holders should examine other market indicators such as equity market etc. in conjunction with CDS market signals. Third, non-default component of the yield spreads increased during crisis and post-crisis period across US, UK and EU. Given that this is driven by amongst other things, bond characteristics, policy holders may wish to create an environment, where companies issues bonds with characteristics that increases the overall market liquidity especially during periods of financial distress. Fourth liquidity is crucial factor driving yield spreads and non-default component of yields. Similarly, liquidity in CDS market is also a significant driver of CDS spreads more so during crisis and post-crisis period. Furthermore, consistent with earlier studies liquidity effects varies across different period of analysis. Thus, policy holders should consider the impact of bond liquidity on yield spreads and CDS liquidity on CDS spreads. With the possibility of illiquidity in a specific market plaguing the liquidity dynamics of other capital markets during a specific period. Policy makers should consider the implication of these issues quickly and dealt with promptly considering the close association between capital markets.

Collectively, the results obtained from this study have important policy implications. As noted earlier, CDS spreads align with the accounting and market based variables more closely in the crisis period then in pre-crisis and post-crisis period. This could mean either the CDS spreads are not correctly manifesting the corporate credit risk behaviour in other sub-period or the variables used in the past studies do not adequately capture the credit risk of firm in the sense these could be efficiently modelled and forecasted. This may imply either a mispricing of risk in the CDS market which needs to further studied and promptly addressed by regulators to ensure it does not lead to inadequate allocation of risk between buyers and sellers of credit protection in the CDS market. Conversely, if the variables (both accounting and market based) either collectively or individually are not capturing the true credit risk dynamics of corporates, there is further need for policy makers to require further mandatory and additional off balance sheet disclosure for firms which have off balance sheet activities as the main drivers of credit risk. Further, this study find that market based variables are better able to explain CDS spreads dynamics than accounting variables. This is expected as market based variables change more frequently than accounting variables and thus is better able to adjust to developments in corporate credit risk dynamics. This also implies a flow of credit risk sensitive information between the CDS and equity market. The extent of information flow and pricing dynamics between the two markets becomes more relevant in the crisis period. Policy makers need to be aware of this inter linkage and use this to quickly address issues in one market by initiating appropriate changes both in the market affected as well as other capital markets to prevent risk from spilling over between capital markets. This study also finds that CDS spreads may have overreacted in the crisis period and illiquidity in the CDS market as well as illiquidity in the bond market may be driving spreads artificially in the crisis and post-crisis period. Policy makers have taken a number of initiatives to address the illiquidity in the CDS market in the post-crisis period. However, from the analysis it is evident that the investor's scepticism is still high, evident from high level of illiquidity and its significant impact on CDS spreads in the post-crisis period across the three markets. Investor's scepticism and lack of confidence and participation by market players may be due to the barrage of policy actions and growing calls for more regulation in the CDS market which may inhibit potential CDS market participants from providing liquidity. Policy makers have a responsibility to ensure that in an effort to make the CDS market more efficient they do not deter market participants by making the 'game too difficult to play'. A clear, unambiguous and sustain effort needs to be directed with an aim to make the market more efficient rather than too prohibitive and punishing.

2.7 Conclusion

This chapter empirically tests the explanatory variables that drive corporate CDS spread in US, UK and EU. CDS spread across the three markets where they are actively traded has increased significantly during the crisis period and is still high in post-crisis era. The empirical model fits both accounting and market-based variables and like Das *et al.*, (2009), finds that this provides a good fit to spread. Market based variables are significant predictors of spreads unlike the accounting variables. However, the combination of accounting and market based variables perform better than each of them individually. The paper also find that CDS spread explanatory variables change significantly over time and note a significant drop in spread prediction power in post-crisis period across the three markets even with the same set of explanatory variables. This suggests variables driving spreads have to be re-estimated on a regular basis, or it might lead to wrong conclusions drawn by policy makers and supervisors. Moreover, there is still a substantial portion of CDS spreads across the three markets that cannot be accounted for using the set of explanatory variables explored in this study.

Next, the dynamics of bond yield spreads is studied by splitting it into default and non-default components. We find a significant proportion of non-default component in yield spreads for all sub-periods. In line with previous studies we also find that liquidity is a crucial driving factor for both yield spreads and non-default component of yield spreads and its effect becomes more pronounced during crisis period across markets. However, contrary to popular belief the liquidity effect is found to be substantial even in post-crisis period. All these point towards investor's scepticism and preference for quality which has not plunged even in post-crisis era. CDS market liquidity dynamics is also regressed on CDS spreads and this study find a significant effect especially in crisis and post crisis period. The finding in this paper challenge the past literature that considers CDS spread as pure measure of credit risk and conclude it is driven by market liquidity effect among other noise elements. Furthermore, CDS market liquidity may be pushing CDS spreads which may not necessarily be indicating higher risk of credit default in post-crisis period but more of non-default noise components.

CHAPTER 3

EFFECT OF POLICY ANNOUNCEMENTS ON US AND UK CORPORATE CDS RETURNS DURING THE FINANCIAL CRISIS

CHAPTER 3 – EFFECT OF POLICY ANNOUNCEMENTS ON US AND UK CORPORATE CDS RETURNS DURING THE FINANCIAL CRISIS

Abstract

This paper uses event study methodology to investigate the impact of monetary and fiscal policy announcements on corporate CDS returns for both US and UK. This study employs a range of parametric and non-parametric tests to access the significance of CDS abnormal returns across a range of narrow event windows. Interest rate announcement are found to have an opposite impact on CDS abnormal return across US and UK, QE announcements leads to higher abnormal returns across both samples and fiscal policy announcements is characterised by small positive gain which is short-lived. Daily CDS returns estimated for each firm and aggregated independently, provides the flexibility to test the differential effect on each subsample grouped on the basis of sector, credit quality, firm size and liquidity. The effect of policy announcement is different based on the firm idiosyncratic characteristics and without splitting the sample into sub-categories these effects would have been undetected. By splitting the sample this study is able to disentangle the differential effect and inconsistency across US and UK. By comparing the abnormal return dynamics pre and post announcement days, a higher median return can be noted in the post announcement days for US, while an opposite effect can be noted for the UK sample. This indicates policy announcements in US were more effective in lowering risk in corporate CDS market than those for UK. Furthermore, the process is reversed and tested if a particular policy announcement has a significant effect on firms with certain idiosyncratic characteristics. Overall we note the differences in firm idiosyncratic characteristics is mostly associated with liquidity and gearing for interest rate, difference in liquidity and firm size related to QE and firm capitalisation related to fiscal policy announcements. The results are found to be robust and consistent for alternative specifications of event windows.

Keywords: Interest rate, Quantitative easing, Fiscal policy, event study, CDS returns

JEL Classification: E52, E58, E62, G01, G23, H32

3.1 Introduction

Since the start of the financial crisis triggered by the collapse of Lehmann Brothers in September 2008, financial market landscape has undergone a tremendous change. Instability in the financial system briefly threatened insolvency of large systematically important financial institutions prompting Monetary and Fiscal authorities to intervene. Central banks across US and UK reduced interest rates to unprecedented levels to offset the increase in private sector risk premia and to underpin aggregate demand as well as employed non-conventional measures in the form of quantitative easing and qualitative or credit easing to reduce risk premia and provide liquidity to the ailing financial system. As stated in Klomp (2013) between 2008 and 2009 fiscal and monetary authorities of 18 OECD[33] countries spend about 5% of their GDP on direct intervention along with Government providing about 15% of GDP as liability and debt guarantees. These monetary and fiscal policy interventions were aimed at normalising credit conditions, avoid widespread bankruptcies and restore confidence in the financial system. How effective were these policy measures in calming the financial markets and reducing the overall credit risk in the system is therefore a critical avenue to explore. This research aims to address this important research question. Specifically, this study explores if the macroeconomic policy announcements were effective in reducing the stress in the corporate Credit Default Swap (CDS) market. Were the effects following the policy interventions similar across all types of policy announcements? If certain policy announcements have similar effect across all types of firms or are there firm specific characteristics that determine the effectiveness of these policy announcements?

Klomp (2013) claims that empirical evidence on the effectiveness of monetary and fiscal policy interventions during the financial crisis are inconclusive and most studies in this domain can be broadly classified into three main strands. First group of studies including Fratianni and Marchionni (2009), Tong and Wei (2011) uses stock returns of financial firms as a measure of credit risk and find that government interventions are priced by the market as cumulative abnormal returns over the event window. Another group of studies including Panetta, Faeh, Grande, Ho, King, Levy, Signoretti, Tabago, and Zaghini (2009) find that bank equities display a statistically significant (although economically small) positive reaction to the announcements and argue that government interventions are only marginally effective in

[33] The Organization for Economic Cooperation and Development (18 countries) includes Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Sweden, Switzerland, United Kingdom and United States.

reducing banking risk. Other group of studies including Berndt, Douglas, Duffie, Ferguson and Schranz (2005), King (2009) among others find no significant positive impact of policy announcements on bank's equity prices. These studies note a modest gain in stock price immediately after the announcement followed by resumption to pre-announcement downward trend a few days following the announcement.

Klomp (2013) rationalises the difference in the outcomes of these studies as mainly attributed to difference in the impact across different intervention instruments. Apart from Aït-Sahalia, Andritzky, Jobst, Nowak and Tamirisa (2012) and Greatrex and Rengifo (2010) most studies do not differentiate the impact across various fiscal and monetary instruments. Moreover, the different policy interventions may also have a varying effect on market perception of firm's credit risk. Besides, as stated in Aït-Sahalia *et al.*, (2012) system wide interventions may be less effective because of the difficulty in accessing their impact. Also as rationalised in Dullman and Sosinska (2007) equity markets may be less informative and therefore not suitable to capture credit risk due to firm's substantial off balance sheet activities and well known opaqueness in financial reporting.

The second strand of studies focusses on changes in credit default premium as a measure of banking risk to overcome the problem associated with using equity market price. Recent studies have rationalised CDS premium are a better proxy for credit risk hence change in premium more directly relates to changes in credit quality of the underlying firm. Studies including King (2009), Xiao (2009) and IMF (2009) find that announcement of system wide rescue packages are followed by reduction in premium paid and hence support the effectiveness of policy interventions in reducing bank's credit risk. Aït-Sahalia *et al.*, (2012) note a similar outcome by finding a reduction in interbank risk premia following a policy intervention.

The third strand of studies focusses on the contagion effect following government interventions. As detailed in Aït-Sahalia *et al.*, (2012) a high degree of integration in the global financial system causes potential spillover effect of domestic policy announcement on interbank credit and liquidity risk premia more so during periods of financial stress. Goldsmith-Pinkhanand and Yorulmazer (2010) analyse spillover effect of bank run (specifically Northern rock in 2007) and find a significant calming effect in the UK banking system following Government Intervention. Greatrex and Rengifo (2010) is the only study till date that examines the effect of government intervention in the business sector and finds that financial sector firms respond more favourably to financial sector policy and interest rate announcements whereas non-financial firms respond more favourably to conventional fiscal policy tools.

Without taking a view at priori on the effectiveness of the policy actions, this study intends to provide an empirical justification of the effectiveness of macroeconomic policies announcements in US and UK during the recently financial crisis. Using the well-established event study methodology this study tests if the interventions were effective in lowering system wide corporate credit risk. This paper builds on the work by Greatrex and Rengifo (2010) and aims to investigate the relative effectiveness of the monetary and fiscal policy announcement on aggregate credit risk dynamics of corporate using CDS returns. Government and Central Bank's unprecedented intervention to stem the systematic effect of the credit shock during the financial crisis provides the motivation for this study. This study specifically investigates; if the series of monetary and fiscal policy announcements achieved the intended goal of reducing corporate credit risk in US and UK. By extracting the firm specific credit risk dynamic, this study is able to determine the effectiveness of these announcements and their relative effect on aggregate corporate credit risk during the financial crisis.

Previous studies including Aït-Sahalia *et al.*, (2012) have used LIBOR-OIS spreads to study the effect of policy announcement on credit and liquidity risk premia for the global interbank market. Although their study uses alternative measures of financial distress including New York funding rate to Overnight index swap (NYFR-OIS) spreads, TED[34] spreads, LIBOR-OIS future spreads, repo risk-free spread, Implied volatility index (VIX), CDS composite index and Equity composite index to provide robustness of their results. None of these measures could be partitioned in a way this study is able to split and collate aggregate level measures using CDS returns for firms trading in a given economy. CDS spreads obtained from Markit[35] and aggregated independently provides us the flexibility to

[34] TED spread is the difference between the interest rates on interbank loans and on short-term U.S. government debt i.e. T-bills

[35] Markit provides composite prices. The Markit Group collects more than a million CDS quotes contributed by more than 30 major market participants on a daily basis. The quotes are subject to filtering that removes outliers and stale observations. Markit then computes a daily composite spread only if it has two or more contributors. Once Markit starts pricing a CDS contract, data is available on a continuous basis, although there may be missing observations in the dataset. Markit is one of the most widely employed dataset. Papers that employ this dataset include: Acharya and Johnson (2007), Zhang, Zhou and Zhu (2009), Jorion and Zhang (2007, 2009), Zhu (2006), Micu, Remolona and Wooldridge (2004) and Cao, Yu and Zhong (2010) to name a few (Mayordomo, Peña and Schwartz, 2014)

break down the effect based on sector - financial and non-financial, credit quality - investment grade and speculative grade, firm size - small, medium and large and CDS liquidity – low, medium and high, to test the effect across the samples for both US and UK. Furthermore, this study tests if a particular policy announcement had a significant effect on firms with certain characteristics operating within the economy. This will provide Central banks and regulators useful insights on the effectiveness of a particular policy initiative on the types of firms especially during periods of economic distress. These findings will provide useful insights enabling them to take appropriate policy actions or inactions to control aggregate level credit risk within the economy by using the right tool for the kind of economic problem at hand.

This paper is closely related to Greatrex and Rengifo (2010) that checks the effect of fiscal policy, monetary policy and financial sector policy announcements on CDS index for US sample; specifically North American investment grade index CDX-IG and North American high yield index CDX-HY. Rather than relying on CDS spreads of a pre-defined credit index, this paper studies the effect on daily CDS return rather than using CDS spreads directly. Greatrex and Rengifo (2010) employed use of CDS spreads which are at-market spreads for newly issued default swap contracts with constant maturity as there are no time series data on actual transaction price for a specific CDS contract. As such using CDS spreads to check the effect is an incorrect estimation of the underlying firm's credit dynamics in an event study context. Unlike other studies in the past, we convert spreads into returns using the procedure detailed in Brendt and Obreja (2010) thus addressing the limitation of Greatrex and Rengifo (2010). Thus this study is more comprehensive, in the sense that firstly, it uses CDS return for individual firms operating in the economy and secondly, we have the flexibility to collate and aggregate returns for firms in the economy as per carefully considered sub-sample criteria. This study also employs the use of extensive parametric (ordinary t-test, Patell and Boehmer, Musumeci and Poulsen - BMP) and alternative specifications of non-parametric tests (Rank tests and Sign tests) to test the significance of the estimates obtained across both the US and UK economy.

There are a few potential roadblocks that limit the scope of inquiry in the context of this study. Firstly, policy announcements are too frequent and close by to entirely separate the effect of one from the other. Majority of policy interventions were announced in close proximity, which poses the risk of results being contaminated by effect of multiple announcements on CDS return. To counter this problem, this study focusses on small event windows i.e. [0], [-1, 0, +1], and [-3, 0, +3]. It is worth noting that none of the policy announcements were within a span of 7 days and so this study employs a baseline analysis of one day window [0] and confirms the validity of the result to alternative smaller event windows of 3 days [-1,0,+1] and 7 day [-3,0,+3]. One issue with isolating impact of policy intervention (announcements) on CDS spreads as detailed in Greatrex and Rengifo (2010) is the effect of total clustering i.e. covariance of abnormal return across all firms does not equal zero. This is mainly due to announcements affecting all firms in the sample simultaneously. This is addressed by employing alternative specification of non-parametric test statistics (rank and sign tests) that takes into consideration the non-zero covariance dynamics of abnormal return rather than relying only on parametric measures. This study also acknowledges that empirically it is difficult to prove causality between effect of policy announcements and firm's credit risk. This problem exist due to the complex nature of the financial system and corporate credit risk environment particularly during the financial crisis which makes it impossible to reliably ascribe how much credit risk reduction in CDS market could be attributed to the policy announcements, particularly in real time. This could be attributed to the design specific challenge which event study cannot address directly is controlling for the multitude of factors that may have a bearing on market response to announcements. The author acknowledges these limitations in the context of this study.

The remainder of this paper is as follows. Section 3.2 provides a brief literature review on the major studies in this domain. Section 3.3 provides the estimation of CDS returns and the event study methodology along with the parametric and non-parametric tests used in this study. Section 3.4 provides the empirical results along with the main findings from the analysis. Section 3.5 discusses the conclusions drawn and policy implications and scope for further research investigation.

3.2 Literature Review

Past literature has a long running debate on the role and effectiveness of monetary and fiscal policies in containing the economic crisis. These debates can be broadly categorised into two main schools of thoughts. Firstly, research including Taylor (2009), Miskin (2009) among others believes that monetary policy is a powerful tool for countercyclical stabilisation, as such is the only effective means to stem a crisis. Eickmeier and Hofmann (2013) claims monetary policy shocks causes risk spreads to increase significantly pointing to the relevance of 'balance sheet' or 'risk taking' channels. Consequently, a relaxed monetary policy especially during period of crisis should help firms by increasing access to funding. Taylor (2009) supports the use of monetary policy in containing the crisis and claims that fiscal policy is particular leads to inflation, crowding-out and inefficient use of resources and so is ineffective during period of recessions.

Fiordiliso, Galloppo and Ricci (2014) claims monetary policy interventions have played a central role in restoring the stability of financial and banking system during the financial crisis. Dunbar and Amin (2012) indicate a contractionary monetary policy; will usually lead to increase in credit risk while an expansionary monetary policy reduces credit risk. Laeven and Tong (2012) rationalises that, in theory monetary policy may influence a firm's stock price by changing the future cash flow or by altering the rate at which these cash flows are discounted i.e. fall in interest rate should improve firms growth prospects by allowing interest rate sensitive firms that were unable to afford projects at higher rate to increase their investment. Alternatively, falling interest rate triggered by contractionary monetary policy should in theory improve a firm's risk profile by lowering the cost of external borrowing, thereby reducing firm's risk premium which will vary across firms depending on their degree of financial dependence. Dunbar, (2008), Houweling and Vorst, (2005), Jarrow and Turnbull, (1995) suggests that credit risk transfer mechanism is sensitive to changes in short term interest rates. This implies any changes to the interest rate should influence the debt financing and short term cash flow financing needs of the firms. Consequently an expansionary monetary policy intervention specifically interest rate reduction should decrease the credit risk for firms operating within the policy regime. A similar effect can be attributed to the quantitative easing mechanism whereby more capital available in the financial system would in term help reduce negative spillover to the real economy. Dunbar and Amin (2012) find that during periods of contractionary monetary policy counterparty risk responds more favourably when Federal Reserve unexpectedly lowers its target rate. They also find a strong influence on firm's debt financing through the 'credit channel' for both expansionary and contractionary monetary policy implying Central Bank has managed to stem the systematic counterparty credit risk fears in financial markets through this channel. Bernanke, Gertler and Gilchrist (1996) affirms that financial intermediaries respond to tighter monetary policy i.e. higher interest rate with a 'flight to quality' which implies a reverse effect could be expected by a relaxed monetary policy announcement.

Studies including Thorbecke, (1997); Cassola and Morana (2004); Rigobon and Sack, (2004) Bernanke and Kutter, (2005) among others have well documented the relationship between monetary policy and stock market However, a number of studies (Andersen, Bollersev, Diebold and Vega, 2007; Bernanke and Kuttner, 2005; Chuliá, Martens and van Dijk, 2010; Guo, 2004; Gurkaynak, Sack and Swanson, 2005; Wongswan, 2009 among others) suggests financial markets do not respond to anticipated monetary policy changes. Monetary policy could also have a negative effect on the economy too. Taylor (2009) claims that a relaxed Monetary policy was a major contributing factor for excessive risk taking by banks, leading to the global financial crisis of 2007-2008. Adrian and Shin, (2008) and Borio and Zhu, (2008) refer to this transmission mechanism as 'the risk taking channel' where 'low interest rates for too long' leads to increase in 'risk tolerance' by banks. Empirical evidence for this has been detailed in Ioannidou, Ongena and Peydro (2009); Altunbas, Gambacorta and Marques-Ibanez (2010); Maddaloni and Peydró (2011) among others.

On the other hand, economists including Nobel laureate Paul Krugman believe fiscal policy is the only effective means to counter a crisis and criticizes monetary policy for creating liquidity trap, zero bound interest rate, inflation and asset bubble (Silvia and Iqbal, 2011). This view is further supported by Christiano, Eichenbaum and Rebelo (2010) and Eggertsson and Krugman, (2012). These studies believe fiscal policy is one of the main factors determining the macro-economic environment in which a Central bank operates. During the financial crisis, governments around the world embarked beyond monetary policy measures by introducing large simulative fiscal packages raising important questions on the effectiveness of temporary fiscal policy actions in stabilising system-wide credit risk and the potential long-run negative effects on the economy due to debt accumulation resulting from the fiscal stimulus. Many staunch opponents of active and continuous fiscal policy suggests, fiscal stimulus to be used as one-off emergency measures. Gramlich (1999) argues it is difficult for fiscal policy to deliver its stimulus in a "timely, targeted and temporary" manner. Taylor (2000) argues the role of fiscal policy to be limited to minimizing distortion and "letting automatic stabilizers"[36] work. Although, his study does recommend use of fiscal policy in a situation when nominal interest rates are close to zero and further conventional discretionary monetary policy is undesirable which was true during the recent financial crisis. Freedman, Kumhof, Laxton, Muir and Mursula (2010) concludes that if fiscal stimulus leads

[36] Automatic stabilizers describe the channel through which fiscal policy can be mildly counter cyclic even if fiscal instruments are not varied in any discretionary way in response to business cycle (Freedman et al. 2010)

to permanently higher deficit and therefore debt the benefits may be favourable in the short run but at the expense of long run consequences.

As detailed in Allard, Catenaro, Vidal and Wolswijk (2013), fiscal policy affects the short term environment for monetary policy via three channels namely; automatic financial stabilisers, discretionary fiscal measures and measures having a direct price impact (e.g. value-added or sales tax rate). Their study suggests that expansionary fiscal measure have a positive effect on growth and price development in the short run. However, unsustainable fiscal policy in the long run has adverse economic effect causing inflation, higher taxes and government default. Likewise, empirical studies on effect of fiscal policy on consumption reports contradictory findings[37]. The Standard Real Business Cycle model by Barro and King (1984); Baxter and King, (1993) predicts that an increase in government spending lowers private consumption because the rational agent regards an increase in government spending as an increase in tax. However studies by Blanchard and Perotti (2002); Perotti, (2004); Ravn, Stephanie and Martin (2007); Mountford and Uhlig, (2009) among others report positive effects of Fiscal stimulus on consumption. Later studies by Tagkalakis (2008) focused on the relationship between the effects of fiscal policy and liquidity constraints; reports that fiscal policy becomes more effective in a recession when liquidity constraints bind for a large fraction of households. Sutherland (1997) reports that the power of fiscal policy to affect consumption can vary depending on the level of public debt. Based on these observations, they implies the effect of Fiscal policy announcement may have a varying effect on market perception depending on whether the market perceives the benefit in the short run to outweigh the effects in the long run following a policy announcement. Moreover the effect may also vary depending on the type of Fiscal policy interventions. Studies by Alesina and Ardagna (2010) supports this using a regression analysis and concludes that fiscal stimulus based on tax cuts are more likely to increase growth than those based upon spending increase.

Klomp (2013) claims that the effect of fiscal policy intervention on credit risk of banks is larger compared to monetary policy interventions based on observations drawn from reduction in premium on banks CDS spreads. Klomp (2013) rationalised this firstly, because fiscal interventions is only conducted if there are no real other option left. Secondly, financial markets anticipate more on Central bank's monetary interventions, while interventions by

[37] This conflict between theoretical and empirical results of fiscal policy is commonly referred to as the government spending puzzle.

fiscal authorities are more unexpected and ad-hoc. Thirdly, only financially troubled (banks) firms benefit from fiscal intervention whereas it is not the case with monetary interventions like interest rate cuts in which all (banks) firms benefit. Fiscal policy employed in the 'Keynesian' manner can support aggregate demand, boosting the economy and potentially driving stock prices higher. In contrast, 'Classical' economic theory focussing on the crowding out effect claims fiscal policy could potentially drive stock prices lower. The above two perspectives is based on the notion that fiscal policy influences the level of economic activity which in turn would have an impact on financial markets. Furthermore, the 'Ricardian' perspective (Barrow, 1974, 1979) claims fiscal policy would have no effect on stock markets. In short the effect of fiscal policy on financial market may be positive, negative or inconsequential depending on the Keynesian, Classical or Ricardian view respectively. At the empirical level, few studies have analysed the relationship between Fiscal policy and: 1) asset market returns (Arin, Mamun and Purushothman 2009; Darrat, 1988) 2) stock prices (Ardagna, 2009) 3) interest rates (Maclennan, More and More, 1999) and 4) risk premium (Akitoby and Stratmann, 2008).

In effect, past empirical evidence on the effectiveness of policy interventions is limited and ambiguous which can be partly attributed to the models employed to study them. Klomp (2013) notes that majority of these studies use models that assume one single effect (across firms) of government interventions, which can be challenged on the grounds of firm specific heterogeneity. According to King (2009) the reaction of financial market on announcement of policy intervention may vary considerably across banks (and firms) due to difference in the exposure of subprime related risk. Hanson, Pesaran and Schuermann (2008) suggest that neglecting this heterogeneity may lead to biased or inconsistent estimates. Accordingly, this study employ a number of ways to cut the sample based on firm specific characteristics that have a bearing on firm specific credit risk. Although the past literature provides differences in opinion on the effectiveness of policy interventions in limiting the effects of the financial crisis, it can be noted that many countries including US, UK, EU, Japan and China employed both fiscal and monetary policies simultaneously. Silvia and Iqbal (2011) observes that many Central banks cut key interest rates and increased money supply within the economy as well as Governments implemented fiscal stimulus order to limit the impact of financial crisis, raising important questions on the effectiveness and suitability of both monetary and fiscal policy in limiting the economic downturn.

3.3 Estimation procedure

3.3.1 CDS return estimation

The 5 year constant maturity CDS spreads used in the analysis is extracted from Markit dataset. Markit collates an extensive record of single name CDS spreads on a daily frequency. The reported CDS spreads are at-market spreads for newly issued default swap contracts with constant maturity and no time series data on actual transaction price for a specific CDS contract is available. As such spreads do not represent the actual transaction price for the specific CDS contract and using it directly into estimating the effect will result in an incorrect estimation of the underlying firm's credit dynamics and so requires computation of CDS returns. To convert CDS spreads into daily returns, this study follows the procedure detailed in Berndt and Obreja, (2010). The estimation process and assumptions are as below,

Consider a 100% leveraged portfolio, made up of long position of T-years defaultable bond, issued by a firm *i*, trading at par value and short position in a T-years par value riskless bond. Berndt and Obreja, (2010) argues that this portfolio will generate cash-flows that are similar to those from selling credit protection on firm *i*, via a T-years CDS contract with a nominal value at par[38]. The initial value of both the CDS contract and the long-short portfolio position is zero. Over some time interval the change in the value of the CDS contract to the investor ΔV_{CDS} will be equal to the change in the value of the long-short bond position, i.e.

$$\Delta V_{CDS} = \Delta P_D - \Delta P_{RF} \tag{3.1}$$

Where, ΔP_D and ΔP_{RF} denotes the changes in the value of the risky and risk free bond. On dividing each side of the Eqn. (3.1) by the par value, the CDS implied excess return on defaultable debt, r_D^e could be represented as,

$$r_D^e = \Delta V_{CDS} \tag{3.2}$$

The above equation indicates that the rate of return on the defaultable bond is equal to the rate of return on the riskless bond plus the change in value of the CDS contract divided by par. Over a short interval, the change in the value of the CDS contract to the investor is equal to minus the change in the CDS rate, i.e. - ΔCDS multiplied by the value of a defaultable T-year annuity, *A (T)*

$$\Delta V_{CDS} = -\Delta CDS * A(T) \tag{3.3}$$

[38] This assumption ignores the possibility that the fixed rate Treasury bond may not be selling at par value in an event of default.

Where,

$$A(T) = \frac{1}{4}\sum_{j=1}^{4T} \delta\left(\frac{j}{4}\right) q\left(\frac{j}{4}\right) \tag{3.4}$$

In the above equation $\delta(s)$ denotes the risk free discount rate for s years out, and $q(s)$ denotes the risk neutral survival probability of firm i, over the next s years. The discount factors are interpolated using standard cubic spline algorithm using daily generic government bond yields[39] downloaded from Bloomberg. To obtain estimates for $q(s)$, this study assumes a constant risk neutral default intensity λ for firm (i)[40]. The survival probability simplifies to,

$$q(s, \lambda) = e^{-\lambda s} \tag{3.5}$$

Which allows to express the annuity factor $A(T)$ as a function of λ, where λ can be computed directly from observed CDS rates by solving for equation,

$$CDS\ A(T, \lambda) = L \sum_{j=1}^{4T} \delta\left(\frac{j}{4}\right) [q\left(\frac{j-1}{4}, \lambda\right) - q\left(\frac{j}{4}; \lambda\right)] \tag{3.6}$$

Where L, represents the risk neutral expected fraction of notional lost in the event of default. We assume a constant L of 60%[41]. The right hand side of the equation represents the value of the protection seller leg at initiation of the default swap contract, whereas *CDS A(t)* equals the value of the protection buyer leg. Equality holds since at-market CDS rates are set so that both of these values agree. Using Eqn. (3.5) to solve for Eqn. (3.6) gives,

$$\lambda = 4\log(1 + \frac{CDS}{4L}) \tag{3.7}$$

Unlike Berndt and Obreja, (2010), who use weekly CDS rates to estimate r_D^e, this study uses daily CDS spreads to estimate daily CDS returns for all firms in US and UK that have CDS spreads data available in Markit dataset. The estimation process considers a constant L of 60%, and estimate daily risk neutral default intensity for each firm i, using Eqn. (3.7). The risk free discount rate for each period (as above) is interpolated using cubic spline algorithm from daily generic government bond yields obtained from Bloomberg. Next, the value of the defaultable 5 year annuity, $A(5, \lambda)$ is estimated using Eqn. (3.6). Finally, the CDS implied excess daily returns is estimated as given in Eqn. (3.3).

39 Generic government bonds yields with maturity ranging from 3m, 6m, 1y, 2y, 3y and 5y are used to interpolate the corresponding risk free discount function

40 This simplifying assumption represents a trade-off between a loss of generality on the one side and a potentially incorrect measurement of λ due to model misspecification error on the other.

41 Our assumption of L is similar to the one used by Berndt and Obreja (2010) and considers a constant recovery rate of 40% across all CDS in our sample

Table 3.1: Table below reports the descriptive statistics for daily CDS spreads and daily CDS returns for US and UK, broken down as per year (Panel A and Panel C) and sector (Panel B and Panel D)

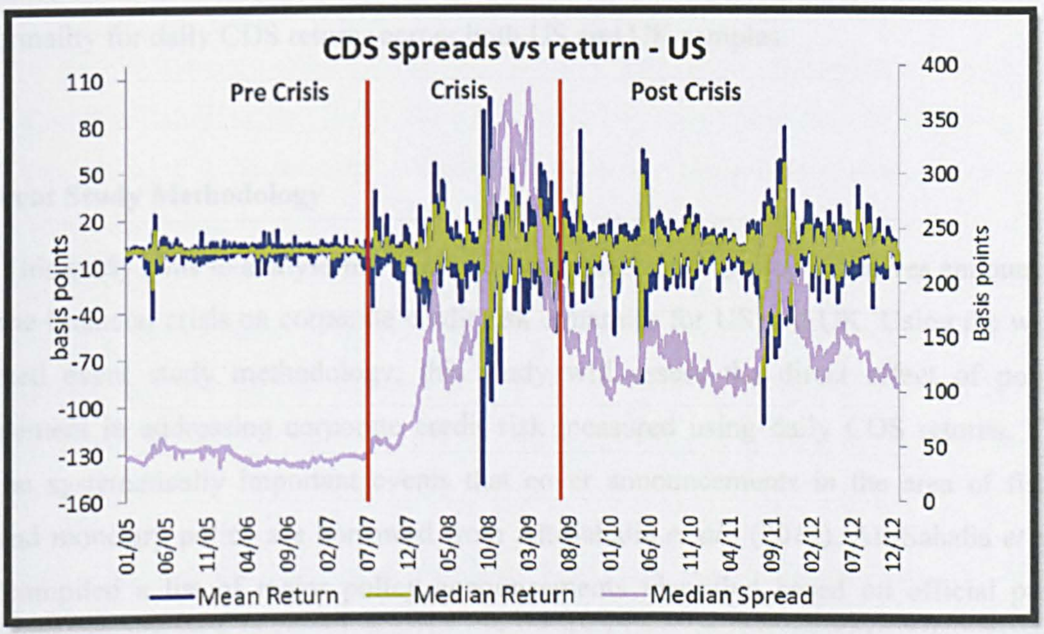
US	Panel A - Daily CDS Spreads (basis points)							
Year	**N**	**Mean**	**Median**	**Min**	**Max**	**Stdev**	**Skew**	**Kurt**
2007	176,006	124.18	47.53	2.28	5,402.92	249.20	9.38	139.91
2008	44,398	372.54	155.02	5.13	13,179.25	734.51	6.68	65.68
2009	69,699	550.09	169.00	9.86	43,776.96	1,504.33	8.85	117.60
2010	47,427	405.76	124.53	13.28	3,456,000.00	15,947.72	214.54	46,482.54
Total	**337,530**	**284.36**	**85.96**	**2.28**	**3,456,000.00**	**6,028.05**	**558.26**	**319,988.60**
UK								
Year	**N**	**Mean**	**Median**	**Min**	**Max**	**Stdev**	**Skew**	**Kurt**
2007	38,379	89.26	34.32	3.93	5,498.43	375.49	13.08	181.95
2008	38,393	197.00	108.59	12.00	5,272.00	286.55	6.53	74.91
2009	37,276	262.28	128.92	14.88	10,714.75	529.11	10.46	156.97
2010	34,001	153.53	104.56	16.68	1,772.64	157.95	3.68	21.32
Total	**148,049**	**175.52**	**87.34**	**3.93**	**10,714.75**	**371.64**	**12.13**	**222.82**

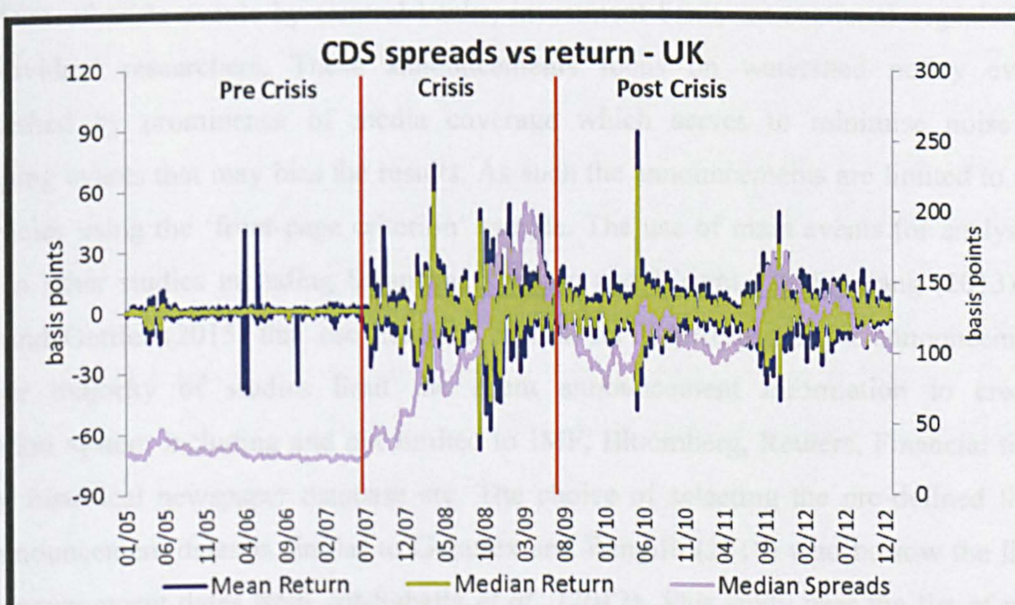
US	Panel B – Daily CDS Spreads (basis points)							
Sector	**N**	**Mean**	**Median**	**Min**	**Max**	**Stdev**	**Skew**	**Kurt**
Basic Materials	22,342	179.46	96.42	8.74	1,775.00	243.09	3.55	18.60
Consumer Goods	46,602	368.30	89.42	3.55	30,380.96	1,438.54	10.75	144.21
Consumer Serv.	53,056	516.61	153.82	5.04	3,456,000	15,089.48	226.37	51,834.64
Energy	22,389	99.26	47.82	2.28	785.01	118.38	2.26	8.43
Financials	73,100	344.95	100.50	3.84	43,776.96	944.61	8.87	156.11
Healthcare	19,841	119.03	49.18	3.06	1,442.05	167.36	2.56	10.94
Industrials	43,029	222.53	87.05	3.32	9,762.13	522.58	9.84	126.09
Technology	13,597	134.31	65.34	4.89	2,192.72	179.24	3.36	21.99
Telecom	12,934	146.39	73.28	7.77	1,438.09	179.00	2.45	10.87
Utilities	30,640	140.44	56.55	7.68	2,428.74	248.37	4.46	26.92
Total	**337,530**	**284.36**	**85.96**	**2.28**	**3,456,000**	**6,028.05**	**558.26**	**319,988.60**
UK								
Sector	**N**	**Mean**	**Median**	**Min**	**Max**	**Stdev**	**Skew**	**Kurtosis**
Basic Materials	6,750	471.76	129.16	11.57	10,714.75	1,115.48	5.57	39.87
Consumer Goods	17,244	142.96	64.45	7.04	2,956.76	283.38	6.38	54.82
Consumer Serv.	32,702	183.87	108.03	7.42	1,998.13	206.74	2.53	11.46
Energy	4,629	56.17	50.00	3.98	614.04	51.78	4.30	35.72
Financials	38,916	176.30	121.91	3.93	2,668.87	219.64	3.72	23.68
Healthcare	2,051	50.67	45.81	4.27	198.31	35.37	1.28	5.36
Industrials	11,792	203.76	129.04	12.16	4,809.22	298.52	7.23	79.96
Technology	76	234.59	235.53	157.57	307.98	41.03	-0.47	2.41
Telecom	6,069	220.44	169.03	14.85	1,332.93	190.19	1.31	5.17
Utilities	27,820	120.06	65.97	7.25	5,498.43	435.91	11.33	134.99
Total	**148,049**	**175.52**	**87.34**	**3.93**	**10,714.75**	**371.64**	**12.13**	**222.82**

US	Panel C - Daily CDS returns (basis points)							
Year	**N**	**Mean**	**Median**	**Min**	**Max**	**Stdev**	**Skew**	**Kurt**
2007	173,447	-1.27	-0.02	-4,758.87	5,140.39	32.17	21.81	9,507.37
2008	44,079	-5.55	-0.83	-2,134.72	2,245.99	66.62	1.90	234.94
2009	68,684	3.96	0.63	-1,603.67	2,294.10	51.18	1.55	159.01
2010	45,752	-0.59	-0.02	-1,104.97	1,254.22	36.56	0.64	167.92
Total	**331,962**	**-0.66**	**-0.01**	**-4,758.87**	**5,140.39**	**43.17**	**6.21**	**1,784.86**
UK								
Year	**N**	**Mean**	**Median**	**Min**	**Max**	**Stdev**	**Skew**	**Kurt**
2007	38,260	-0.65	0.00	-473.81	4,244.97	27.44	96.66	14,996.49
2008	38,316	-3.55	-0.29	-1,434.67	1,614.70	41.49	-1.22	192.11
2009	37,178	2.81	0.23	-1,764.00	1,266.03	39.05	-1.49	385.43
2010	33,934	-0.17	0.01	-644.32	626.47	25.37	1.00	111.85
Total	**147,688**	**-0.42**	**0.00**	**-1,764.00**	**4,244.97**	**34.33**	**11.75**	**1,861.74**

US	Panel D - Daily CDS returns (basis points)							
Sector	**N**	**Mean**	**Median**	**Min**	**Max**	**Stdev**	**Skew**	**Kurt**
Basic Materials	22,004	-0.36	-0.01	-1,729.18	2,294.10	48.37	8.08	767.11
Consumer Goods	45,764	-1.02	0.01	-696.25	984.67	33.34	-0.23	61.59
Consumer Serv.	52,038	-0.43	0.00	-4,758.87	4,789.86	47.87	0.27	3,851.91
Energy	21,970	-0.13	0.00	-498.10	348.25	19.01	-2.78	101.15
Financials	72,282	-1.16	-0.03	-2,134.72	2,245.99	57.47	0.85	211.54
Healthcare	19,471	-0.24	-0.01	-560.32	595.66	19.85	-2.75	160.21
Industrials	42,357	-0.49	0.00	-1,220.11	5,140.39	48.37	27.29	3,137.99
Technology	13,445	-0.98	-0.02	-639.69	565.63	24.00	-2.39	148.95
Telecom	12,615	-0.47	-0.01	-766.41	1,245.42	32.21	8.07	373.98
Utilities	30,016	-0.38	-0.02	-1,104.97	1,254.22	27.60	0.28	512.65
Total	**331,962**	**-0.66**	**-0.01**	**-4,758.87**	**5,140.39**	**43.17**	**6.21**	**1,784.86**
UK								
Sector	**N**	**Mean**	**Median**	**Min**	**Max**	**Stdev**	**Skew**	**Kurtosis**
Basic Materials	6,736	-0.44	0.01	-602.39	710.53	39.74	0.25	48.29
Consumer Goods	17,205	-0.51	0.01	-1,434.7	1,255.67	28.20	-5.77	761.87
Consumer Serv.	32,655	-0.49	0.00	-1,024.6	1,024.25	30.58	-0.61	161.62
Energy	4,616	-0.27	-0.01	-437.01	442.74	19.39	-4.17	216.13
Financials	38,809	-0.66	-0.01	-1,764	1,614.70	41.44	-1.30	343.59
Healthcare	2,050	-0.22	0.00	-98.22	87.08	9.47	-0.85	22.03
Industrials	11,780	-0.38	0.14	-849.28	974.92	33.98	-0.35	118.76
Technology	69	0.41	2.15	-85.14	109.95	27.78	0.13	6.27
Telecom	6,053	-0.32	0.05	-238.08	563.39	28.99	1.28	35.87
Utilities	27,715	-0.03	0.00	-716.09	4,244.97	33.95	70.73	8,879.38
Total	**147,688**	**-0.42**	**0.00**	**-1,764**	**4,244.97**	**34.33**	**11.75**	**1,861.74**

Fig 3.1: CDS return for the US and UK sample estimated on a daily basis for all corporate CDS spreads available in Markit Dataset from 1st Jan 2005 till 31st Dec 2012. The graph plots the mean and median CDS returns in basis points (primary Y axis) and CDS spreads (secondary Y axis). The pre-crisis period is defined as 1st Jan 2005 to 30th Jun 2007; crisis period from 1st Jul 2007 to 30th Jun 2009 and post-crisis period from 1st Jul 2009 to 31st Dec 2012 as given in Breitenfellner and Wagner, (2012).





From Table 3.1 and Fig. 3.1 it can be seen that CDS spreads have risen dramatically following the financial crisis where the rise is effectively from Q3 2007 across both US and UK. Panel A shows, median CDS spreads is specifically high following the crisis as compared to 2007 across both the sample. Panel B breaks down CDS spreads as per sector evidencing high variability in spreads across GICS sectors. Panel C and Panel D highlights, mean and median CDS return are mostly similar across the years and sectors although, there is a high variability in the daily returns. Both mean and median returns are widely dispersed across the years and sector, evident from high kurtosis and skewness indicating deviation from normality for daily CDS returns across both US and UK samples.

3.3.2 Event Study Methodology

This study aims to analyse the impact of macroeconomic policy initiatives announced during the financial crisis on corporate credit risk dynamics for US and UK. Using the well-established event study methodology, this study will assess the direct effect of policy announcement in addressing corporate credit risk measured using daily CDS returns. The details on systematically important events that cover announcements in the area of fiscal policy and monetary policy are borrowed from Aït-Sahalia *et al.*, (2012). Aït-Sahalia *et al.*, (2012) compiled a list of major policy announcements identified based on official press release, major newspaper and news search engine which are cross checked based on similar comparison of crisis events by Central banks, investment bank, international organisations and individual researchers. These announcements focus on watershed policy events, distinguished by prominence of media coverage which serves to minimise noise and overlapping events that may bias the results. As such the announcements are limited to front page articles using the 'front-page criterion' sample. The use of main events for analysis in similar to other studies including Swanson, Reichlin and Wright (2011), Yang (2013) and Karadi and Gertler (2015) that use headline criteria for identifying major announcements. Moreover majority of studies limit the event announcement information to credible information system including and not limited to IMF, Bloomberg, Reuters, Financial times, proquest historical newspaper database etc. The choice of selecting the pre-defined list of event announcement dates is similar to Greatrex and Rengifo (2010) who borrow the list of event announcement dates from Aït-Sahalia *et al.*, (2012). This study uses the list of major events as identified and elaborated in Aït-Sahalia *et al.*, (2012) which is comprehensive and fits with the scope of this study both in terms of the type of events and the time period of analysis. This study focuses on the effect following the policy announcements rather than dwelling on the event identification logic.

From the scope of analysis, this study focusses on monetary and fiscal policy announcements. Specifically the Monetary policy announcements includes interest rate decisions and quantitative easing – which involves Central banks purchasing government securities and Credit easing – which involves purchase of private sector debt in primary or secondary markets, including mortgage backed securities. Fiscal measures include all policy actions that aim to stimulate domestic demand, through increase in expenditure or reduction in taxes. Greatrex and Rengifo (2010) use a similar list of announcements on monetary and fiscal policy as used in this study, although their study extends the analysis to other announcements including liquidity support and financial sector policy in US and uses CDS spreads to evaluate the effect in CDS market. However within the context of the monetary and fiscal policy announcements the finding from this study would provide a useful way of comparing our results within the US sample with those from Greatrex and Rengifo (2010). The scope of analysis is limited to the list of announcements in US and UK as detailed in Table 3.2,

Event study methodology has a long history with the first study published by Dolley (1933) and later introduced to the accounting and finance discipline by Ball and Brown (1980) and Fama, Fisher, Jensen and Roll (1969). These seminal studies mainly focused on the informational content of earning and the effect of stock split respectively (Campbell, Lo and MacKinlay, 1997). Subsequent studies focussed on the relevance of using daily instead of monthly returns and further sophistication to the method of estimating abnormal return and their statistical significance (Brown and Warner, 1980, 1985). Event study approach in general, have a number of advantages including its simplicity, parsimony and focus on immediate market response to an event including the suitability of working with limited and missing data unlike alternative methodology[42]. However; neither does it lend itself to the analysis of causality nor can it provide a comprehensive evaluation of policy effectiveness which limits its effectiveness (Aït-Sahalia *et al.*, 2012).

[42] Specifically the regression analysis used in Taylor and William (2009)

Table 3.2: Table details the list of Monetary and Fiscal policy announcements across US and UK sample taken from Aït-Sahalia *et al.*, (2012)

Policy - US	Dates	Description
1. Monetary Policy		
1.1 Interest Rate Cuts	18/09/07	FOMC reduces target rate to 4.75%
	31/10/07	FOMC reduces target rate to 4.50%
	11/12/07	FOMC reduces target rate to 4.25%
	22/01/08	FOMC reduces target rate to 3.5%
	30/01/08	FOMC reduces target rate to 3%
	18/03/08	FOMC reduces target rate to 2.25%
	30/04/08	FOMC reduces target rate to 2%
	08/10/08	FOMC reduces target rate to 1.5%
	29/10/08	FOMC Reduces Target Rate to 1% and Primary Credit Rate to 1.25%
	16/12/08	FOMC establishes target range for federal funds rate of 0-0.25%
	28/01/09	FOMC maintains the target range for the fed funds rate at 0 to .25%
	18/03/09	FOMC maintains the target range for the fed funds rate at 0 to .25%
	29/04/09	FOMC maintains the target range for the fed funds rate at 0 to .25%
	24/06/09	FOMC maintains the target range for the fed funds rate at 0 to .25%
	12/08/09	FOMC maintains the target range for the fed funds rate at 0 to .25%
	04/11/09	FOMC maintains the target range for the fed funds rate at 0 to .25%
	27/01/10	FOMC maintains the target range for the fed funds rate at 0 to .25%
	15/03/10	FOMC maintains the target range for the fed funds rate at 0 to .25%
	28/04/10	FOMC maintains the target range for the fed funds rate at 0 to .25%
1.2 Quantitative Easing	07/10/08	Commercial Paper Funding Facility (CPFF)
	14/10/08	Commercial Paper Funding Facility (CPFF)
	21/10/08	Money Market Investor Funding Facility (MMIFF)
	25/11/08	GSE Securities Purchase
	05/01/09	New York Fed Begins Purchasing Mortgage-Backed Securities
	28/01/09	FOMC to purchase long-term Treasury securities
	18/03/09	FED to purchase agency debt and MBS
	29/04/09	FOMC Maintains the amount of US Treasury purchase, agency debt and MBS purchase

2. Fiscal Policy	18/01/08	President Bush Asks Congress to Enact An Economic Growth Package that Bolsters Business Investment and Consumer Spending
	24/01/08	President Bush Discusses the Bipartisan Economic Growth Agreement
	29/01/08	Economic Stimulus Act of 2008 passed by Congress
	13/02/08	Economic Stimulus Act of 2008
	15/01/09	Stimulus Package
	09/02/09	US Stimulus Plan passes Senate
	11/02/09	US Stimulus Plan Agreement Reached
	17/02/09	US Stimulus Plan signed by Obama
	26/02/09	Fed Budget Released

Policy - UK	**Dates**	**Description**
1. Monetary Policy		
1.1 Interest Rate Cuts	06/12/07	BoE Reduces Bank Rate to 5.5%
	07/02/08	BoE Reduces Bank Rate to 5.25%
	10/04/08	BoE Reduces Bank Rate to 5.0%
	08/10/08	BoE Reduces Bank Rate to 4.5%
	06/11/08	BoE Reduces Bank Rate to 3%
	04/12/08	BoE Reduces Bank Rate to 2.0%
	08/01/09	BoE Reduces Bank Rate to 1.5%
	05/02/09	BoE Reduces Bank Rate to 1.0%
	05/03/09	BoE Reduces Bank Rate to .5%
1.2 Quantitative Easing	08/10/08	BoE Discount Window Facility
	19/01/09	BoE Asset Purchase Facility
	06/02/09	Commercial Paper Facility, Corporate Bond Secondary Market Scheme
	05/03/09	Asset Purchase Facility: CP Facility, Gilt Purchases and Corporate Bond Secondary Market Scheme
	19/03/09	Corporate Bond Secondary Market Purchase Scheme: Details
2. Fiscal Policy	24/11/08	UK Stimulus Package: Ensuring Financial Stability (2010-2011)

The key assumption underlying the event study methodology is the hypothesis that CDS spreads/returns fully and immediately incorporate all available information i.e. the CDS market is efficient. As such policy announcements should leads to rapid adjustment of spreads for corporates that have active CDS contract trading in the market. An asset pricing model is used to access the significance of this price adjustment by employing a market model approach[43]. This study adapts and modifies this approach as follows,

$$R_{it} = a_i + b_i R_{et} + e_{it} \tag{3.8}$$

Where: R_{it} is the CDS return for a firm (i) for a given day (t), R_e is the return on the equity (e) for a given day (t), e_{it} is the white noise random component which is not correlated with R_{et} and is the statistical error term having an expected value $E(e_{it}) = 0$, with a constant variance $Var\ (e_{it}) = \sigma^2_{ei}$ and $E(e_{it}, e_{i,t-j}) = 0$, for every i≠j, a_i and b_i are the model coefficients. The econometric estimation of a_i and b_i is carried out using Ordinary Least Square (OLS) regression for the period between 252 and 21 trading days[44] prior to announcement date similar to as in Asimakopoulos and Athanasoglou (2013). The above specification provides estimation for the parameters of normal period model which is not influenced by the event-related returns.

Competing studies have proposed alternative approaches called the constant mean return - CMR (Milonas, 1987; Schroeder, Blair and Mintert, 1990; Mckenzie, Thomsen and Dixon; 2004 among others). However, CMR model suffer from two main drawbacks namely, the issue of parameter constancy leading to trade-off effect i.e. the precision gained from using longer normal period is traded off against the loss associated with changes in the normal return over time and is computationally difficult to estimate (Mckenzie, Thomsen and Dixon, 2004). Moreover, as detailed in Campbell, Lo and Mackinlay (1997), the market model represents a potential improvement over the CMR model, as it lends to an increased ability to detect event effects. Other studies including Park (2004) recommended the use of a four factor model. However, in practise the gains from employing multifactor models are found to be limited (Campbell, Lo and MacKinlay, 1997). Hence, this study employs the use of single factor model for estimating the expected return. In addition to OLS estimation, Eqn. (3.8) can also be estimated using a Generalised Autoregressive Conditional

[43] A linear relationship between the expected return on a CDS and the market portfolio

[44] The estimation window comprises of 232 days prior to event day and is chosen such that it does not overlap with the event window.

Heteroskedasticity (GARCH) type model, under the pretext that returns could be characterised by time varying volatility and volatility clustering effects as detailed in Asimakopoulos and Athanasoglou (2013). Under general conditions, OLS is a consistent estimation procedure for the market model parameters and is efficient. Hence, this study prefers the OLS model rather than using a GARCH model. The estimated coefficients are then replaced in Eqn. (3.8), to calculate the expected return $\hat{R}_{it}$ for each firm (i). Abnormal return (AR_i) for each firm (i) is derived using Eqn. 3.9,

$$AR_{it} = R_{it} - \hat{R}_{it} \tag{3.9}$$

Where $\hat{R}_{it} = a_i + b_i R_{et}$

In order to draw inferences regarding a specific event, calculated AR must be first aggregated. The aggregation is done along two dimensions – through time and across securities. Firstly, the aggregation through time is considered for an individual security followed by aggregation through both across securities and through time. Standardised Abnormal return (SAR) is estimated as,

$$SAR_{it} = {}^{AR_{it}}/_{S(AR_i)} \tag{3.10}$$

Where $S(AR_i)$ is the standard deviation of the regression prediction error in AR computed as in Campbell, Lo and Mackinlay, (1997). The cumulative abnormal return (CAR) is introduced to accommodate multiple sampling intervals within the event window, $CAR_i\,(t_1\ t_2)$ as the CAR for security (i) from t_1 to t_2. Various estimations of the length of CAR have been proposed in previous studies. However, due to close proximity of events explored, this study employs estimation of narrow event windows namely; 7 day window[45], 3 day window[46] and 1 day window[47]. The smaller windows allow for a more protracted than usual absorption of news which will be appropriate as most policy initiatives were unprecedented and/or complex, without any apparent benchmark to evaluate their effects (Aït -Sahalia *et al.*, 2012). CAR for a given (i) across the range of event windows is estimated as,

$$CAR_i(t_1, t_2) = \sum_{t=t1}^{t2} AR_{it} \tag{3.11}$$

[45] Three days before and three days following the announcement days CAR[-3,0,+3]
[46] One day before and one day following the announcement day CAR[-1,0,-1]
[47] The day of the announcement CAR[0]

Next the standardised cumulative abnormal return (*SCAR*) is estimated as,

$$SCAR_i(t_1, t_2) = \frac{CAR_i(t_1, t_2)}{\widehat{\sigma_\iota}(t_1, t_2)} \tag{3.12}$$

Where $\widehat{\sigma_\iota^2}(t_1, t_2)$ is estimated as standard deviation of the *ARs* adjusted for forecasted errors. Under the null hypothesis of no event effect $SCAR_i(t_1, t_2)$ is distributed with mean of zero and approximately unit variance (Campbell, Lo and Mackinlay, 1997). To aggregate the *ARs* across securities and through time, we assume no significant correlation across the *ARs* of the different securities. This is true in the absence of clustering i.e. overlap in the event window of the included securities. The absence of overlap and the maintained distributional assumption implies that *ARs* will be independent across securities (Campbell, Lo and Mackinlay, 1997). The average abnormal return (*AAR*) for a given (*t*) across securities is estimated as,

$$AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{it} \tag{3.13}$$

Where, *N* is the number of firms that have actual CDS return available for a given day (*t*). Although, *AR* provides an indication of the impact of event, this indication refers to an individual point in time. To investigate the ongoing impact of an event on CDS returns, *AAR* is aggregated through time as in Eqn. (3.14),

$$CAAR_{\{t1,t2\}} = \sum_{t=t1}^{t2} AAR_t \tag{3.14}$$

$CAAR_{\{t1,\ t2\}}$ is the cumulative average abnormal return for the period $\{t_1, t_2\}$. This study estimates *CAAR* [-3,0,+3], *CAAR* [-2,0,+2] and CAR[0] for event analysis.

Further parametric and non-parametric tests are employed to evaluate the economical and statistically significance of *CAR/CAAR*. The basic difference between the two methods is the underlying assumption regarding the nature of the population distribution. Some commonly used parametric tests including standard t-statistics - Zo , test statistics derived by Patell (1976) - Zp and Boehmer, Musumeci and Poulsen (1991)[48] - Zb.

The frequency of return is a key consideration for isolating security price reaction to a particular event. However, as detailed by Fama (1976) and Brown and Warner (1985), daily

[48] BMP henceforth

(stock) normal and abnormal return depart from normality more than the monthly return series, resulting in a fat-tailed distribution relative to the generally assumed normal distribution. This violates the key assumption underlying the use of parametric test statistics in event studies. Non parametric tests do not require such stringent assumption of normality unlike its parametric counterparts. Rank test and Sign tests are the most commonly used non-parametric test statistics. The non-parametric rank test by Corrado (1989) and Corrado and Zivney (1992) based on standardised return is claimed to be superior measure in comparison to the standard t-tests. Moreover, rank test is found to be robust against event induced volatility (Campbell and Wasley, 1996) and to cross-correlation due to event-day clustering (Kolari and Pynnonen, 2010). Another non-parametric test, the sign test based on standardised excess return that does not assume a median of zero, but instead uses a sample excess return median to calculate the sign of an event date excess return is found to be more reliable and robust (Corrado, 2011 and Corrado and Zivney, 1992).

Kolari and Pynnonen, (2011) utilize the rank testing approach of Corrado (2011) and Corrado and Zivney (1992) and propose a generalised rank test approach that can be utilised to test both *CAR* and *CAAR*. They claim the generalised rank test approach is 1) robust to event induced volatility, 2) their empirical power proves to dominate both popular parametric test as well as existing rank test, 3) are reasonably robust to autocorrelation of abnormal returns 4) robust under certain degree of cross correlation caused by event day clustering and 5) is distribution free and thus less sensitive to distributional assumption than its parametric counterparts. This study estimate two variants of rank test namely; t_R and Z_R . As claimed in Kolari and Pynnonen, (2011) the simplicity of Z_R makes it an attractive alternative to t_R especially in case when the event days across the sample firms are not clustered. However, in presence of event day clustering which causes cross-sectional correlation between the returns t_R is much more robust than Z_R test statistics.

Apart from rank test, Sign test are another set of non-parametric test statistics widely used in event study literature. Sign test based on standardised excess return that does not assume a median of zero, but instead employs sample excess return median to calculate the sign of an event day excess return was developed by Corrado and Zivney (1992). Their simulation study found sign test to be reliable and well-specified. Sign test proposed by Cowan (1992) Z_G compares the proportion of positive AR's around an event to the proportion from a period unaffected by the event, thus taking into account the possible asymmetric return distribution under the null hypothesis. Cowan (1992) claims Z_G to be a powerful statistics and that it becomes relatively more powerful as the length of the CAR window increases. Cowan (1992) concludes sign test is better suited to investigation of CAR over event window of several days and is a better measure when the sample consist of thinly traded securities. Two alternative specifications of sign test (t_S and Z_S) based on generalised SAR are proposed by Luoma (2011). This study claims t_S to be more robust and preferable when cross-sectional correlation or clustering is present.

In summary this study estimates, Zo, Zp and Zb as parametric test statistics, t_R, Z_R as estimates of rank test and Z_G, t_S and Z_S as estimate of sign test which collectively represents the non-parametric test statistics for evaluating CAR and $CAAR$.

3.4 Empirical Evidence

3.4.1 Sample splitting approach

This study splits the sample based on the following criteria,

Sector: Firms are categorised into financial *(Fin)* and non-financial *(NonFin)* sectors. For both US and UK, the sample is highly biased towards non-financial sector firm observations[49]. Without checking the effect separately across the two sectors, the outcomes could be subject to biasness. This study does not attempt to further sub-classify the non-financial sector observations into other subsector due to ease of interpretation and lack of compelling theoretical rationale.

Quality: Firms are categorised into investment *(Inves)* and speculative *(Spec)* grade firms based on implied credit rating data as of Sept 2007 obtained from Markit dataset. Firms with rating AAA, AA, A and BBB are classified as *(Inves)* while those with implied rating BB, B and CCC are categorised as *(Spec)*. The US sample consists of 487 firms (53.8%) belonging to *(Inves)* category compared to 278 firms (30.7%) belonging to *(Spec)* category, while for UK 125 firms (51.0%) belong to *(Inves)* category compared to 38 firms (15.5%) belonging to *(Spec)* category. For the remaining 141 firms (15.6%) in US sample and 82 firms (33.5%) in UK sample, the implied rating is unavailable or missing and hence excluded from either of the two categories. This study tests the effect of macroeconomic policy

[49] For US non-financial sector observations represent 80.2% whereas for UK it represents 75.1% of the total observations

announcements on firms with varying credit quality. Klomp (2013) studies the effect of financial sector rescue package announcement on banks CDS spreads and find no significant effect on low risk banks but a significant effect on high risk banks. This study hypothesises firms with poor credit quality to show a greater reduction in credit risk following policy interventions that those that have better credit quality. Credit rating is used as a means to identify low risk and high risk firms and a similar relationship for firms across all sectors is expected.

Firm Size: Firms are categorised based on their level of total asset (TA) as of Q2 2007, into three main buckets i.e. Small, Medium and Large. Due to wide range of event dates ranging from 18th Sept 2007 to 28th April 2010, classifying firms based on last available quarter data will lead to overlap and confusion. This study conveniently selects the Q2 2007 total asset value as it most appropriately represents the start of the financial crisis. Next the sample is split into three buckets, the group with the lowest total asset value lower than the 33.33 percentile value of the sample total assets is categorised as 'Small' firms (for US N=220 and UK N=62). Firms with total assets larger than the 66.66 percentile value (for US N=241 and UK N=68) are categorised as 'Large' firms. All other firms are grouped into 'Medium' size category (for US N=230 and UK N=72). The remaining 215 firms in US sample and 43 firms in UK sample have no data on total asset available in Bloomberg and are excluded from the analysis. Small firms are more susceptible to monetary policy tightening and this has been documented in earlier studies by Bach and Huizenga (1960) and Galbraith (1957). The reasons are mainly attributed to the smaller collateralizable net worth leading to greater incentive incompatibility, lower unconditional survival rates, less diversified hence higher idiosyncratic risk and higher bankruptcy cost (Kandrac, 2012). Consequently, in an event of relaxed monetary policy announcements the benefit for small firms should be more in proportion to large firms. This study hypothesises that, in an event of favourable macroeconomic policy announcements small firm's credit risk should decrease more in comparison to big firms.

The other approaches for splitting samples i.e. the median splitting approaches and dividing the sample into four quartiles (25, 50, 75 and 100 percentiles) were also considered. Although the median splitting approach would help in identifying two groups (i.e. Small and Large) there would not be a clear rationale for inclusion or exclusion in one group or the other for firms near the median total assets value. This has the potential to plague the firm size based categorisation logic. On the other hand, although dividing the sample into four quartiles would give a clear 'Large' (TA > 75 percentile), 'Small' (TA < 25 percentile) and 'Medium' (TA > 25 percentile but < 75 percentile) categories. Splitting the samples into more than three groups leads to loss of valuable observations and too little observations in either of the two extreme categories will limit attempts to draw statistically significant outcomes. Moreover, there are sample independent approaches for categorising firm based on Size. One of such approach is using an externally determined benchmark using total assets, annual receipts or number of employee as detailed in US Small Business administration website (*www.sba.gov*). This study employs the three group sample splitting approach as it gives more flexibility to work around the required sample size in the 'Large' and 'Small' size categories and to draw statistically significant results as well as justify logically sound classification logic.

CDS Liquidity: Firms are categorised based on the CDS '*5 year composite depth*' [50]measure as of Q2 2007 into three groups i.e. Low, Medium and High Liquidity. This measure is a proxy for CDS liquidity obtained from Markit dataset on a daily basis. The average value of Sept 2007 is used for a given CDS return series. The logic of selecting Sept 2007 and the reason for categorising into three groups are similar to as justified earlier. The group with lowest composite depth value lower than 33.33 percentile value of the sample is categorised as 'Low liquidity' firms (for US N=240 and UK N=64). Firms with composite depth larger than the 66.66 percentile value (for US N=250 and UK N=54) are categorised as 'High Liquidity' firms. All other firms are grouped into 'Medium' liquidity category (for US N=241 and UK N=58). The remaining 175 firms in US sample and 69 firms in UK sample have no data on '*Composite depth 5Y*' available in Markit and are excluded from the sample. This study hypothesises that firms with high liquidity will be more sensitive to policy interventions as frequent trading will help assimilate the new informational content in the asset pricing.

Additionally, although this study does not split the sample into further sub-categorise, past studies including Madura and Schnusenberg (2000) suggests that more capitalised banks are less exposed to monetary policy changes. This could be attributed to two main reasons; Firstly, they are perceived to be safer by investors so expected change has a minor impact on their value. Secondly, they have smaller leverage so their interest margins are less sensitive to interest rate changes. Similar conclusions were obtained in Yin and Yang (2013) who find

[50] Composite depth 5y refers to the number of dealers that submit end of day quotes that are collated by Markit on a daily basis

that banks with higher capital to asset ratio are better able to withstand market shocks as such are less susceptible to unexpected interest rate changes. Since credit risk dynamics for corporates can be also attributed to their level of gearing and capital to asset ratios and hence their riskiness during the financial crisis. This testable hypothesis is extended to include all firms across sectors and not just the financial sector. The expansionary policy announcements specifically interest rate cuts, during the crisis period is expected to reduce the credit risk for firms that have higher gearing and lower capital to asset ratios than those that have lower gearing and higher capital to asset ratios. This effect is not tested in this study and could be a scope for further investigation. Following the sample splitting approach sufficient numbers of observations in each sub-group can be noted across the US and UK samples. Moreover, for the full sample the variables are not normally distributed (not reported here), evident from high skewness and kurtosis value. Overall huge variations in total asset and *'Composite depth 5Y'* variables further support the attempt to categorise firms into subgroups than using the full sample in evaluating the overall effect.

3.4.2 Effect of Policy Announcement on CDS abnormal returns

The abnormal returns are estimated from daily CDS returns across the three event windows AAR[0], CAAR[-1,0,+1] and CAAR[-3,0,+3] for Monetary (MON) and Fiscal (FIS) policy announcements across US and UK samples. The MON announcements are further sub-classified into Interest rate (IR) and Quantitative easing (QE) announcements. Result for IR policy is reported in Table 3.3, QE policy in Table 3.4 and FP policy in Table 3.5. Panel A of Table 3.3, 3.4 and 3.5 presents the 1 day event window or AAR[0] CDS return, Panel B and Panel C displays the CAAR[-1,0,+1] and CAAR[-3,0,+3] across the 3 days and 7 days event window respectively to test for robustness. Observations are reported for full sample as well as the differential effect across each sub-sample on the basis of sample splitting approach as described earlier. The significance of AAR/CAAR are tested across a range of parametric (Zo, Zp, Zb) and non-parametric test statistics (Rank test – t_R and Z_R , Sign tests – Z_G, t_S, and Z_S). From Table 3.1, the asymmetric distribution characteristics of CDS returns is evident from high kurtosis and skewness value and hence relying on parametric test statistics (Zo, Zp, Zb) alone would not provide a correct estimation of CAAR significance. To draw a statistically significant outcome this study expects CAAR's to be significant for non-parametric test statistics. Next, at least one variant of non-parametric test statistics i.e. rank (t_R or Z_R) or sign test (Z_G, t_S, or Z_S) is expected to be significant to draw statistically significant outcome.

Table 3.3: The table reports the CDS AAR/CAAR (basis points) for the IR across 1 day event window i.e. AAR [0] in Panel A, 3 days event window CAAR[-1,0,+1] in Panel B and 7 days event window CAAR [-3,0,+3] in Panel C. N represents the number of daily observations used to estimate the CAAR. The significance of AAR/CAAR are tested across a range of parametric (Zo, Zp, Zb) and non-parametric test statistics (Rank test – t_R and Z_R , Sign tests – Z_G, t_S, and Z_S). Values in Bold imply significance at 5% level.

IR	**US**										**UK**									
Panel A –AAR [0]			**Parametric Test**			**Non Parametric Test**							**Parametric Test**			**Non Parametric Test**				
						Rank Test		**Sign test**								**Rank Test**		**Sign test**		
	N	AAR	Zo	Zp	Zb	t_R	Z_R	Z_G	t_S	Z_S	N	AAR	Zo	Zp	Zb	t_R	Z_R	Z_G	t_S	Z_S
All Firms	494	2.93	**4.18**	**4.16**	**4.18**	0.57	**3.29**	0.49	0.18	0.27	90	-4.33	**-3.02**	**-3.01**	**-3.02**	**-3.73**	**-5.58**	**-3.16**	**-2.93**	-1.31
Fin	79	2.49	1.23	1.23	1.23	0.99	0.78	0.08	-0.28	-0.06	22	-0.90	-0.25	-0.25	-0.25	0.06	0.02	-0.46	-1.41	-0.16
NonFin	415	3.02	**4.06**	**4.05**	**4.06**	0.63	**3.23**	0.50	0.24	0.33	68	-5.43	**-3.63**	**-3.61**	**-3.63**	**-5.86**	**-6.66**	**-3.40**	**-4.30**	-1.48
Quality	477	3.40	**4.78**	**4.76**	**4.78**	0.73	**4.18**	0.71	0.33	0.49	81	-5.47	**-3.82**	**-3.81**	**-3.82**	**-4.00**	**-5.69**	**-3.36**	**-3.16**	-1.33
Invest	318	2.20	**3.92**	**3.91**	**3.92**	0.86	**3.36**	0.23	0.34	0.34	66	-5.27	**-3.28**	**-3.27**	**-3.28**	**-4.06**	**-4.88**	**-2.66**	**-3.12**	-1.10
Spec	159	5.79	**3.21**	**3.20**	**3.21**	1.69	**3.28**	0.84	0.98	0.52	15	-6.33	**-1.98**	**-1.97**	**-1.98**	**-18.30**	**-2.95**	**-2.17**	**-13.23**	-0.77
Size	481	3.00	**4.21**	**4.19**	**4.21**	0.59	**3.38**	0.56	0.21	0.32	90	-4.33	**-3.02**	**-3.01**	**-3.02**	**-3.73**	**-5.58**	**-3.16**	**-2.93**	-1.31
Large	167	2.81	**3.18**	**3.16**	**3.18**	1.79	**3.84**	1.31	0.95	0.53	36	0.65	0.25	0.25	0.25	**-2.06**	-1.44	-0.91	-1.38	-0.28
Medium	163	2.59	**2.55**	**2.54**	**2.55**	0.12	0.25	-0.69	-0.10	-0.06	33	-8.50	**-4.54**	**-4.52**	**-4.54**	**-13.46**	**-5.36**	**-3.09**	**-9.36**	-1.31
Small	151	3.65	**2.10**	**2.09**	**2.10**	1.27	**2.07**	0.37	0.39	0.17	21	-6.28	**-2.56**	**-2.55**	**-2.56**	**-9.45**	**-2.96**	-1.46	**-9.51**	-0.85
Liquidity	474	3.40	**4.75**	**4.73**	**4.75**	0.72	**4.17**	0.90	0.31	0.48	83	-5.38	**-3.85**	**-3.83**	**-3.85**	**-3.98**	**-5.74**	**-3.45**	**-3.11**	-1.33
High	185	4.12	**3.91**	**3.89**	**3.91**	1.48	**4.68**	**2.35**	0.93	0.76	34	-7.25	**-3.32**	**-3.31**	**-3.32**	**-6.52**	**-4.74**	**-2.15**	**-4.49**	-0.96
Medium	170	3.41	**4.01**	**3.99**	**4.01**	1.47	**3.08**	0.49	0.82	0.45	31	-4.62	**-1.86**	**-1.85**	**-1.86**	**-5.33**	**-2.95**	**-2.03**	**-4.13**	-0.67
Low	119	2.25	1.13	1.13	1.13	-0.50	-0.47	-1.61	-1.02	-0.27	18	-3.15	-1.25	-1.24	-1.25	**-12.17**	**-2.04**	-1.79	**-11.25**	-0.64

IR	**US**										**UK**									
Panel B –CAAR [-1,0,+1]			**Parametric Test**			**Non Parametric Test**							**Parametric Test**			**Non Parametric Test**				
						Rank Test		**Sign test**								**Rank Test**		**Sign test**		
	N	**CAAR**	***Zo***	***Zp***	***Zb***	t_R	Z_R	Z_G	t_S	Z_S	**N**	**CAAR**	***Zo***	***Zp***	***Zb***	t_R	Z_R	Z_G	t_S	Z_S
All Firms	493	8.03	**5.00**	**4.96**	**4.98**	0.86	**5.02**	**2.44**	0.43	0.66	90	-6.62	**-2.14**	**-2.13**	**-2.14**	**-3.15**	**-4.75**	**-2.31**	**-2.56**	-1.15
Fin	78	0.91	0.23	0.18	0.18	1.51	1.18	0.84	-0.31	-0.06	22	-8.21	-1.60	-1.59	-1.60	**-3.70**	-1.36	-1.02	**-4.28**	-0.47
NonFin	415	9.38	**5.34**	**5.32**	**5.34**	0.96	**4.97**	**2.30**	0.54	0.75	68	-6.11	-1.62	-1.61	-1.62	**-3.92**	**-4.63**	**-2.08**	**-2.91**	-1.02
Quality	477	8.99	**5.60**	**5.57**	**5.60**	0.99	**5.70**	**2.62**	0.57	0.86	81	-9.29	**-3.67**	**-3.65**	**-3.67**	**-3.26**	**-4.69**	**-2.62**	**-2.78**	-1.18
Invest	318	3.69	**3.79**	**3.77**	**3.79**	1.16	**4.54**	1.51	0.70	0.71	66	-8.03	**-2.86**	**-2.85**	**-2.86**	**-2.85**	**-3.48**	-1.82	**-2.51**	-0.90
Spec	159	19.60	**4.56**	**4.54**	**4.56**	**2.61**	**5.03**	**2.33**	1.71	0.90	15	-14.83	**-2.55**	**-2.54**	**-2.55**	**-33.51**	**-3.50**	**-2.17**	**-16.32**	-0.86
Size	480	8.00	**4.90**	**4.87**	**4.89**	0.89	**5.05**	**2.60**	0.44	0.66	90	-6.62	**-2.14**	**-2.13**	**-2.14**	**-3.15**	**-4.75**	**-2.31**	**-2.56**	-1.15
Large	166	6.50	**2.88**	**2.83**	**2.84**	**2.08**	**4.41**	**2.15**	1.17	0.64	36	2.10	0.34	0.34	0.34	**-2.01**	-1.41	-0.45	-1.86	-0.38
Medium	163	6.57	**2.45**	**2.44**	**2.45**	0.78	1.60	1.08	0.18	0.10	33	-16.53	**-4.13**	**-4.11**	**-4.13**	**-11.09**	**-4.76**	**-2.39**	**-8.40**	-1.21
Small	151	11.20	**3.19**	**3.17**	**3.19**	1.80	**2.91**	1.26	1.11	0.49	21	-6.00	-1.63	-1.62	-1.63	**-5.67**	**-1.96**	-1.17	**-5.55**	-0.55
Liquidity	474	8.96	**5.55**	**5.53**	**5.55**	0.98	**5.70**	**2.76**	0.56	0.84	83	-9.08	**-3.67**	**-3.66**	**-3.67**	**-3.16**	**-4.62**	**-2.57**	**-2.70**	-1.16
High	185	8.63	**3.33**	**3.32**	**3.33**	1.42	**4.51**	**2.04**	0.92	0.75	34	-8.39	**-2.73**	**-2.72**	**-2.73**	**-3.57**	**-2.75**	-0.98	**-3.20**	-0.70
Medium	170	10.56	**3.86**	**3.84**	**3.86**	1.48	**3.10**	1.92	0.78	0.43	31	-7.32	**-2.07**	**-2.06**	**-2.07**	**-5.04**	**-2.80**	**-2.03**	**-4.22**	-0.68
Low	119	7.20	**2.28**	**2.27**	**2.28**	**2.19**	**2.07**	0.69	0.88	0.23	18	-13.42	**-1.71**	**-1.70**	**-1.71**	**-15.96**	**-2.37**	-1.49	**-12.59**	-0.68

IR					**US**											**UK**				
Panel C –CAAR [-3,0,+3]			**Parametric Test**			**Non Parametric Test**							**Parametric Test**			**Non Parametric Test**				
						Rank Test		**Sign test**								**Rank Test**		**Sign test**		
	N	CAAR	Zo	Zp	Zb	t_R	Z_R	Z_G	t_S	Z_S	N	CAAR	Zo	Zp	Zb	t_R	Z_R	Z_G	t_S	Z_S
All Firms	492	8.26	**3.52**	**3.39**	**3.40**	0.40	**2.32**	1.16	0.13	0.20	90	-3.20	-0.59	-0.59	-0.59	-1.75	**-2.68**	-1.88	-1.68	-0.76
Fin	77	-2.59	-0.40	-0.61	-0.61	-0.76	-0.58	-0.52	**-2.02**	-0.41	22	-7.19	-0.58	-0.58	-0.58	-0.61	-0.23	-0.46	**-2.23**	-0.25
NonFin	415	10.29	**4.13**	**4.08**	**4.09**	0.54	**2.78**	1.50	0.29	0.40	68	-1.90	-0.32	-0.32	-0.32	**-2.50**	**-3.01**	-1.91	**-2.10**	-0.74
Quality	476	9.36	**3.99**	**3.92**	**3.94**	0.51	**2.93**	1.26	0.25	0.38	81	-8.68	**-2.13**	**-2.12**	**-2.13**	-1.87	**-2.73**	**-2.32**	-1.76	-0.75
Invest	317	-0.32	-0.20	-0.24	-0.24	-0.04	-0.17	-0.23	-0.41	-0.42	66	-9.58	**-1.99**	**-1.98**	**-1.99**	-1.67	**-2.06**	-1.65	-1.74	-0.63
Spec	159	28.66	**4.82**	**4.76**	**4.78**	**3.12**	**5.97**	**2.44**	**2.08**	1.09	15	-4.71	-0.77	-0.76	-0.77	**-9.94**	**-2.10**	-1.85	**-7.45**	-0.52
Size	479	8.28	**3.51**	**3.38**	**3.39**	0.44	**2.51**	1.30	0.17	0.25	90	-3.20	-0.59	-0.59	-0.59	-1.75	**-2.68**	-1.88	-1.68	-0.76
Large	166	4.16	1.14	0.95	0.95	0.39	0.84	0.46	-0.05	-0.03	36	9.59	0.79	0.78	0.79	0.10	0.07	0.24	-0.88	-0.18
Medium	162	3.57	0.99	0.95	0.96	0.33	0.68	0.35	-0.23	-0.13	33	-14.27	**-2.68**	**-2.67**	**-2.68**	**-6.56**	**-3.19**	**-2.39**	**-5.55**	-0.86
Small	151	17.93	**3.64**	**3.61**	**3.63**	1.89	**3.04**	1.48	1.42	0.62	21	-7.72	**-1.94**	**-1.93**	**-1.94**	**-5.99**	**-2.06**	-1.17	**-6.08**	-0.60
Liquidity	473	9.25	**3.93**	**3.86**	**3.88**	0.50	**2.92**	1.46	0.25	0.37	83	-8.49	**-2.13**	**-2.12**	**-2.13**	-1.82	**-2.68**	**-2.28**	-1.69	-0.73
High	185	4.97	1.17	1.17	1.18	0.22	0.71	0.61	0.06	0.05	34	-4.53	-0.85	-0.84	-0.85	-0.74	-0.58	-0.98	-0.65	-0.15
Medium	170	10.77	**2.91**	**2.91**	**2.92**	0.74	1.55	0.49	0.24	0.13	31	-10.13	-1.28	-1.27	-1.28	**-3.41**	**-1.95**	-1.55	**-2.77**	-0.46
Low	118	13.62	**3.41**	**3.28**	**3.29**	**3.58**	**3.31**	1.54	**2.36**	0.61	18	-13.17	**-1.78**	**-1.77**	**-1.78**	**-15.06**	**-2.30**	-1.49	**-14.87**	-0.75

From Table 3.3, for IR policy in the US sample, AAR[0] shows a small increase of 2.93bp for the full sample, which marginally increase to 8.03bp for CAAR[-1,0,+1] and 8.26bp for CAAR[-3,0,+3] indicating across the 3 days and 7 days event window the effect of IR announcements has very miniscule effect on CDS abnormal return. The effect is significant across the event windows for the full sample. However for UK sample, AAR[0] shows a negative gain of -4.33bp, which further reduces to -6.62bp for the 3 days and -3.20bp for 7 days event window, highlighting that IR announcements has an opposite (albeit small) effect on CDS abnormal return compared to the US sample. The effect is significant across the three event windows.

Further for US sample, *(Non-Fin)* firms have a positive and significant abnormal return across the three event windows, while for *(Fin)* firms the effect is not significant across the event windows. For UK sample, *(Fin)* firms show a greater negative loss than the full sample, while the effect is not significant for the AAR[0]. Across the two samples the finding based on sector differences support Ricci (2014) that suggests banks are less sensitive to traditional monetary policy measure like IR. The results also shed some light on the differential effect of IR announcement based on the sector of the firms under consideration and the sample being analysed. By categorising firm based on credit quality, across the three event windows, abnormal return for *(Spec)* firm is higher (AAR [0] = 5.79bp, CAAR[-1,0,+1] = 19.6bp and CAAR[-3,0,+3] = 28.66bp) and significant than *(Inves)* firms for US sample. For UK the results are mixed across the three event windows. This implies the effect of IR announcement has a favourable effect on speculative grade firms and this effect is statistically significant at least for the US sample. Categorising firms based on *(Size)* provides mixed results. For US sample *(Small)* firms have higher ARs than (*Large*) size firms the effect is significant and consistent across the event windows. For the UK sample, we note an opposite effect *(Small)* firms have a lower ARs than *(Large)* firms and this is consistent and significant across the event windows. For UK sample, *(Large)* firms report positive and significant abnormal return compared to other firms for the 1 day and 3 day event window, while the result is not significant for the 7 day event window. Classifying firms based on the level of CDS liquidity does not provide clear outcomes. For US sample, firms with *(High)* liquidity, have higher ARs (for 1 day event window AAR[0] = 4.12bp and CAAR[-1,0,+1] = 8.63bp) and is statistically significance but this result does not hold for the 7 day event window. For the UK sample the results are inconclusive.

Table 3.4: The table reports the CDS AAR/CAAR (basis points) for the QE across 1 day event window i.e. AAR [0] in Panel A, 3 days event window CAAR[-1,0,+1] in Panel B and 7 days event window CAAR [-3,0,+3] in Panel C. N represents the number of daily observations used to estimate the CAAR. The significance of AAR/CAAR are tested across a range of parametric (Zo, Zp, Zb) and non-parametric test statistics (Rank test – t_R and Z_R , Sign tests – Z_G, t_S, and Z_S). Values in Bold imply significance at 5% level.

QE	US										UK									
Panel A –AAR [0]			**Parametric Test**			**Non Parametric Test**							**Parametric Test**			**Non Parametric Test**				
						Rank Test		**Sign test**								**Rank Test**		**Sign test**		
	N	AAR	Zo	Zp	Zb	t_R	Z_R	Z_G	t_S	Z_S	N	AAR	Zo	Zp	Zb	t_R	Z_R	Z_G	t_S	Z_S
All Firms	226	29.21	**5.86**	**5.84**	**5.86**	-0.71	**-2.92**	**5.63**	-0.70	-1.20	81	7.25	**3.17**	**3.16**	**3.17**	**2.78**	**4.00**	1.56	1.60	0.70
Fin	41	45.63	**3.20**	**3.18**	**3.20**	0.77	0.51	1.79	0.80	0.21	21	16.78	**2.33**	**2.32**	**2.33**	**8.15**	**2.74**	0.79	**4.99**	0.54
NonFin	185	25.57	**4.94**	**4.91**	**4.94**	-0.97	**-3.37**	**5.39**	-0.96	-1.41	60	3.91	**2.39**	**2.38**	**2.39**	**3.27**	**3.62**	1.34	**1.99**	0.68
Quality	218	29.66	**5.80**	**5.77**	**5.80**	-0.68	**-2.76**	**5.46**	-0.67	-1.14	73	7.66	**3.05**	**3.04**	**3.05**	**3.19**	**4.38**	1.38	1.91	0.79
Invest	167	26.19	**6.25**	**6.23**	**6.25**	-0.67	**-2.05**	**5.93**	-0.66	-0.79	58	8.47	**2.82**	**2.80**	**2.82**	**3.91**	**4.31**	1.57	**2.29**	0.77
Spec	51	41.02	**2.40**	**2.39**	**2.40**	-1.34	-1.29	0.91	-1.32	-0.63	15	4.52	1.19	1.19	1.19	**3.59**	1.01	-0.03	**2.78**	0.22
Size	223	28.51	**5.75**	**5.72**	**5.75**	-0.67	**-2.74**	**5.64**	-0.66	-1.12	81	7.25	**3.17**	**3.16**	**3.17**	**2.78**	**4.00**	1.56	1.60	0.70
Large	91	37.78	**5.04**	**5.01**	**5.04**	-0.50	-0.84	**4.85**	-0.49	-0.31	35	13.43	**3.33**	**3.31**	**3.33**	**5.84**	**3.66**	1.75	**3.81**	0.73
Medium	76	28.79	**3.46**	**3.44**	**3.46**	-1.87	**-2.71**	**3.89**	-1.85	-1.11	28	3.59	1.16	1.15	1.16	**4.63**	**2.29**	0.96	**2.69**	0.42
Small	56	13.05	1.24	1.24	1.24	-1.16	-1.16	0.90	-1.14	-0.53	18	0.93	0.24	0.23	0.24	**2.28**	0.71	-0.28	0.13	0.01
Liquidity	217	29.80	**5.80**	**5.78**	**5.80**	-0.69	**-2.78**	**5.55**	-0.68	-1.14	74	7.56	**3.05**	**3.04**	**3.05**	**3.18**	**4.37**	1.42	1.94	0.80
High	119	35.22	**5.76**	**5.74**	**5.76**	-1.04	**-2.39**	**7.77**	-1.02	-0.83	30	10.65	**2.69**	**2.68**	**2.69**	**4.70**	**3.14**	1.27	**2.91**	0.60
Medium	69	27.58	**2.30**	**2.29**	**2.30**	**-2.04**	**-2.69**	**2.43**	**-2.03**	-1.17	27	9.23	**2.30**	**2.29**	**2.30**	**7.82**	**3.62**	1.06	**4.87**	0.72
Low	29	12.85	**2.45**	**2.44**	**2.45**	**2.49**	1.24	-1.52	**2.50**	0.72	17	-0.57	-0.11	-0.11	-0.11	1.51	0.37	-0.05	-0.19	-0.01

QE	US										UK									
Panel B –CAAR [-1,0,+1]			**Parametric Test**			**Non Parametric Test**							**Parametric Test**			**Non Parametric Test**				
						Rank Test		**Sign test**								**Rank Test**		**Sign test**		
	N	CAAR	Zo	Zp	Zb	t_R	Z_R	Z_G	t_S	Z_S	N	CAAR	Zo	Zp	Zb	t_R	Z_R	Z_G	t_S	Z_S
All Firms	226	53.61	**5.58**	**5.55**	**5.58**	-0.84	**-3.48**	**5.81**	-0.83	-1.43	81	11.45	**3.30**	**3.29**	**3.30**	**3.01**	**4.33**	1.71	1.77	0.77
Fin	41	60.19	**2.85**	**2.84**	**2.85**	0.30	0.20	1.79	0.33	0.08	21	25.85	**3.37**	**3.36**	**3.37**	**10.05**	**3.20**	1.08	**7.18**	0.74
NonFin	185	52.15	**4.83**	**4.81**	**4.83**	-1.12	**-3.90**	**5.60**	-1.11	-1.63	60	6.41	**1.75**	**1.74**	**1.75**	**2.97**	**3.30**	1.34	1.48	0.51
Quality	218	54.90	**5.59**	**5.57**	**5.59**	-0.80	**-3.23**	**5.65**	-0.79	-1.34	73	13.58	**3.78**	**3.76**	**3.78**	**3.73**	**5.09**	1.53	**2.41**	0.99
Invest	167	42.41	**6.45**	**6.42**	**6.45**	-0.59	**-1.81**	**6.70**	-0.58	-0.70	58	13.92	**3.61**	**3.59**	**3.61**	**4.46**	**4.86**	1.57	**3.03**	1.01
Spec	51	95.82	**2.69**	**2.67**	**2.69**	-1.82	**-1.75**	0.06	-1.80	-0.86	15	12.26	1.30	1.29	1.30	**6.14**	1.64	0.30	**2.95**	0.24
Size	223	50.68	**5.42**	**5.39**	**5.42**	-0.80	**-3.27**	**5.82**	-0.79	-1.34	81	11.45	**3.30**	**3.29**	**3.30**	**3.01**	**4.33**	1.71	1.77	0.77
Large	91	53.59	**5.16**	**5.13**	**5.16**	-0.30	-0.50	**5.92**	-0.29	-0.18	35	12.32	**2.29**	**2.28**	**2.29**	**3.52**	**2.30**	1.53	1.81	0.35
Medium	76	59.91	**2.61**	**2.60**	**2.61**	**-2.32**	**-3.36**	**3.73**	**-2.30**	-1.38	28	11.68	**2.35**	**2.34**	**2.35**	**7.16**	**3.35**	1.21	**4.90**	0.74
Small	56	33.43	**2.85**	**2.84**	**2.85**	-1.25	-1.25	0.23	-1.24	-0.57	18	9.38	1.05	1.04	1.05	**6.16**	**1.81**	0.02	**2.69**	0.26
Liquidity	217	55.16	**5.60**	**5.57**	**5.60**	-0.81	**-3.25**	**5.73**	-0.80	-1.34	74	13.40	**3.77**	**3.76**	**3.77**	**3.72**	**5.07**	1.42	**2.43**	1.00
High	119	52.94	**5.47**	**5.45**	**5.47**	-1.15	**-2.65**	**8.06**	-1.14	-0.92	30	16.91	**2.71**	**2.70**	**2.71**	**5.12**	**3.40**	1.51	**2.98**	0.61
Medium	69	72.84	**2.85**	**2.84**	**2.85**	-1.92	**-2.53**	**3.07**	-1.91	-1.10	27	19.16	**4.64**	**4.62**	**4.64**	**11.27**	**4.71**	1.31	**8.81**	1.18
Low	29	22.20	**1.83**	**1.82**	**1.83**	0.60	0.30	**-2.25**	0.63	0.18	17	-1.96	-0.25	-0.25	-0.25	0.72	0.18	-0.68	-0.06	0.00

QE	US										UK									
Panel C –CAAR [-3,0,+3]			**Parametric Test**			**Non Parametric Test**							**Parametric Test**			**Non Parametric Test**				
						Rank Test		**Sign test**								**Rank Test**		**Sign test**		
	N	**CAAR**	Zo	Zp	Zb	t_R	Z_R	Z_G	t_S	Z_S	**N**	**CAAR**	Zo	Zp	Zb	t_R	Z_R	Z_G	t_S	Z_S
All Firms	226	43.92	**3.23**	**3.22**	**3.23**	-1.72	**-7.06**	1.31	-1.70	**-2.91**	81	14.31	**2.18**	**2.18**	**2.18**	1.13	**1.65**	0.38	0.39	0.17
Fin	41	55.13	1.53	1.52	1.53	**-3.47**	**-2.25**	-0.28	**-3.42**	-0.86	21	39.50	**2.60**	**2.58**	**2.60**	**6.35**	**2.24**	0.51	**3.68**	0.41
NonFin	185	41.44	**2.84**	**2.82**	**2.84**	-1.94	**-6.72**	1.60	-1.93	**-2.81**	60	5.50	0.81	0.81	0.81	0.52	0.59	0.14	-0.15	-0.05
Quality	218	47.29	**3.49**	**3.48**	**3.49**	-1.66	**-6.67**	1.38	-1.65	**-2.76**	73	15.31	**2.19**	**2.18**	**2.19**	1.53	**2.13**	0.31	0.77	0.32
Invest	167	38.52	**3.54**	**3.53**	**3.54**	**-2.03**	**-6.21**	**2.49**	**-2.02**	**-2.41**	58	14.66	**2.03**	**2.02**	**2.03**	1.89	**2.12**	0.54	1.03	0.35
Spec	51	75.99	**1.66**	**1.65**	**1.66**	**-2.68**	**-2.55**	-1.30	**-2.65**	-1.26	15	17.84	0.88	0.88	0.88	1.91	0.55	-0.36	0.99	0.08
Size	223	39.94	**3.04**	**3.02**	**3.04**	-1.71	**-6.94**	1.29	-1.70	**-2.85**	81	14.31	**2.18**	**2.18**	**2.18**	1.13	**1.65**	0.38	0.39	0.17
Large	91	51.93	**2.86**	**2.85**	**2.86**	**-2.60**	**-4.28**	**2.24**	**-2.57**	-1.62	35	22.53	**2.13**	**2.12**	**2.13**	**2.45**	1.62	1.30	0.98	0.19
Medium	76	49.92	**1.76**	**1.75**	**1.76**	**-3.42**	**-4.89**	0.48	**-3.40**	**-2.02**	28	10.76	1.09	1.08	1.09	**2.37**	1.21	-0.29	1.12	0.18
Small	56	6.93	0.35	0.35	0.35	**-2.58**	**-2.54**	-0.59	**-2.56**	-1.17	18	3.85	0.26	0.26	0.26	-0.83	-0.26	-0.58	-1.03	-0.10
Liquidity	217	47.52	**3.50**	**3.48**	**3.50**	-1.67	**-6.69**	1.45	-1.66	**-2.77**	74	15.09	**2.18**	**2.17**	**2.18**	1.53	**2.13**	0.20	0.80	0.33
High	119	39.63	**2.57**	**2.56**	**2.57**	**-2.90**	**-6.59**	**3.35**	**-2.88**	**-2.31**	30	20.44	**1.66**	**1.65**	**1.66**	**2.61**	**1.80**	0.29	1.45	0.30
Medium	69	75.18	**2.31**	**2.30**	**2.31**	**-2.89**	**-3.77**	1.15	**-2.87**	-1.64	27	24.45	**3.24**	**3.23**	**3.24**	**7.29**	**3.42**	1.06	**5.37**	0.78
Low	29	14.07	0.79	0.79	0.79	-1.14	-0.57	**-2.61**	-1.11	-0.32	17	-9.19	-0.56	-0.56	-0.56	**-9.43**	**-1.97**	-1.31	**-6.61**	-0.44

From Table 3.4, for QE announcements in the US sample, AAR[0] shows an increase of 29.21bp for the full sample, which increases to 53.61bp for CAAR[-1,0,+1] and 43.92bp for CAAR[-3,0,+3] indicating across the 3 days and 7 days event window the effect of QE announcements has a major effect on CDS abnormal return. The effect is significant across the event windows for the full sample. In line with observations from US sample, for the UK sample, AAR[0] shows a positive gain of 7.25bp, which further increases to 11.45bp for the 3 days and 14.31bp for 7 days event window, highlighting that QE announcements has similar effect on CDS abnormal return across the two samples. The effect is significant across the three event windows.

Further for US sample, *(Non-Fin)* firms have a lower and significant abnormal return across the three event windows compared to full sample, while for *(Fin)* firms the effect is not significant across the event windows. For UK sample, *(Fin)* firms show a higher and significant AR than the full sample ([AAR [0] = 16.78bp, CAAR[-1,0,+1] = 25.85bp and CAAR[-3,0,+3] = 39.50bp). By categorising firm based on credit quality, across the three event windows, abnormal return for *(Spec)* firm is higher [AAR [0] = 41.02bp, CAAR[-1,0,+1] = 95.82bp and CAAR[-3,0,+3] = 75.99bp) and significant than *(Inves)* firms for US sample. For UK the results are opposite across the three event windows abnormal return for *(Spec)* firm is lower [AAR [0] = 4.52bp, CAAR[-1,0,+1] = 12.26bp and significant than *(Inves)* firms for 1 day and 3 day event window. The effect is not significant for the 7 day event window. This implies, QE announcements had a favourable and significant effect on speculative grade firms for US sample while investment grade firms have lower ARs following QE announcements. By categorising firms based on (*Size*), for US sample *(Large)* firms have higher ARs than *(Small)* size firms the effect is significant and consistent across the event windows. For the UK sample, the results are consistent and significant across the event windows. Classifying firms based on the level of CDS liquidity, this study notes that for US sample, firms with *(High)* liquidity have higher and significant abnormal returns across the event windows. These results hold true for the UK sample and across all event windows.

Table 3.5: The table reports the CDS AAR/CAAR (basis points) for the FP across 1 day event window i.e. AAR [0] in Panel A, 3 days event window CAAR[-1,0,+1] in Panel B and 7 days event window CAAR [-3,0,+3] in Panel C. N represents the number of daily observations used to estimate the CAAR. The significance of AAR/CAAR are tested across a range of parametric (Zo, Zp, Zb) and non-parametric test statistics (Rank test – t_R and Z_R , Sign tests – Z_G, t_S, and Z_S). Values in Bold imply significance at 5% level.

FP	**US**										**UK**									
Panel A –AAR [0]			**Parametric Test**			**Non Parametric Test**							**Parametric Test**			**Non Parametric Test**				
						Rank Test		**Sign test**								**Rank Test**		**Sign test**		
	N	AAR	Zo	Zp	Zb	t_R	Z_R	Z_G	t_S	Z_S	N	AAR	Zo	Zp	Zb	t_R	Z_R	Z_G	t_S	Z_S
All Firms	117	5.36	**2.43**	**2.42**	**2.43**	1.34	**2.03**	**-11.81**	0.60	0.74	77	-1.36	-0.20	-0.20	-0.20	-0.84	-1.26	-1.53	-0.84	-0.38
Fin	30	4.57	1.30	1.30	1.30	**2.86**	0.98	**-3.97**	1.49	0.33	21	-15.96	-0.90	-0.90	-0.90	**-2.27**	-0.92	-0.54	**-2.28**	-0.27
NonFin	87	5.63	**2.07**	**2.06**	**2.07**	1.47	**1.74**	**-11.17**	0.63	0.64	56	4.12	0.63	0.63	0.63	-0.81	-0.91	-1.46	-0.80	-0.28
Quality	113	5.18	**2.27**	**2.26**	**2.27**	1.24	**1.83**	**-11.95**	0.50	0.61	71	0.23	0.03	0.03	0.03	-0.46	-0.67	-1.71	-0.46	-0.20
Invest	81	2.30	1.12	1.11	1.12	1.40	1.49	**-9.67**	0.80	0.67	57	-4.18	-0.50	-0.50	-0.50	-1.17	-1.38	**-2.19**	-1.16	-0.41
Spec	32	12.49	**2.07**	**2.06**	**2.07**	1.40	1.49	**-7.03**	0.26	0.10	14	18.18	**1.83**	**1.82**	**1.83**	**9.58**	**2.21**	0.49	**9.53**	0.66
Size	115	4.76	**2.17**	**2.16**	**2.17**	1.28	**1.91**	**-11.68**	0.62	0.75	77	-1.36	-0.20	-0.20	-0.20	-0.84	-1.26	-1.53	-0.84	-0.38
Large	47	5.59	**1.87**	**1.86**	**1.87**	**2.10**	1.38	**-6.54**	1.05	0.48	32	-12.17	-1.10	-1.09	-1.10	**-2.30**	-1.55	-1.89	**-2.31**	-0.46
Medium	31	1.46	0.41	0.41	0.41	1.86	0.79	**-7.55**	1.18	0.46	27	-8.10	-0.94	-0.94	-0.94	**-3.23**	-1.63	-1.53	**-3.20**	-0.50
Small	37	6.45	1.33	1.32	1.33	**2.46**	1.07	**-6.11**	0.79	0.30	18	27.97	**1.79**	**1.79**	**1.79**	**3.40**	1.14	1.17	**3.40**	0.35
Liquidity	112	5.24	**2.28**	**2.27**	**2.28**	1.26	**1.87**	**-11.86**	0.50	0.61	72	0.23	0.03	0.03	0.03	-0.49	-0.71	-1.64	-0.49	-0.21
High	47	5.24	**1.65**	1.64	**1.65**	**2.45**	**2.01**	**-6.82**	1.67	0.85	30	3.59	0.67	0.67	0.67	-0.15	-0.11	-0.99	-0.15	-0.03
Medium	33	13.35	**2.64**	**2.63**	**2.64**	**3.03**	1.40	**-7.83**	1.16	0.47	27	-20.78	-1.62	-1.62	-1.62	**-2.54**	-1.33	-1.40	**-2.55**	-0.40
Low	32	-3.14	-0.88	-0.88	-0.88	-1.12	-0.34	**-5.79**	-0.95	-0.29	15	31.34	1.58	1.58	1.58	0.74	0.17	-0.33	0.80	0.06

FP	**US**										**UK**									
Panel B–CAAR [-1,0,+1]			**Parametric Test**			**Non Parametric Test**							**Parametric Test**			**Non Parametric Test**				
						Rank Test		**Sign test**								**Rank Test**		**Sign test**		
	N	**CAAR**	Zo	Zp	Zb	t_R	Z_R	Z_G	t_S	Z_S	**N**	**CAAR**	Zo	Zp	Zb	t_R	Z_R	Z_G	t_S	Z_S
All Firms	116	6.42	**2.02**	**2.19**	**2.19**	1.25	**1.87**	**-11.99**	0.61	0.75	77	28.86	**2.73**	**2.71**	**2.73**	1.14	**1.70**	0.85	1.14	0.52
Fin	30	1.28	0.15	0.15	0.15	-0.37	-0.13	**-4.70**	-0.37	-0.08	21	-24.23	**-1.75**	**-1.74**	**-1.75**	**-5.00**	**-1.95**	-1.12	**-5.01**	-0.57
NonFin	86	8.21	**2.63**	**2.86**	**2.87**	1.88	**2.20**	**-11.03**	0.97	0.97	56	48.77	**3.85**	**3.83**	**3.85**	**2.79**	**3.10**	1.66	**2.79**	0.95
Quality	112	5.73	**1.77**	**1.94**	**1.95**	1.20	**1.75**	**-12.07**	0.55	0.67	71	31.86	**2.84**	**2.83**	**2.84**	1.63	**2.33**	0.58	1.63	0.70
Invest	81	7.17	**2.24**	**2.23**	**2.24**	1.21	1.29	**-9.67**	0.67	0.56	57	14.39	1.60	1.59	1.60	1.31	1.55	0.39	1.32	0.47
Spec	31	2.06	0.25	0.49	0.49	1.21	1.29	**-7.24**	0.71	0.27	14	103.02	**2.64**	**2.63**	**2.64**	**10.83**	**2.41**	0.49	**10.72**	0.71
Size	114	5.75	**1.80**	**1.97**	**1.98**	1.19	**1.75**	**-11.86**	0.62	0.76	77	28.86	**2.73**	**2.71**	**2.73**	1.14	**1.70**	0.85	1.14	0.52
Large	47	5.05	0.95	0.95	0.95	0.72	0.47	**-7.06**	0.21	0.10	32	-2.20	-0.22	-0.22	-0.22	0.36	0.24	0.23	0.36	0.07
Medium	30	2.16	0.38	0.74	0.74	**2.56**	1.04	**-7.34**	1.60	0.61	27	29.73	1.54	1.53	1.54	1.22	0.63	0.72	1.22	0.19
Small	37	9.66	**1.72**	**1.71**	**1.72**	**3.69**	1.58	**-6.11**	1.84	0.69	18	82.79	**3.18**	**3.17**	**3.18**	**9.43**	**2.74**	0.57	**9.45**	0.85
Liquidity	111	5.79	**1.77**	**1.94**	**1.95**	1.22	**1.79**	**-11.98**	0.56	0.67	72	31.44	**2.84**	**2.83**	**2.84**	1.58	**2.27**	0.63	1.58	0.69
High	47	-1.64	-0.31	-0.31	-0.31	0.72	0.60	**-7.61**	0.44	0.23	30	42.12	**2.50**	**2.49**	**2.50**	**2.81**	**2.04**	0.71	**2.80**	0.61
Medium	33	20.87	**3.49**	**3.48**	**3.49**	**4.12**	**1.87**	**-7.33**	1.74	0.70	27	12.81	0.92	0.91	0.92	**3.50**	**1.81**	0.56	**3.50**	0.55
Low	31	1.08	0.22	0.62	0.62	**2.20**	0.63	**-5.66**	1.07	0.32	15	43.61	1.33	1.32	1.33	-0.72	-0.17	-0.33	-0.69	-0.05

FP	US										UK									
Panel C–CAAR [-3,0,+3]			**Parametric Test**			**Non Parametric Test**							**Parametric Test**			**Non Parametric Test**				
						Rank Test		**Sign test**								**Rank Test**		**Sign test**		
	N	CAAR	Zo	Zp	Zb	t_R	Z_R	Z_G	t_S	Z_S	N	CAAR	Zo	Zp	Zb	t_R	Z_R	Z_G	t_S	Z_S
All Firms	116	-14.30	**-2.02**	**-1.95**	**-1.96**	-0.91	-1.36	**-13.56**	-0.84	-1.03	77	-51.99	**-3.17**	**-3.15**	**-3.17**	**-2.65**	**-3.90**	**-2.72**	**-2.65**	-1.18
Fin	30	-41.10	**-2.70**	**-2.69**	**-2.70**	**-8.24**	**-2.54**	**-5.57**	**-5.83**	-1.21	21	-56.15	**-2.35**	**-2.34**	**-2.35**	**-7.03**	**-2.62**	-1.71	**-7.01**	-0.77
NonFin	86	-4.99	-0.64	-0.57	-0.57	-0.31	-0.37	**-12.36**	-0.49	-0.49	56	-50.35	**-2.41**	**-2.41**	**-2.42**	**-2.73**	**-3.03**	**-2.15**	**-2.73**	-0.93
Quality	112	-16.22	**-2.25**	**-2.18**	**-2.19**	-1.04	-1.52	**-13.65**	-0.95	-1.14	71	-50.18	**-3.01**	**-3.00**	**-3.01**	**-2.43**	**-3.45**	**-2.93**	**-2.42**	-1.04
Invest	81	-18.09	**-2.88**	**-2.87**	**-2.88**	-1.92	**-2.03**	**-11.23**	-1.56	-1.30	57	-67.80	**-3.79**	**-3.77**	**-3.79**	**-3.64**	**-4.20**	**-3.23**	**-3.63**	-1.26
Spec	31	-11.40	-0.56	-0.47	-0.48	-1.92	**-2.03**	**-7.76**	-0.65	-0.24	14	22.35	0.58	0.55	0.55	**2.17**	0.58	-0.16	**2.15**	0.17
Size	114	-14.41	**-2.01**	**-1.94**	**-1.95**	-0.94	-1.39	**-13.39**	-0.86	-1.04	77	-51.99	**-3.17**	**-3.15**	**-3.17**	**-2.65**	**-3.90**	**-2.72**	**-2.65**	-1.18
Large	47	-38.01	**-3.29**	**-3.27**	**-3.29**	**-3.93**	**-2.53**	**-8.29**	**-3.30**	-1.48	32	-97.49	**-3.32**	**-3.30**	**-3.31**	**-6.15**	**-3.89**	**-2.84**	**-6.14**	-1.15
Medium	30	-11.02	-0.93	-0.80	-0.80	-0.23	-0.09	**-8.07**	-0.39	-0.15	27	-45.84	**-2.14**	**-2.13**	**-2.14**	**-3.72**	**-1.86**	-1.03	**-3.75**	-0.58
Small	37	12.87	1.06	1.06	1.06	0.71	0.31	**-6.78**	0.06	0.02	18	19.20	0.68	0.68	0.68	-1.16	-0.39	-0.64	-1.14	-0.12
Liquidity	111	-16.36	**-2.25**	**-2.18**	**-2.19**	-1.03	-1.51	**-13.56**	-0.96	-1.15	72	-49.45	**-3.00**	**-2.99**	**-3.01**	**-2.43**	**-3.46**	**-2.85**	**-2.43**	-1.05
High	47	-47.64	**-3.68**	**-3.66**	**-3.68**	**-2.83**	**-2.31**	**-8.99**	**-2.77**	-1.40	30	-28.77	-1.39	-1.38	-1.39	**-3.31**	**-2.39**	-1.71	**-3.31**	-0.72
Medium	33	15.30	1.51	1.50	1.51	1.11	0.52	**-7.93**	0.19	0.08	27	-72.79	**-3.13**	**-3.11**	**-3.13**	**-7.13**	**-3.43**	**-2.87**	**-7.11**	-1.03
Low	31	-2.83	-0.29	-0.11	-0.11	**-2.03**	-0.59	**-6.40**	-1.38	-0.41	15	-50.66	-0.95	-0.91	-0.91	-1.31	-0.31	-0.01	-1.30	-0.09

From Table 3.5, for FP policy in the US sample, AAR[0] shows a small increase of 5.36bp for the full sample, which marginally increase to 6.42bp for CAAR[-1,0,+1] before dropping to -14.30bp for CAAR[-3,0,+3] indicating across the 3 days and 7 days event window the effect of FP announcements has very miniscule effect on CDS abnormal return which is not consistent for longer event window. The effect is significant across the event windows for the full sample. However, for UK sample, AAR[0] is not significant for the full sample, while for the 3 day event window CAAR[-1,0,+1] = 28.86bp drops to -51.99bp for the 7 days event window, highlighting that FP announcements in UK sample has an similar effect on CDS abnormal return compared to the US sample.

Further for US sample, *(Fin)* firms have a lower and significant abnormal return across the three event windows, while for *(NonFin)* firms the effect is higher than the full sample but negative and significant across the event windows (AAR [0] = -15.96bp, CAAR[-1,0,+1] = -24.23bp and CAAR[-3,0,+3] = -56.15bp). For UK sample, *(Fin)* firms show lower *AR* than the full sample across the event windows. The results also shed some light on the differential effect of FP announcement based on the sector of the firms under consideration and the sample being analysed similar to that of IR announcements. By categorising firm based on credit quality, across the three event windows, a higher and significant abnormal return for *(Spec)* firm than *(Inves)* firms can be noted for both the US and UK sample. This implies the effect of FP announcement has a favourable effect on speculative grade firms and this effect is statistically significant and positive across the event windows.

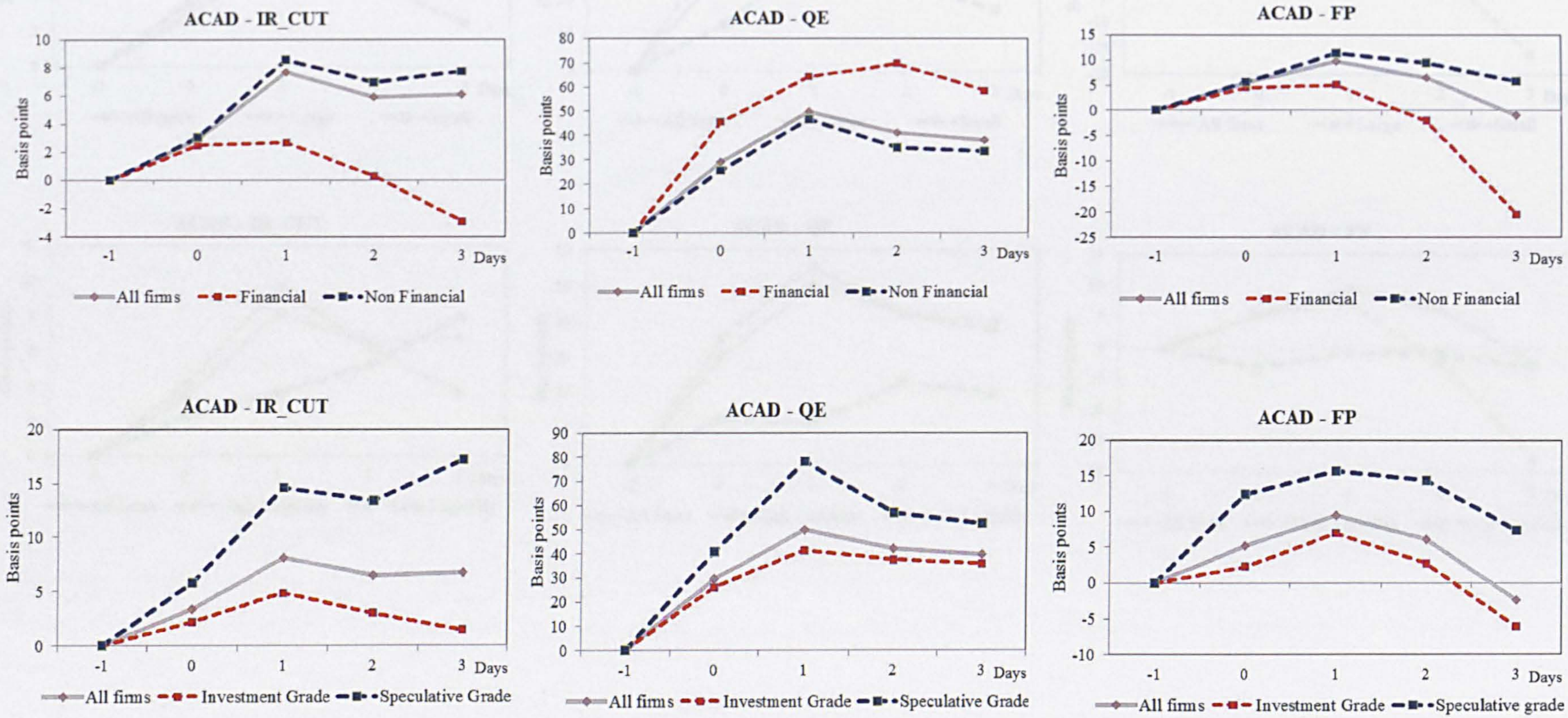
Categorising firms based on *(Size)* shows; across the US and UK sample *(Small)* firms have higher *ARs* than *(Large)* size firms the effect is significant and consistent across the event windows except for 7 day event window in UK sample. For the UK sample, unlike the full sample *AR*, a positive abnormal return for *(Small)* firms consistent with the US sample can be noted although the overall effect for 7 day event window is not significant. Classifying firms based on the level of CDS liquidity does not provide clear outcomes. For US sample, firms with *(High)* liquidity, have lower *ARs* (for US sample CAAR[-1,0,+1] = -1.64bp and CAAR[-3,0,+3] = -47.64bp) and is statistically significance but this result does not hold for the 1 day event window. For the UK sample the results are inconclusive.

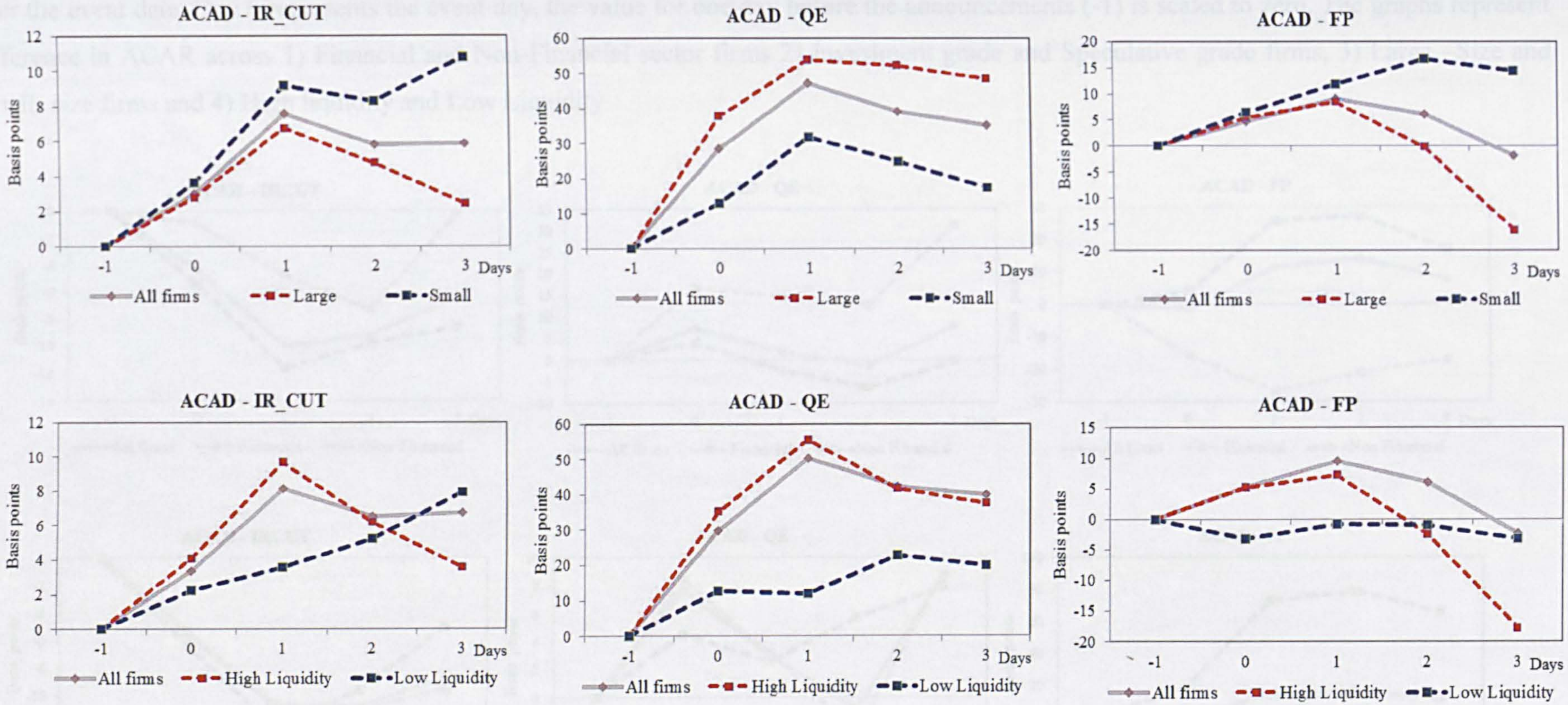
Overall, the study notes the effect on cumulative abnormal return is different based on the type of government intervention i.e. policy announcement. Moreover, there are differences within the samples analysed (US and UK). In addition, the effect of a specific policy announcement is different based on the firm idiosyncratic characteristics and without splitting the sample into sub-categorises these effects would have been overlooked. By splitting the sample, this study entangles the differential effect of policy announcement based on firm idiosyncratic characteristics namely; sector, quality, size and liquidity. Across the different length of the event windows, the effect on abnormal returns is not always consistent. This may indicate that policy announcement effect may be fading out at a faster rate due to which the cumulative abnormal returns may not be capturing the dynamic post announcement day effects. Moreover, the cumulative abnormal return windows may be plagued by return dynamics of the pre-announcement days. To estimate the effect on abnormal returns following the event announcement, this study estimates average cumulative abnormal return (ACAR) for the 3 day window following (and including) the announcement day across the three policy type.

Fig. 3.2 and Fig. 3.3 plot the ACAR (in basis points) for IR, QE and FP for the event window – one day before the announcements and three days after (including) the event day. Day 0 represents the event day and the value for one day before the announcement is scaled to zero. ACAR for the full sample and for each sub-categorises is plotted across both US (Fig. 3.2) and UK (Fig. 3.3) samples. For US sample, following IR announcement; non-financial firms record higher abnormal returns than those for financial firms while this effect is opposite in the UK sample. A similar trend can be noticed following FP announcements for both the US and UK sample. However, following QE announcements financial firms record higher abnormal returns than their non-financial counterparts. Across the three policies, QE announcement record the highest gain in abnormal returns across both the samples.

For US sample, following IR announcement; speculative grade firms record higher abnormal returns than those for investment grade firms while this effect is opposite in the UK sample. A similar trend can be noted following FP announcements for both the US and UK sample and for QE announcement for US sample. For the UK sample, following the QE announcements speculative grade firm record overall comparable abnormal returns to that of investment grade firms over the 3 days window although, investment grade firms have higher abnormal returns on the day of announcement but this effect fluctuates over the event window. Across the three policy QE announcement record the highest gain in abnormal returns for the US sample while FP announcement record the highest gain for the UK sample.

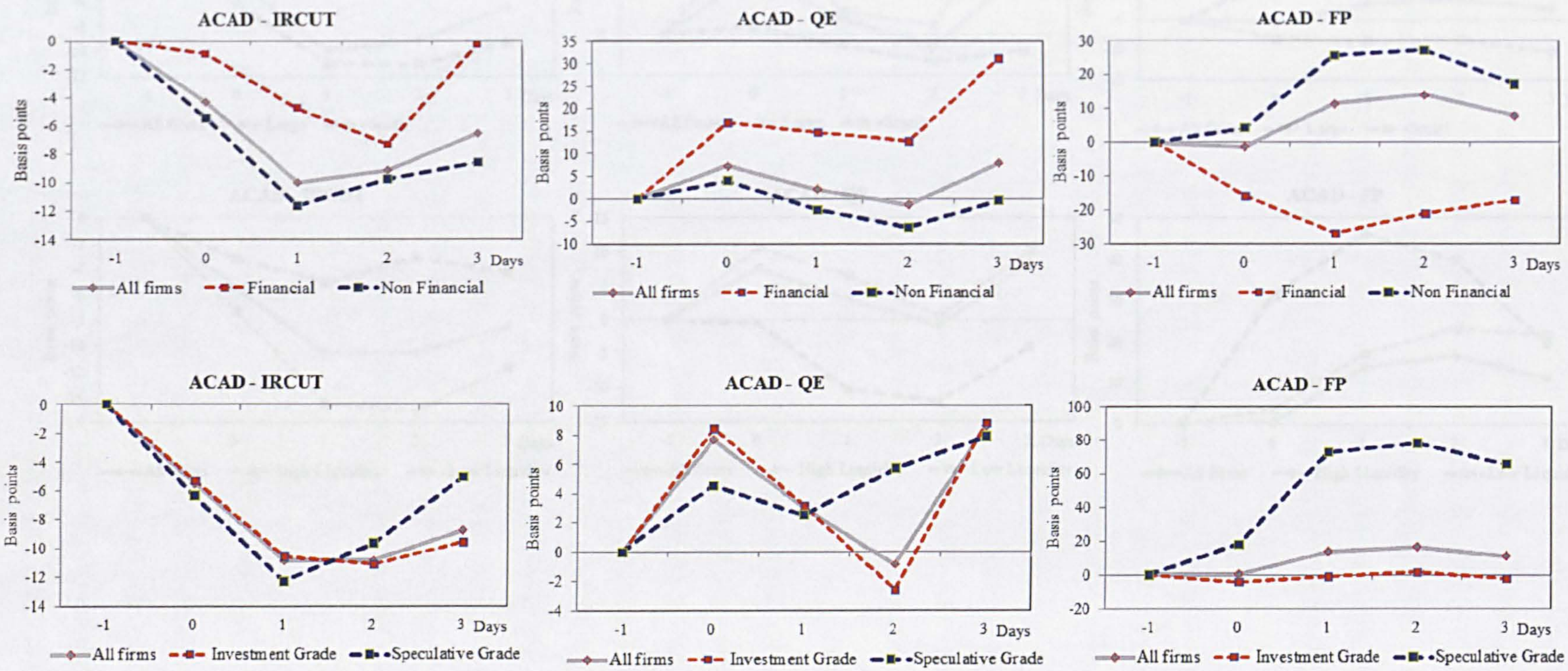
Fig 3.2: The figure below plots the average cumulative abnormal CDS return in basis points for the US sample for the three policy events (Interest rate cuts - IR, Quantitative easing – QE and Fiscal policy - FP) for the event window - one day before the announcement and three days after the event date. Day 0 represents the event day, the value for one day before the announcements (-1) is scaled to zero. The graphs represent difference in ACAR across 1) Financial and Non-Financial sector firms 2) Investment grade and Speculative grade firms, 3) Large –Size and Small- size firms and 4) High liquidity and Low Liquidity.

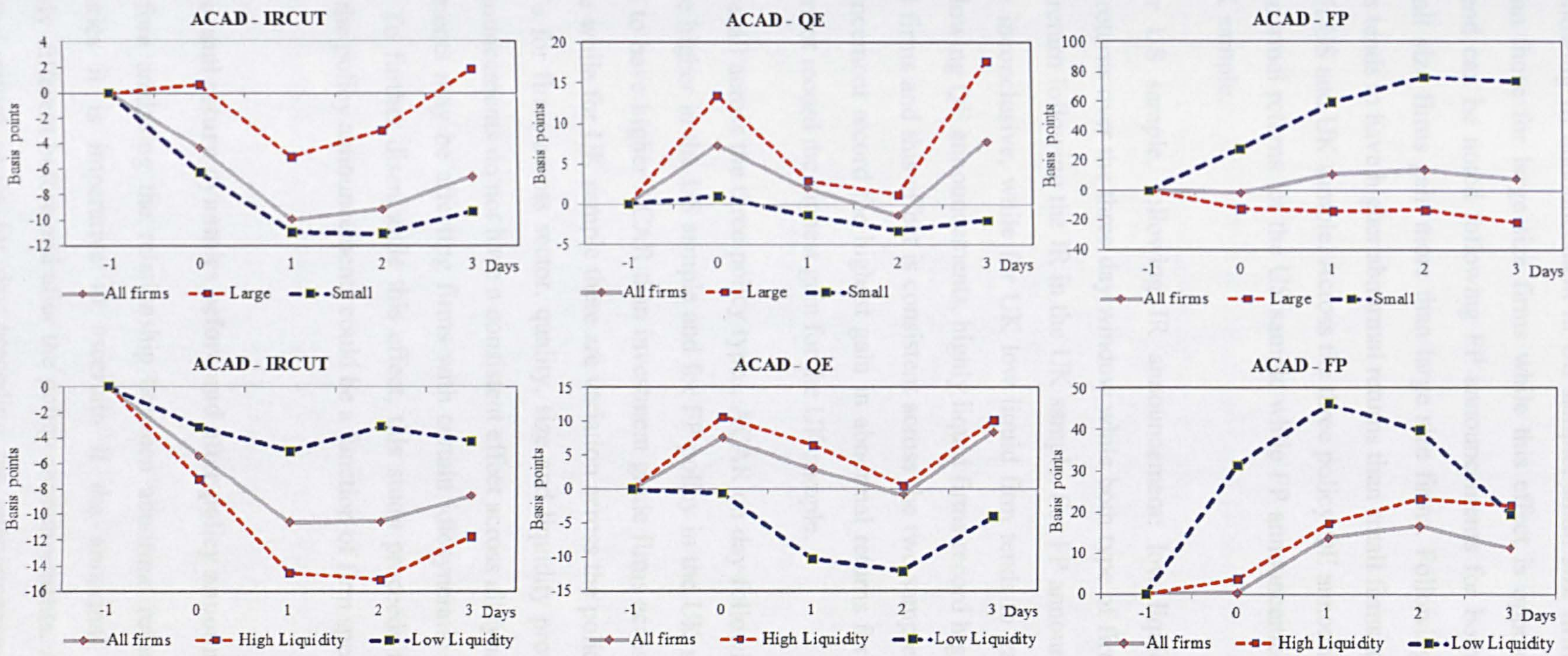




ACAD - IR_CUT
ACAD - QE
ACAD - FP
Basis points
Days
All firms
Large
Small
ACAD - IR_CUT
ACAD - QE
ACAD - FP
Basis points
Days
All firms
High Liquidity
Low Liquidity

Fig 3.3: The figure below plots the average cumulative abnormal CDS return in basis points for the UK sample for the three policy events (Interest rate cuts - IR, Quantitative easing – QE and Fiscal policy - FP) for the event window - one day before the announcement and three days after the event date. Day 0 represents the event day, the value for one day before the announcements (-1) is scaled to zero. The graphs represent difference in ACAR across 1) Financial and Non-Financial sector firms 2) Investment grade and Speculative grade firms, 3) Large –Size and Small- size firms and 4) High liquidity and Low Liquidity




ACAD - IRCUT
ACAD - QE
ACAD - FP
Basis points
Days
All firms
Large
Small
ACAD - IRCUT
ACAD - QE
ACAD - FP
Basis points
Days
All firms
High Liquidity
Low Liquidity

Following IR announcement in US sample; small size firms record higher abnormal returns than those for large size firms while this effect is opposite in the UK sample. A similar trend can be noted following FP announcements for both the US and UK sample where small size firms gain more than large size firms. Following the QE announcements, large firms tends to have higher abnormal returns than small firms and this effect is consistent across both US and UK sample. Across the three policy QE announcement record the highest gain in abnormal returns for the US sample while FP announcement record the highest gain for the UK sample.

For US sample, following IR announcement; low liquidity firms record higher abnormal returns over the three day window while both type of firms tends to have negative abnormal return following the IR in the UK sample. For FP announcement in US sample the results are inconclusive, while for UK low liquid firm tends to gain more than high liquid firms. Following QE announcements, highly liquid firms record higher abnormal returns than low liquid firms and this effect is consistent across the two samples. Across the three policy QE announcement record the highest gain in abnormal returns for the US sample while FP announcement record the highest gain for the UK sample.

Overall across the three policy types, ACAR on day following the QE announcement tends to be higher in the US sample and for FP policy in the UK sample. Speculative grade firms tend to have higher ACAR than investment grade firms across the three policies in the US sample while for UK sample there are variation across the policy type. These differences in ACAR's for firms across sector, quality, size and liquidity provide some indication that policy announcements do not have a consistent effect across all types of firms. Certain policy announcements may be affecting firms with certain idiosyncratic characteristics more than the other. To further disentangle this effect, this study proceeds to test if abnormal return following the policy announcements could be a function of firm specific characteristics.

3.4.3 Abnormal return dynamics before and after policy announcements

Before analysing the relationship between abnormal return and firm idiosyncratic characteristics it is imperative to ascertain if the abnormal return characteristics is significantly different before and after the policy announcements. A significant difference in the abnormal return series for day preceding the announcement and day following the announcements will points towards the effect of announcement on abnormal returns. This test is undertaken in an attempt to attribute the difference in abnormal return before and after the announcement days to the effect of policy announcement. The mean and median AAR for one day before the announcement AAR[-1] and one day following the announcements AAR[0] as well as three day before the announcement CAAR[-3,-1] and three days following the announcement CAAR[-0,+2] are estimated. To attribute a statistical significance of the difference in mean AAR/CAAR before and after the policy announcement, this study uses the Sign-rank test (SRT) statistics. SRT tests the equality of matched pairs of observations by using the Wilcoxon matched-pairs signed-rank test (Wilcoxon 1945). Specifically the null hypothesis assumes both distributions before and after the policy announcements to be same. The p-value for statistical significance difference in mean AAR/CAAR is reported under *Sig-w*. This study also employs the Sign-test, to estimate the statistical significance of the difference in median CAAR before and after the policy announcement. Sign-test tests the equality of matched pairs of observations, for the null hypothesis that the median of the differences in CAAR before and after the policy differences is zero without making any further assumptions about the distributions. The p-value for sign-test is reported under *Sig-t*. Table 3.6 reports the results for the full sample and subsamples for IR policy (Panel A for US, Panel B for UK), QE policy (Panel C for US and Panel D for UK) and for FP policy (Panel E for US and Panel F for UK). For each panel, the full sample is split based on sectors - *(Fin)* and *(Non-Fin)*, Quality - *(Inves)* and *(Spec)*, firm size *(Small)* and *(Large)* and CDS liquidity - *(Low)* and *(High)*.

Table 3.6: This table reports the mean and median AAR one day before AAR[-1] and one day following the policy announcement AAR[0] as well as three days before the announcements CAAR[-3,-1] and three days following a policy announcement CAAR[0,+2]. Panel A and Panel B reports the changes in CAAR's following policy announcements on IR for US and UK, Panel C and Panel D for QE across US and UK and Panel E and Panel F for FP announcements in US and UK. For each panel, the full sample is split based on sectors - (*Fin*) and (*Non-Fin*), Quality - (*Inves*) and (*Spec*), firm size (*Small*) and (*Large*) and CDS liquidity - (*Low*) and (*High*). The p-value for statistical significance difference in mean CAAR's is reported using Wilcoxon matched-pairs signed-ranks test in the column labelled '*Sig-w*' and the p-value for equality of matched paired median observations using the sign test for matched pair in column labelled '*Sig-t*'

Panel A - US	AAR [-1]		AAR [0]				CAAR [-3,-1]		CAAR [0,+2]			
IR	Mean	Med	Mean	Med	Sig-w	Sig-t	Mean	Med	Mean	Med	Sig-w	Sig-t
All firms	0.37	0.19	4.73	1.58	**0.00**	**0.00**	2.22	0.33	5.78	2.08	**0.00**	**0.00**
Fin	-1.77	0.39	0.19	1.55	0.27	0.14	0.27	0.62	0.07	2.13	0.54	0.49
Non-Fin	0.78	0.16	5.58	1.58	**0.00**	**0.00**	2.59	0.33	6.85	2.06	**0.00**	**0.00**
Invest	-1.21	0.04	2.70	1.15	**0.00**	**0.00**	-1.77	-0.08	2.95	0.94	**0.00**	**0.01**
Spec	5.02	1.17	8.79	2.95	**0.00**	**0.00**	11.54	4.40	13.15	5.63	0.11	0.20
Small	2.00	0.54	5.55	1.33	**0.00**	**0.00**	7.15	1.52	8.21	2.41	0.16	1.00
Large	-0.25	0.28	3.94	1.79	**0.00**	**0.00**	1.78	0.09	4.62	2.09	0.14	0.19
Low	3.60	0.32	1.35	0.52	0.30	0.14	5.78	0.91	4.68	0.86	0.37	0.93
High	-1.07	-0.40	5.58	2.95	**0.00**	**0.00**	1.44	0.00	6.22	2.09	**0.02**	0.08

Panel B - UK	AAR [-1]		AAR [0]				CAAR [-3,-1]		CAAR [0,+2]			
IR	Mean	Med	Mean	Med	Sig-w	Sig-t	Mean	Med	Mean	Med	Sig-w	Sig-t
All firms	3.35	1.95	-5.64	-4.07	**0.00**	**0.00**	3.36	2.15	-9.14	-5.60	**0.00**	**0.00**
Fin	-3.46	-1.78	-3.85	-2.34	0.83	0.83	-6.91	1.03	-7.32	0.15	0.91	1.00
Non-Fin	5.55	3.48	-6.23	-4.32	**0.00**	**0.00**	6.68	2.54	-9.73	-7.80	**0.00**	**0.00**
Invest	2.49	2.01	-5.24	-4.21	**0.00**	**0.00**	0.00	1.56	-11.08	-5.60	**0.00**	**0.00**
Spec	-2.57	0.31	-5.93	-4.18	0.26	0.30	0.32	4.08	-9.64	-9.91	0.33	0.61
Small	4.97	1.71	-4.69	-1.04	**0.01**	**0.03**	1.61	1.77	-11.09	-5.42	**0.04**	0.19
Large	7.09	2.39	-5.64	-6.65	**0.00**	**0.00**	7.72	3.97	-2.92	-3.45	**0.03**	0.13
Low	-8.37	-0.30	-1.91	0.00	0.68	1.00	-8.91	0.63	-3.08	-2.84	0.40	0.10
High	6.17	6.99	-7.31	-6.65	**0.00**	**0.00**	7.20	6.85	-15.08	-8.75	**0.00**	**0.02**

Panel C - US	AAR [-1]		AAR [0]				CAAR [-3,-1]		CAAR [0,+2]			
QE	**Mean**	**Med**	**Mean**	**Med**	**Sig-w**	**Sig-t**	**Mean**	**Med**	**Mean**	**Med**	**Sig-w**	**Sig-t**
All firms	3.83	-0.21	20.57	7.55	**0.00**	**0.00**	5.70	-2.96	41.33	21.74	**0.00**	**0.00**
Fin	-4.02	-0.41	18.58	6.41	**0.00**	**0.01**	-3.40	-8.03	69.82	44.83	**0.00**	**0.00**
Non-Fin	5.57	-0.21	21.01	7.68	**0.00**	**0.00**	7.72	-0.59	35.01	18.32	**0.00**	**0.00**
Invest	0.98	0.53	15.24	7.59	**0.00**	**0.00**	2.67	-1.08	37.48	21.20	**0.00**	**0.00**
Spec	17.73	-1.41	37.08	4.72	**0.00**	**0.00**	23.62	-7.23	56.94	27.58	**0.02**	**0.01**
Small	1.41	-0.64	18.96	6.48	**0.01**	**0.04**	-10.61	-7.21	24.96	19.33	**0.00**	**0.00**
Large	-0.33	1.68	16.13	6.98	**0.00**	**0.00**	3.42	0.33	52.35	23.01	**0.00**	**0.00**
Low	10.16	-0.41	-0.81	-0.05	0.64	0.46	-5.97	-7.20	22.82	10.44	**0.00**	**0.00**
High	-2.64	-0.21	20.36	7.51	**0.00**	**0.00**	2.11	-2.89	41.72	21.91	**0.00**	**0.00**

Panel D - UK	AAR [-1]		AAR [0]				CAAR [-3,-1]		CAAR [0,+2]			
QE	**Mean**	**Med**	**Mean**	**Med**	**Sig-w**	**Sig-t**	**Mean**	**Med**	**Mean**	**Med**	**Sig-w**	**Sig-t**
All firms	9.49	6.23	-5.30	-2.56	**0.00**	**0.00**	6.51	3.56	-1.42	0.72	0.10	0.18
Fin	11.19	3.16	-2.12	-4.26	0.10	0.08	8.20	2.41	12.72	9.05	0.34	0.38
Non-Fin	8.90	6.29	-6.41	-1.88	**0.00**	**0.00**	5.91	4.43	-6.37	0.24	**0.01**	**0.03**
Invest	10.74	6.57	-5.29	-2.72	**0.00**	**0.00**	5.86	4.43	-2.58	1.48	0.14	0.15
Spec	9.74	6.23	-2.00	0.73	0.10	0.30	9.94	7.47	5.72	0.66	0.82	1.00
Small	10.80	6.74	-2.34	0.12	0.05	0.48	5.92	4.37	-3.38	0.62	0.13	**0.03**
Large	9.37	6.24	-10.47	-4.26	**0.00**	**0.00**	4.76	2.41	1.16	0.89	0.33	0.50
Low	8.35	2.38	-9.73	-0.19	0.08	0.14	-5.12	-2.35	-12.07	0.15	0.52	0.33
High	10.43	7.28	-4.16	-2.64	**0.00**	**0.00**	10.25	8.84	0.48	0.21	**0.04**	0.10

Panel E - US	AAR [-1]		AAR [+1]				CAAR [-3,-1]		CAAR [0,+2]			
FP	**Mean**	**Med**	**Mean**	**Med**	**Sig-w**	**Sig-t**	**Mean**	**Med**	**Mean**	**Med**	**Sig-w**	**Sig-t**
All firms	-3.31	-1.16	4.37	2.06	**0.00**	**0.01**	-13.33	-4.37	6.65	3.93	**0.00**	**0.00**
Fin	-3.74	-0.95	0.45	0.17	0.38	0.58	-20.68	-2.37	-2.00	-0.39	0.40	0.58
Non-Fin	-3.16	-1.16	5.74	2.29	**0.00**	**0.01**	-10.80	-5.65	9.67	4.59	**0.00**	**0.00**
Invest	0.18	-0.59	4.69	2.18	**0.00**	**0.01**	-11.99	-6.02	2.75	3.51	**0.00**	**0.00**
Spec	-13.60	-6.22	3.17	0.82	**0.03**	0.28	-18.80	-4.16	15.26	5.62	0.10	0.28
Small	-2.08	0.04	5.29	0.76	0.27	0.51	-1.63	0.15	16.72	4.06	0.11	0.10
Large	-3.42	-2.69	2.87	1.70	**0.05**	0.08	-21.90	-10.37	-0.11	-0.20	**0.01**	0.08
Low	1.88	0.23	2.34	0.82	0.70	1.00	0.38	0.22	-0.46	0.64	0.71	1.00
High	-8.82	-3.57	1.95	2.32	**0.00**	**0.00**	-29.97	-15.26	-2.40	1.50	**0.00**	**0.00**

Panel F - UK	AAR [-1]		AAR [+1]				CAAR [-3,-1]		CAAR [0,+2]			
FP	**Mean**	**Med**	**Mean**	**Med**	**Sig-w**	**Sig-t**	**Mean**	**Med**	**Mean**	**Med**	**Sig-w**	**Sig-t**
All firms	17.51	11.29	12.72	5.38	0.13	0.49	-59.91	-38.89	14.08	10.40	**0.00**	**0.00**
Fin	-3.46	-1.78	-3.85	-2.34	0.83	0.83	-6.91	1.03	-7.32	0.15	0.91	1.00
Non-Fin	5.55	3.48	-6.23	-4.32	**0.00**	**0.00**	6.68	2.54	-9.73	-7.80	**0.00**	**0.00**
Invest	15.02	10.16	3.54	2.74	**0.02**	0.18	-65.72	-41.05	1.53	9.92	**0.00**	**0.00**
Spec	30.00	21.58	54.84	31.89	0.14	0.42	-44.43	-5.56	78.41	43.88	**0.00**	**0.01**
Small	23.31	10.71	31.50	13.67	0.27	0.10	-54.55	-46.66	76.44	36.08	**0.00**	**0.00**
Large	11.62	11.27	-1.65	6.89	0.06	0.38	-76.09	-41.03	-12.73	9.79	**0.01**	**0.02**
Low	-2.65	1.09	14.91	0.72	0.31	0.61	-68.41	-6.35	39.80	11.07	**0.00**	**0.01**
High	24.91	13.92	13.62	1.29	**0.04**	0.10	-50.36	-41.03	23.05	9.30	**0.00**	**0.01**

Note: Values in bold represent significance at 5% level.

Across the three policy announcements, the mean and median CAAR's for the full sample is significant for the 1 day as well as the 3 day event window for the US sample. For the UK sample, the pre and post returns series are not significant for the 3 day event window for QE policy and for the one day event window for FP policy. For IR policy in US sample, the mean and median return for *(Non-Fin)*, *(Inves)* and *(High-Liq)* firms are lower in the pre than the post announcement window. An opposite effect can be noted for the UK sample, where pre-announcement mean and median are higher than post announcement window return for the *(Non-Fin)*, *(Inves)* and *(High-Liq)* firms. These differences are significant at 5% level. The study also notes a significant difference in both mean and median returns for *(Spec)*, *(Small)* as well as *(Large)* firms but this is true only for the 1 day event window and does not hold for the 3 day event window. For QE policy, in the US sample, the mean and median returns are higher in the post announcements than the pre-announcement windows across the full sample and all subcategories and for both the 1 day and 3 day event window. While the mean and median return is lower in post announcement than pre announcement window and is significant only for *(Non-Fin)* and *(High-Liq)* firms in the UK sample. For FP policy in the US sample, a similar effect for IR policy can be noted, where the mean and median return for *(Non-Fin)*, *(Inves)* and *(High-Liq)* firms are lower in the pre than the post announcement window. While for UK sample in the 3 day event window the *(Non-Fin)* firms have higher return in the pre-announcement than the post announcement window. Although, there are some other significant differences across the 3 day window the results do not hold for the 1 day event window and hence this study refrains from drawing further inferences.

3.4.4 What drives CDS Abnormal returns across the policy announcement days

From the previous section, this study concludes that abnormal return following a policy announcement is different across firms with different idiosyncratic characteristics namely; (Sector, Quality, Size and Liquidity). This raises an important question if abnormal return following a policy announcement is a function of firm specific characteristics. This study considers the following independent variables in the regression model to proxy for firm idiosyncratic characteristics; 1) Sector - financial sector dummy *(Fin_d)* (coded as 1 if the firm belong to financial sector and 0 otherwise) 2) Quality - investment grade dummy *(Inves_d)* (coded as 1 if the firm belong to investment grade and 0 otherwise) 3) Liquidity *(Liq)* – *'Composite depth 5Y'* is used as proxy for CDS contract liquidity obtained from

Markit 4) Size *(ln_TA)* – measured using logarithm of previous quarter total assets, 5) Gearing *(Gear)* – measured as previous quarter debt to equity ratio 6) Level of firm capitalisation *(Cap)* – measured as total capital to total assets ratio and 7) ROA *(ROA)* – previous quarter return on assets as a proxy for firm profitability. The choices of independent variables are limited to avoid multi-collinearity among independent variables and to control for endogenity issue within the regression model. For the set of independent variables used in the model, this study proceeds to test for correlation among predictor variables to ensure multi collinearity does not have a bearing on the results. Overall, all independent variables are weakly correlated *($r<0.53$)* and it can be ascertained that the results are not plagued by multi-collinearity issues (This is further supported by VIF and tolerance test not reported here). We run a standard OLS regression (with robust standard errors) to test if CDS abnormal return for the event day AR[0] is a function of firm specific characteristics.

$$AR = \alpha + \beta_1 Fin_D + \beta_2 Inves_D + \beta_3 Liq + \beta_4 ln\_TA + \beta_5 Gear + \beta_6 Cap + \beta_7 ROA + \varepsilon \qquad (3.15)$$

To differentiate the effect of the announcement, the process is repeated using abnormal return 1 day prior to policy announcement AR[-1]. This study also checks for robustness of the findings by comparing this relationship across a range of event windows i.e. CAR[0,+1] and CAR [-1,-2] as well as for CAR[0,+2] and CAR[-1,-3]. This study also tests if this relationship is consistent across the three policy announcements. Table 3.7 provides the result of the regression for US and UK sample for IR policy in Panel A, QE policy in Panel B and FP policy in Panel C.

From Table 3.7, across the three policy types, the sign and significance of the independent variables in the model changes depending on the event window the abnormal returns are analysed. Two levels of comparison is undertaken; firstly pre and post policy announcement where the regressions results for one day before the announcement AR[-1] is compared to one day following the announcement AR[0]. To ensure robustness of the results the cumulative abnormal return for two days before the announcements CAR[-1,-2] is compared to two days following the announcement CAR[0,+1] as well as three days before the announcement CAR[-1,-3] to three days following the announcement CAR[0,+2]. Secondly, the similarities and difference in sign and significance of the independent variables for the pre and post policy announcement event windows is compared across Panel A, Panel B and Panel C.

Table 3.7: Table below presents the regression output for abnormal return (day 0) for the three policy IR (in Panel A), QE (in Panel B) and FP (in Panel C) event days. *(Fin_d)* is the financial sector dummy variable coded as 1 for financial sector firms and 0 otherwise, *(Inves_d)* is the investment grade dummy variable coded as 1 for firms with credit rating higher than BB and 0 otherwise. Liquidity of CDS contract is measured using composite depth 5y *(Liq)*. *(Gear)* is calculated as the debt to equity ratio. *(Cap)* is the level of firm capitalisation measured as total capital over total assets. *(ROA)* is the measure of firm profitability. AR[0] is the abnormal return on the event day, AR[-1] is abnormal return one day before the event day, CAR[0,+1] and CAR[0,+2] is the cumulative abnormal return for Day0+Day1 and Day0+Day1+Day2. Similarly CAR[-1,-2] and CAR[-1,-3] is the cumulative abnormal return for 2 days and 3 days prior to the announcement. The coefficients of the independent variables and their sign is compared for AR[0] and AR[-1] and this relationship is tested for robustness across CAR[0,+1] vs. CAR[-1,-2] and CAR[0,+2] vs. CAR[-1,-3]

Panel A	**US**						**UK**					
IR	**AR[0]**	**AR[-1]**	**CAR[0,+1]**	**CAR[-1,-2]**	**CAR[0,+2]**	**CAR[-1,-3]**	**AR[0]**	**AR[-1]**	**CAR[0,+1]**	**CAR[-1,-2]**	**CAR[0,+2]**	**CAR[-1,-3]**
Constant	-9.1	4.71	-7.34	8.43	-18.1	16.29	-23.34*	-6.84	-39.81*	-18.56	-58.17	-35.43
Fin_d	3.92	-0.48	2.73	1.51	6.1	1.69	-4.39	-16.77*	-1.99	-34.26***	-12.53	-29.7**
Inves_d	1.75	-4.9*	-1.66	-8.99***	-3.46	-12.27***	0.19	10.62	-0.2	6.29	-6.06	5.99
Liq	0.95***	0.56**	1.95***	0.87***	2.25***	1.1***	-1.04***	-0.65	-1.14**	-1.81***	-1.89**	-1.39**
ln_TA	-0.43	-0.85	-0.45	-0.93	-0.44	-1.1	2.53**	1.27	2.86	3.75	6.25**	4.16
Gear	0.01	-0.01	-0.01	-0.01	-0.01	-0.01	0.01	0.01**	0.01	0.01	0.01	0.01
Cap	11.64*	2.42	7.42	-3.85	16.01	-13.41	10.04	-1.79	24.56	9.43	30.04	24.13
ROA	-0.33**	0.02	-0.51**	0.12	-0.24	0.16	-0.24**	-0.23	-0.46***	-0.47	-0.96***	-0.58
N	3464	3445	3426	3401	3397	3374	662	661	661	660	661	660
R^2	1.03%	0.58%	1.83%	0.77%	1.67%	0.83%	2.92%	1.80%	2.38%	2.93%	3.08%	1.88%

Panel B	US						UK					
QE	AR[0]	CAR[-1]	CAR[0,+1]	CAR[-1,-2]	CAR[0,+2]	CAR[-1,-3]	AR[0]	AR[-1]	CAR[0,+1]	CAR[-1,-2]	CAR[0,+2]	CAR[-1,-3]
Constant	-94.99**	41.17	-61.09	39.82	-54.77	48.02	-29.51	-6.59	-34.05	-14.84	-89.35	-22.49
Fin_d	11.76	-18.27***	12.37	-11.37	20.63	-29.72*	-10.93	1.58	-4.29	-11.38	-15.26	-8.95
Inves_d	-18.71*	-5.8	-22.86*	-6.33	-20.45	-8.18	-5.79	-2.66	-8.45	-7.51	-11.66	-6.68
Liq	3.76***	-2.51***	4.38***	-1.89*	3.71***	-4.57***	-0.05	0.99*	-0.57	0.63	-1.34	0.16
ln_TA	8.69**	0.42	7.39**	0.27	6.85*	1.17	5.67***	0.67	4.65	2.24	11.92**	2.65
Gear	-0.01	-0.01**	-0.01	-0.01	-0.01	-0.01	0.01	0.01**	0.01	0.01***	0.01	0.02***
Cap	35.75	-26.28	13.1	-32.32	18.75	-50.37	-21.66	0.72	3.41	8.58	4.92	9.56
ROA	-0.64*	-0.17	-1.2**	-0.26	-1.42**	-0.12	-0.33*	-0.07	-0.58**	-0.34	-1.23***	-0.34
N	888	883	886	874	884	873	371	370	371	370	371	370
R^2	5.37%	2.37%	5.24%	0.96%	4.17%	2.13%	6.06%	3.36%	2.13%	3.03%	3.36%	2.34%

Panel C	US						UK					
FP	AR[0]	CAR[-1]	CAR[0,+1]	CAR[-1,-2]	CAR[0,+2]	CAR[-1,-3]	AR[0]	AR[-1]	CAR[0,+1]	CAR[-1,-2]	CAR[0,+2]	CAR[-1,-3]
Constant	-4.02	-3.12	-43.81*	20.7	-3.12	66.31*	112.28	25.37	203.25**	40.56	254.13**	-82.06
Fin_d	4	-7.13	-2.35	-5.22	-6.14	-3.67	-17.59	-22.09*	-58.71**	9.39	-2.69	28.89
Inves_d	-10.37*	10.07*	-6.87	13.82	-3.76	9.15	-5.95	-12.94	-43.13*	-23.14	-48.11*	-12.6
Liq	1.47***	-1.47***	1.2**	-1.65***	0.08	-1.05	-2.49	1.7*	-2.84	3.13	0.3	2.87
ln_TA	-0.26	0.74	2.23	-2.54	-0.8	-5.85*	-6.62	0.45	-7.35	-5.16	-16.92*	-1.08
Gear	-0.01	-0.01	-0.01	0.01	-0.01	-0.01	0.01	-0.01	0.01	-0.01	0.01	0.01
Cap	5.46	2.77	39.43**	-6.34	30.23	-27.71	-35.29	-17.09	-78.36	-48.78	-93.19	25.11
ROA	0.28	-0.22	0.04	0.11	-0.12	0.28	-0.74*	-0.12	-1.71	-0.22	-0.04	-0.47
N	874	872	871	871	870	871	73	73	73	73	73	73
R^2	2.40%	2.60%	1.71%	2.12%	0.72%	1.51%	12.87%	17.30%	30.57%	9.26%	18.28%	4.57%

Note: *, **, *** denote significance at 10%, 5% and 1% level

From Panel A, for IR policy, *(Liq)* is positive and significant both before and after the event days indicating highly liquid CDS contracts tend to have higher abnormal return. This effect is significant across the three comparative event windows for the US sample. However for the UK sample, the liquidity coefficient is negative and significant (except for AR[-1]) across all event windows signifying highly liquid CDS contracts tend to have lower abnormal return for the UK sample. *(Invest_D)* is negative and significant for pre-announcement days while it becomes insignificant following IR announcement days. This indicates, investment grade firms tends to have lower abnormal return compared to speculative grade firms before the announcements while this relationship becomes insignificant on days following IR announcements. No such effect is observed in the UK sample. Similarly, for the UK sample *(Fin_D)* is negative and significant across the three event days preceding IR announcement while this effect is not significant for days following the announcement. No such effect is observed for the US sample. For both US and UK, *(ROA)* is negative and significant for days following the announcement (except for CAR[0,+2] in US) while this relationship is not significant for day preceding the announcement. This highlights that following IR announcements, less profitable firms tends to have higher abnormal return.

For QE policy in Panel B, a series of effect before and after the announcement event windows can be noted for the US sample. *(Liq)* is negative and significant for days preceding the QE announcements while this relationship becomes positive and significant following the QE announcement. This highlights that firms with lower CDS liquidity have higher abnormal returns for day preceding QE announcements while following QE announcements firms that are actively traded in the CDS market have higher abnormal returns. No such effect is observed in the UK sample. *(ln_TA)* is positive and significant indicating for day following QE announcements large firms tend to have higher abnormal returns while no such relationship exist for the days preceding the QE announcements. This effect is observed across both US and UK sample (except for CAR[0,+1]). Similarly *(ROA)* is negative and significant for both US and UK, indicating firms with lower profitability show higher abnormal return following the QE announcements similar to the effect from the IR policy. The other effects are not consistent across the event windows and this study avoids drawing further inferences.

From Panel C, following FP announcements, a similar effect of *(Liq)* can be noticed as with the QE announcements for the US sample. The coefficient of *(Liq)* is negative and significant before the announcement but turns positive and significant following the FP announcements. However, this result neither hold for the 3 day event window for US sample nor across the UK sample. For other variables the relationship between the abnormal returns and the independent variables in the model does not show a clear significant relationship as with the other two policy announcements.

Across Panel A, Panel B and Panel C it can be noted that the significance and effect of the explanatory variables are mostly evident for ARs following IR and QE announcements, while the effect is least on AR following FP announcement. Following the monetary policy announcements less profitable firms tends to have higher abnormal return. An opposite effect for IR announcement based on liquidity dynamics of the CDS contract for UK and US samples can be noted. For US sample following IR announcements highly liquid CDS contracts tend to have higher abnormal return, while for UK highly liquid CDS contracts tend to have lower abnormal return. Similarly, following QE announcements US firms that are actively traded in the CDS market have higher abnormal returns. This study notes that large firms as well as less profitability firms record a higher AR following monetary policy announcements. This effect is not as evident across abnormal returns following FP announcements in comparison to AR following the QE announcement especially in the US sample.

Next, the process is reversed and this study queries if there are significant differences in the characteristics of firms that have higher AR following a policy announcement. This study intends to find if these differences are consistent across the type of policy announcements and if the findings are robust across the range of event windows. To address this, AR [0] following the policy announcement is estimated and firms are sorted on the basis of these abnormal returns. Next, firms are categorised into three tiers –

1. Firms with high AR's – represent the top 33 percentile of the AR [0] observations
2. Firms with low AR's – represents the bottom 33 percentile of the AR [0] observations
3. Firms with medium AR's – represents all the remaining firms between the top and bottom 33 percentile of the AR[0] observations

To ensure robustness of the research findings, the process is repeated across the CAR [0,+1] and CAR [0,+2] event windows. For the US sample, AR < -1.62bp are categorised in the Low AR range, AR >-1.62 bp and <7.09 bp are categorised in the Medium AR range and AR >7.086 bp in the High AR range for AR[0]. Similarly, AR < -3.18bp are categorised in the Low AR range, AR >-3.18 bp and <12.04 bp are categorised in the Medium AR range and AR >12.04 bp in the High AR range for CAR[0,+1] and AR < -6.38bp are categorised in the Low AR range, AR >-6.38 bp and <13.09 bp are categorised in the Medium AR range and AR >13.09 bp in the High AR range for CAR[0,+2]. For the UK sample, AR < -6.88bp are categorised in the Low AR range, AR >-6.88 bp and <5.45 bp are categorised in the Medium AR range and AR >5.45 bp in the High AR range for AR[0]. Similarly, AR < -12.17bp are categorised in the Low AR range, AR >-12.17 bp and <6.99 bp are categorised in the Medium AR range and AR >6.99 bp in the High AR range for CAR[0,+1] and AR < -15.26bp are categorised in the Low AR range, AR >-15.26 bp and <14.01 bp are categorised in the Medium AR range and AR >14.01 bp in the High AR range for CAR[0,+2].

The median values for variables *(Liq)*, *(Ln_TA)*, *(Gear)*, *(Cap)* and *(ROA)* are estimated across firms in the three tiers (Low, Med and High) for the three policy announcements for the US (Panel A) and UK sample (Panel B). Kolmogorov-Smirnov and Shapiro-Wilk test (not reported here) are performed and found to be highly significant indicating deviation from normality across all variables for the two samples. Next, we test for a significant difference in the median values of these variables across the three tiers using the Kruskal-Wallis test. Specifically, this study tests if the difference in median values of firm characteristics for those belonging to the top and bottom tiers. Table 3.8 reports the median value of variables for firms with low, medium and high AR values for the AR [0] event window. The process is repeated for CAR [0,+1] and CAR [0,+2] to test for robustness. The *sig.* value represents the adj. sig test results for groups with low AR and high AR and *effect* represents the effect size.

Table 3.8: This table reports the median values of the variables grouped as per Low, Medium and High AR's for the event day AR[0], CAR [0,+1] and CAR [0,+2] across the three policy for US sample (Panel A) and UK sample (Panel B). *Sig* reports the Kruskal-Wallis significance between median values for firms with low and high AR/CAR. *Effect* estimates the effect size of the difference in means for the variables.

Panel A- US	**AR[0]**					**CAR[0,+1]**					**CAR[0,+2]**				
IR	**Low**	**Med**	**High**	**Sig**	**Effect**	**Low**	**Med**	**High**	**Sig**	**Effect**	**Low**	**Med**	**High**	**Sig**	**Effect**
Liq	8.00	8.00	10.00	***	-0.22	8.00	8.00	10.00	***	-0.18	8.00	8.00	10.00	***	-0.16
ln_TA	9.40	9.38	9.44	NS	-0.03	9.40	9.37	9.47	NS	-0.02	9.42	9.37	9.41	NS	0.00
Gear	86.31	72.05	102.10	***	-0.07	89.86	69.12	98.97	**	-0.05	89.76	68.89	101.69	**	-0.05
Cap	0.66	0.66	0.66	NS	0.00	0.66	0.66	0.66	NS	0.00	0.66	0.65	0.67	NS	-0.02
ROA	3.18	5.84	2.97	*	-0.05	3.22	5.83	3.10	NS	-0.02	3.16	5.73	3.13	NS	-0.01

	AR[0]					**CAR[0,+1]**					**CAR[0,+2]**				
QE	**Low**	**Med**	**High**	**Sig**	**Effect**	**Low**	**Med**	**High**	**Sig**	**Effect**	**Low**	**Med**	**High**	**Sig**	**Effect**
Liq	7.00	5.50	9.00	***	-0.28	7.00	6.00	8.00	***	-0.18	7.50	6.00	8.00	***	-0.10
ln_TA	9.25	9.25	9.64	**	-0.10	9.23	9.19	9.81	***	-0.12	9.25	9.35	9.65	*	-0.08
Gear	97.75	75.69	105.50	NS	-0.01	90.55	76.35	106.21	NS	-0.05	94.80	76.56	104.23	NS	-0.02
Cap	0.63	0.67	0.65	NS	0.00	0.67	0.65	0.65	NS	0.00	0.68	0.64	0.65	NS	-0.05
ROA	2.73	6.08	3.10	NS	-0.03	3.13	5.85	2.77	NS	-0.04	3.31	6.08	2.65	NS	-0.04

	AR[0]					**CAR[0,+1]**					**CAR[0,+2]**				
FP	**Low**	**Med**	**High**	**Sig**	**Effect**	**Low**	**Med**	**High**	**Sig**	**Effect**	**Low**	**Med**	**High**	**Sig**	**Effect**
Liq	9.00	7.00	9.00	NS	-0.06	9.00	7.00	9.00	NS	-0.06	9.00	7.00	9.00	NS	-0.04
ln_TA	9.80	9.22	9.64	NS	-0.04	10.00	9.22	9.65	NS	-0.05	9.94	9.31	9.29	**	-0.08
Gear	106.21	77.19	112.04	NS	-0.02	120.11	80.09	105.08	NS	-0.01	119.16	77.34	105.08	NS	-0.01
Cap	0.62	0.65	0.64	**	-0.12	0.61	0.66	0.64	**	-0.11	0.62	0.65	0.64	NS	0.00
ROA	3.06	6.08	2.91	NS	-0.05	2.98	6.04	2.65	NS	-0.08	3.29	6.08	2.98	NS	-0.05

Panel B- UK	AR[0]					CAR[0,+1]					CAR[0,+2]				
IR	**Low**	**Med**	**High**	**Sig**	**Effect**	**Low**	**Med**	**High**	**Sig**	**Effect**	**Low**	**Med**	**High**	**Sig**	**Effect**
Liq	10.00	9.00	9.00	***	-0.20	10.00	9.00	9.00	***	-0.18	11.00	9.00	9.00	***	-0.21
ln_TA	9.24	9.19	9.28	NS	0.00	9.33	9.03	9.32	NS	-0.02	9.34	9.09	9.26	NS	0.00
Gear	106.67	87.82	132.47	NS	-0.08	98.27	92.92	132.47	**	-0.12	98.27	97.66	123.87	NS	-0.10
Cap	0.61	0.63	0.61	NS	0.00	0.61	0.65	0.61	NS	0.00	0.61	0.63	0.61	NS	0.00
ROA	3.34	3.63	2.30	NS	-0.09	3.22	3.68	2.30	NS	-0.09	3.35	3.67	2.20	***	-0.16

	AR[0]					CAR[0,+1]					CAR[0,+2]				
QE	**Low**	**Med**	**High**	**Sig**	**Effect**	**Low**	**Med**	**High**	**Sig**	**Effect**	**Low**	**Med**	**High**	**Sig**	**Effect**
Liq	9.00	7.00	9.00	NS	-0.10	9.00	8.00	9.00	NS	-0.08	9.00	7.50	8.00	NS	-0.13
ln_TA	9.26	9.09	9.64	NS	0.00	9.64	8.93	9.46	NS	0.00	9.26	9.11	9.44	NS	0.00
Gear	119.53	131.39	136.36	NS	0.00	130.48	117.76	136.36	NS	0.00	122.90	109.80	136.36	NS	0.00
Cap	0.59	0.62	0.61	NS	0.00	0.59	0.65	0.59	NS	-0.06	0.61	0.61	0.60	NS	0.00
ROA	0.86	2.64	2.11	NS	0.00	2.11	2.78	0.86	NS	0.00	2.30	2.86	0.85	NS	-0.13

	AR[0]					CAR[0,+1]					CAR[0,+2]				
FP	**Low**	**Med**	**High**	**Sig**	**Effect**	**Low**	**Med**	**High**	**Sig**	**Effect**	**Low**	**Med**	**High**	**Sig**	**Effect**
Liq	9.00	8.00	7.00	NS	0.00	9.00	7.00	9.00	NS	0.00	9.00	8.50	8.50	NS	0.00
ln_TA	9.59	9.21	8.84	NS	0.00	9.98	9.21	8.78	***	-0.44	9.93	9.41	8.80	***	-0.34
Gear	78.12	140.64	163.86	NS	0.00	91.13	98.36	120.95	NS	0.00	62.90	171.52	120.95	NS	0.00
Cap	0.65	0.71	0.57	NS	0.00	0.54	0.70	0.63	NS	0.00	0.68	0.61	0.66	NS	0.00
ROA	3.42	3.67	1.86	NS	0.00	0.95	3.48	3.30	NS	0.00	2.77	2.85	3.35	NS	0.00

Note: *, **, *** denote significance at 10%, 5% and 1% level

Overall, for IR policy, the median *(Liq)* is significantly higher for firms with high AR than those with low AR. This result is significant across the three event windows with a small effect size and for both the US and UK sample. A similar effect can be noted for the QE policy but in the US sample. This relationship is non-significant for FP policy across both US and UK sample. This highlights firms having higher AR following the monetary policy announcement tend to be more liquid that those with lower ARs. For QE policy, firm size *(ln_TA)* is larger for high AR group compared to low AR group with a small effect size in the US sample while it is non-significant for UK sample. This relationship is also not significant for IR policy across the two samples. For FP policy, firm size *(ln_TA)* is smaller for high AR group compared to low AR group with a small effect size in the UK sample for CAR[0,+1] and CAR[0,+2] while this is only significant for CAR[0,+2] in US sample. This highlight firms having higher AR, following the FP policy announcement tend to be smaller in size that those with lower ARs. Firm with high AR's following the IR announcements, have significantly higher gearing *(Gear)* than those with low AR's with a small effect size. This effect is significant across all windows for US sample while only for CAR[0,+1] for the UK sample. This indicates firms having higher AR following the IR announcement tend to be highly geared that those with lower ARs. This effect is neither significant for QE announcement nor for FP policy announcement. For FP policy, firm capitalisation *(Cap)* is larger for high AR group compared to low AR group with a small effect size in the US sample for CAR[0] and CAR[0,+1] while this is only significant for the UK sample.

Overall this study finds, the differences in median value of firm idiosyncratic variables is mostly associated with difference in CDS liquidity and gearing for IR policy, difference in CDS Liquidity and firm size related to QE policy and firm capitalisation related to FP policy announcements. These firm specific differences are not consistent across the three policies. Specifically firm size characteristics are different across QE and FP policy announcements indicating a differential effect across the two policies.

3.5 Conclusion

CDS spreads have risen dramatically following the financial crisis across both US and UK, evidencing the strain in the corporate CDS market following the global financial crisis. This study rationalise that spreads do not represent the actual transaction price for the specific CDS contract and using it directly into estimating the effect will result in an incorrect estimation of the underlying firm's credit dynamics. Consequently, daily CDS returns is computed for all corporate that have active CDS contract available in Markit dataset for both US and UK. The asymmetric distribution characteristics of CDS returns evident from high kurtosis and skewness value can be noted evidencing variability across period and sector of analysis.

Next, this study analyses the impact of macroeconomic policy initiatives announced during the financial crisis on corporate credit risk dynamics measured using daily CDS returns. Using the well-established event study methodology, this study is able to assess the direct effect of monetary and fiscal policy announcement in addressing corporate credit risk for both US and UK. A range of parametric and non-parametric test statistics is employed to access the significance of CDS abnormal returns across a range of narrow event window. Overall, the effect on CAR is different based on the type of policy intervention. IR announcement has an opposite effect on ARs across US and UK sample, for US the effect is positive (small) while it is negative (small) for UK. This highlights policy intervention specifically on IR is not guaranteed to have a similar effect across firms in different economies. However, following QE announcements both US and UK samples show a large positive gain in AR, highlighting its popularity across both US and UK. A similar effect of FP policy can be noted in both US and UK, characterised by a small positive gain immediately following the announcement which is short-lived.

The estimation process used in this paper provides the flexibility to break down the effect based on sector, credit quality, firm size and liquidity to test the effect across the sub-samples and provides a comparative analysis across US and UK. The effect of a specific policy announcement is different based on the firm idiosyncratic characteristics and without splitting the sample into sub-categorises these effects would have been overlooked. By splitting the sample this study is able to entangle the differential effect of policy announcement. This study also notes that across the different length of the event windows the effect on AR is not always consistent. The results are found to be robust for alternative specifications of event windows. We also undertaken mean/median AR comparison for pre and post policy announcement days and note the differences to be mostly significant across the sub-samples for US. For US median AR is mostly higher in the post announcement days, while this effect is opposite for the UK sample. This may indicate, policy announcement in US were more effective in lowering risk in the corporate CDS market than those for UK. The results are found to be robust for alternative specifications of pre and post event windows.

This study also estimates the overall effect on ACAR following the policy announcements and note; ACAR for 3 day event window following the QE announcement is highest in the US sample and for FP policy in the UK sample. Speculative grade firms tend to have higher ACAR than investment grade firms across the three policies in US while for UK there are variation across the policy type. These differences in ACAR for firms across sector, quality, size and liquidity provides indication that policy announcements do not have a consistent effect across all type of firms. Certain policy announcements may be affecting firms with certain idiosyncratic characteristics more than the other. To further disentangle this effect, this study tests if abnormal return following the policy announcements could be a function of firm specific characteristics. This study notes the significance and effect of firm idiosyncratic variables are mostly evident for ARs following IR and QE announcements, while the effect is least on ARs following FP announcement. Following the monetary policy announcements, less profitable firms and large size firms tends to have higher ARs. An opposite effect can also be noted for IR announcement based on liquidity dynamics of the CDS contract for UK and US samples. Also, following QE announcements firms that are actively traded in the CDS market tend to have higher ARs. The results are robust for alternative specifications of event windows. Furthermore, the process is reversed and tested if a particular policy announcement has a significant effect on firms with certain idiosyncratic characteristics operating within an economy. Overall we note the differences in median value of firm idiosyncratic variables is mostly associated with difference in CDS liquidity and gearing for IR policy, difference in CDS liquidity and firm size related to QE policy and firm capitalisation related to FP policy announcements. Overall, these firm specific differences are not consistent across the three policies.

Following the IR announcements, financial firms CAAR's do not have a significant effect compared to non-financial firms, the finding supports Ricci (2014) that claims banks are less sensitive to traditional monetary policy measures like interest rate cuts. This has important policy implications especially in the context of the recent financial crisis. The credit crisis primarily affected the financial sector and government initiatives to counter the crisis should have been directed towards the ailing financial sector. The finding suggests the interest rate related announcement may not be the right policy action to curtail the credit risk (at least) for the financial sector firms. However, it is interesting to note that non-financial sector firms display a significant reduction in corporate credit risk following IR announcements. In the context of monetary policy transmission mechanism this could be explained on the basis of the rational expectation theory whereby Corporates make continuous assessment of the information provided by policy-makers' action on the future value of important variables and make relevant spending decisions. The reduction in interest rate may have been perceived as an easing of credit environment and may have been interpreted as a positive signal in the context of the economic situation. This implies that although IR may not affect the credit risk of financial sector firms but it significantly affects non-financial sector firms and would certainly help improve the short term environment for non-financial firms in the event of future crisis situation.

Across both monetary and fiscal policy announcements, speculative grade firms show a significantly higher reduction in credit risk compared to investment grade firms. Speculative grade firms tend to have higher credit risk compared to investment grade firms hence the possibility of improvement in credit risk following a favourable policy announcement may be higher than for investment grade firms. In terms of the transmission mechanism this effect could be explained in terms of the credit supply view (Bernanke and Gertler, 1995). The easing of credit environment both in terms of reduction in interest rate and increase in money supply through quantitative easing alters the credit and lending criteria for banks. The easing monetary policy may change the credit standards of lenders as well as the rates charged to borrowing firms resulting in a more favourable credit environment for speculative grade firms. Consequently speculative grade firms which would have not been able to borrow funds due to strict lending standards or may have found financing expensive in the past would benefit more from the policy announcements. The higher and positive effect on speculative grade firms provides important signal to policy-makers indicating that the policy announcement achieved the desired results in reducing credit risk of the weakest link (firms) in the economy.

Small firms are generally more susceptible to monetary policy tightening and this has been documented in earlier studies by Bach and Huizenga (1960) and Galbraith (1957). The reasons are mainly attributed to the smaller collateralizable net worth leading to greater incentive incompatibility, lower unconditional survival rates, less diversified hence higher idiosyncratic risk and higher bankruptcy cost (Kandrac, 2012). Consequently, in an event of relaxed monetary policy announcements the benefit for small firms is expected be more in proportion to large firms causing small firm's credit risk to decrease more in comparison to big firms. However, the findings from this study indicate that large firms show a significantly higher reduction in credit risk compared to smaller firms following both IR and QE announcements. This effect could be explained as follows - Although banks are not the primary source of capital for starting a new firm, they are the primary source of funds for small firms once started, providing working capital and funding for investment in plant and equipment (Dunkelberg and Cooper, 1983; Berger and Udell 1998). Changes in the cost and availability of funds at banks that result from changes in monetary policy could have an important effect on small firm spending. However, the change in loan terms and owner's responses to these change as they come to bank for capital takes time to develop. Therefore the changes in interest rate would not have a direct bearing on firms that do not borrow or borrow irregularly. Additionally firms that are not subject to loan repricing or borrow at a fixed rate may have a muted effect of the changes in monetary policy causing small firms that are less active credit market participants to be not directly affected to changes in monetary policy through the traditional monetary policy transmission effect via the asset price/interest rate mechanism. Consequently a given policy change for example; reduction in interest rate may not immediately affect spending in a manner predicted by the investment or the credit channel view. Moreover rate cuts might be followed by reduction in investment spending rather than an increase as predicted by the conventional theory if the policy action is interpreted as a signal of a weakening economy. The findings from this has some important implications, firstly the size of the firm may be in effect manifesting the level of financial or credit dependence and ultimately the effect on credit risk resulting from favourable policy announcement may be coming from the improvement or expectation of improvement in credit environment. Moreover, the recent financial crisis mostly affected financial sector and large firms hence the announcement leading to favourable credit environment by reduction in interest rate and increasing money supply may have met the desired goal of easing environment for the most distressed firms in the economy.

The findings from this study are mainly in agreement with previous related literature in this field. Following the IR announcements the aggregate level CDS returns shows a significant decrease across the three event windows for the US sample. This result is consistent with those of Aït-Sahalia *et al.*, (2012), who also find a significant decrease in Libor-OIS spreads. The reduction in aggregate CDS returns could be reflecting market expectation that lowering of interest rate would increase liquidity in the financial system. Moreover, as indicated earlier the decrease in interest rate could also be interpreted as a signal of increase in access to funding (Eickmeier and Hofmann, 2013), lowering of cost of external borrowing thereby reducing firms' risk premium (Laeven and Tong, 2012) ultimately leading to decrease in credit risk (Dunbar and Amin, 2012). However, the increase in aggregate level CDS returns for the UK sample following interest rate cut announcement does not seem to follow the norm. This could be attributed to the trailing nature of interest rate cut announcements which mostly mirrored the US policy stance. Previous studies including Andersen, Bollersev, Diebold and Vega, (2007), Bernanke and Kuttner (2005), Chuliá, Martens and van Dijk (2010), Guo (2004), Gurkaynak, Sack and Swanson (2005) Wongswan (2009) among others suggests financial markets do not respond to anticipated monetary policy changes due to a variety of reasons including the surprise element of the announcements, the degree of financial dependence of firms in the economy affected by the policy announcement. As UK policy stance on interest rate cut announcements would have been already anticipated by the market the lack of the surprise element of the announcement may have rendered the effect on aggregate level CDS returns ineffective. Also it would be interesting to further explore the dynamics of the firms and their level of financial dependence to further dwell into the issue of the ineffectiveness of interest rate cut announcements on CDS returns for the UK sample. The increase in aggregate level CDS returns following the QE announcements across both the US and the UK sample highlights the popularity of QE during the recent financial crisis. Among all the policy announcements analysed from the scope of this study, the aggregate level CDS returns is highest following the QE announcement. The finding from this study is consistent with those of Aït-Sahalia *et al.*, (2012) and Greatrex and Rengifo (2010) who also note a reduction in credit risk following monetary policy announcement especially following liquidity support announcements (QE). CDS returns following FP announcement show a small significant increase which is short lived across both the US and UK sample. The finding here is consistent with Aït-Sahalia *et al.*, (2012) which also notes no significant reduction in interbank credit and liquidity risk premia. The effect could be attributed to the uncertain effect of FP announcement and contrast with Klomp (2013) that rationalises the FP measures to be more effective than monetary policy measures as they are more unexpected and ad-hoc. However the results from this study support the Ricardian perspective (Barrow, 1974, 1979) that claims fiscal policy to have no effect on financial markets.

Moreover, the differential effect on aggregate level credit risk following the type of policy announcement and based on the firm specific characteristics support study by Klomp (2013) that notes the differential effect (across firms) of government interventions on the grounds of firm specific heterogeneity. Following the monetary policy announcements the results indicate that less profitable firms, speculative grade and large firms show a higher reduction in credit risk. The higher effect across firms with these characteristics could be attributed to a higher degree of financial dependence. Overall, the differential effect following policy announcements based on sector, quality, size and CDS liquidity supports King (2009) that claims the reaction of financial market on announcement of policy intervention varies across firms due to difference in the exposure of subprime related risk. This study factors in the heterogeneity among firms to draw unbiased and consistent estimates of credit risk effect following the policy announcements.

One of the key assumptions underlying the event study methodology is the hypothesis that CDS spreads and hence returns fully and immediately incorporate all available information i.e. the CDS market is efficient. The variable effect on AR across the two economies following the policy announcement may be indicating the inefficiency in CDS markets during the crisis period which may have curtailed the rapid adjustment of credit risk following the policy announcements. The author believes the findings from this study will provide Central banks and regulators useful insights on the effectiveness of a particular policy initiative on the types of firms, especially during periods of economic distress enabling them to take appropriate policy actions or inactions to control aggregate level credit risk within the economy by using the right tool for the kind of economic problem at hand.

This study can be further extended to include a variety of policy interventions as detailed in Aït -Shalia *et al.*, (2012), specifically to test the effect of financial sector policy announcements on CDS returns for firms in the non-financial sector. Aït -Shalia *et al.*, (2012) also notes a high degree of integration in the global financial system which could cause potential spillover effect of domestic policy announcement more so during periods of financial stress. This study tests the effect of country specific policy announcements on corporate CDS return for US and UK. A cross country spillover effect of macroeconomic policies in developed economies on corporates credit risk of firms in developing economies will provide fascinating insights into the degree of financial integrations within these economies and remains an avenue for further exploration.

CHAPTER 4

APPLICATION OF FAMA AND FRENCH FACTOR MODEL TO CDS MARKET

CHAPTER 4 – APPLICATION OF FAMA AND FRENCH FACTOR MODEL TO CDS MARKET

Abstract

One of the main aims of this paper is to test the external validity of the Fama French (FF) three-factor (3F) and the five-factor (5F) models and its application to the CDS market. To identify if the model works, this study examines if the FF model explains the daily CDS returns for the US firms that has active CDS trading data available in Markit database. This study covers the three sub-periods of analysis namely; pre-crisis, crisis and post-crisis. The main findings support the generalizability of the FF factor models, both the 3F and 5F model, in explaining daily excess portfolio returns. This study finds, the 5F model offers significant improvement over the 3F model especially for portfolios with extreme tilts of size, book-to-market, operating profitability and investment quintiles. Moreover, the improvement provided by the 5F model over the 3F model is mostly evident in the crisis and post-crisis period, while for pre-crisis period the improvement is marginal at its best. This study also accesses the external validity of the default risk hypothesis, by testing whether default risk is priced in the cross-section of CDS returns and whether SMB and HML factors are proxying for default risk in the CDS market. Augmenting the FF models with distance-to-default factor, suggests that it is unlikely that SMB and HML are proxying for default risk. Moreover, augmenting FF models with DTD factor, leads to marginal improvement in model's explanatory power and therefore for reasons of parsimony, this paper suggest the FF 5F model to be a preferred model for explaining daily CDS returns.

Keywords: Asset pricing models, CDS spreads, CDS returns.

JEL Classification: G01, G12, G23

4.1 Introduction

The past few decades has witnessed a substantial body of empirical work that reports pattern in average stock return that are inconsistent with the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965). Fama and French (FF henceforth) in a series of research (1992, 1993, 1995 and 1996) take an admittedly ad-hoc approach to show the pragmatic utility of firm size (ME) and book-to-market value of equity (BE/ME) in explaining cross-sectional returns on stocks. These evidences have received a lot of attention in the asset pricing literature and continue to be a hotly debated topic. On one hand, studies including Lakonishok, Shleifer and Vishny (1994), LaPorta (1996), LaPorta, Lakonishok, Shleifer and Vishny (1997), Mun, Vasconcellos and Kish (2000) among others, argue that ME and BE/ME are firm specific variables, as such the risk associated with these variables can be diversified, while others including Kothari, Shanken and Sloan (1995) and MacKinlay (1995) downplays the economic significance of FF factors citing reasons including; sample selection bias, data mining, beta estimation and trading frictions (Simpson and Ramchander, 2008). This divergence in opinion and evidence on the economic argumentation and interpretation of the FF factors is well noted in the asset pricing literature. Apart from this, studies also diverge in their opinion on the kind of risk captured by FF factors; *SMB* and *HML*. Fama and French (1995) suggest that the value premium captures elements of financial distress risk while Vassalou and Xing (2004) point out that, although *HML* contains default-risk information, it also contains important price information unrelated to default risk. Recently, Fama and French (2015) propose two new factors; profitability *(RMW)* and Investment *(CMA)* to further support and strengthen their asset pricing logic. Irrespective of the differences in opinion on the kind of risk captured by FF factors, there are compelling evidence on the importance and value relevance of FF factors in explaining cross-sectional return on stocks. This study queries if the FF model, that has received so much attention in explaining cross section returns on stocks, can be generalised to other capital market, specifically the Credit Default Swaps (CDS) market.

The past decade has witnessed a steady growth in the market for CDS which provides a new information set on corporate credit risk. The increasingly popular CDS is considered to provide an alternative, more reliable, cross-sectional and time-series indicator of corporate credit risk and the literature on credit risk modelling validates CDS spreads to be a better proxy for credit risk compared to other measures like bond yield spreads. Consequently, a wide range of studies have employed CDS spreads as a pure measure of corporate credit risk. These coupled with the existence of large amount of CDS spread data; have yielded a number of studies in the credit risk domain. However, CDS spreads are at-market spreads for newly issued default swap contracts with constant maturity and no time series data on actual transaction price for a specific CDS contract is available. As such, changes in CDS spreads do not represent the return dynamics for the insuring party in a CDS contract. Recently, Berndt and Obreja (2010) provide a unique way of converting CDS spreads into implied returns, which gives the flexibility to estimate daily CDS returns based on changes in daily CDS spreads. These returns are driven by underlying firm's credit risk dynamics and present a pristine source of firm credit risk evolution over time.

Unlike equity returns which are driven by changes in stock price, CDS return is driven by changes in the value of the risky and risk free bonds within Brendt and Obreja (2010) estimation framework. As such, CDS returns could be classified as return driven by changes in the perceived risk dynamics of the underlying firm. Consequently, if the perceived risk of the underlying firm changes, CDS spreads and so returns would adjust to reflect the new risk structure. The availability of large dataset that captures firm level daily CDS spreads and the ease of estimating CDS returns on a daily basis provide a unique opportunity for testing the generalizability of the FF asset pricing model. We expect the FF factors, estimated for the CDS market to be able to explain the cross section of CDS returns just like FF model is able to explain for the equity returns.

One of the main aims of this paper is to test the external validity of the FF three-factor (3F) and the five-factor (5F) models and its application to the CDS market. To the best of the author's knowledge, no other paper has attempted to test the application of FF factor models to explain CDS return dynamics. This study will provide useful insights on the generalizability of the FF models with an attempt to identify whether the model 'works' for the CDS market. To identify if the model works, this study examines if the FF model explains the daily CDS returns for the US firms that has active CDS trading data available in Markit database. Further to investigation of asset pricing application on the CDS market, this study also accesses the external validity of the default risk hypothesis. This study tests whether default risk is priced in the cross-section of CDS returns and whether the *SMB* and *HML* factors are proxying for default risk in the CDS market. Past studies have widely debated on the kind of risk captured by the *SMB* and *HML* factors. *SMB* and *HML* have been associated to capture firm distress risk (Fama and French, 1996), investor bias in earning growth extrapolation (Lakonishok, Shleifer and Vishny, 1994), future GDP growth (Liew and Vassalou, 2000), leverage effect (Ferguson and Schokley, 2003), market risk (Chung, Johnson and Schill, 2006), investors' overreaction (Haugen, 1995) among others. Collectively the literature on asset pricing model signals a lack of clarity on the economic significance of these factors. The underlying theme of majority of these studies reflects that *SMB* and *HML* factors capture some element of (if not exactly) the default risk. Moreover, previous studies that have explored default risk and return relationship within the Fama French model report findings that are inconsistent with the risk based explanation of default. Past studies have attributed default risk as a function of several firm specific characteristics including firm size and firm value. Specifically large firm tend to have more assets to meet any unexpected financial shocks compared to small firms and hence would be better immune to default related risk. This lower risk implies a lower expected return for large firms. Similarly low book-to-market value may be signalling over-priced firms where the market expects a lower return and so intuitively implies a lower default risk for such firm. Consequently under-priced firms would be subject to higher expected return derived from higher default risk. Within the Fama French asset pricing model, the *SMB* factor captures the size premium small firms receive over large firms while *HML* factor captures the return premium high book-to-market firm receive over low book-to-market firms. The interrelationship between the default risk and the expected CDS return dynamics of firms makes the relationship between a firm default risk and *SMB* and *HML* factors interesting to explore. Collectively, the lack of clarity on the type of risk captured by *SMB* and *HML* factors along with the availability of CDS returns where spreads are driven primarily by changes in underlying firms' credit quality provides an interesting avenue to explore the relevance of *SMB* and *HML* factors. This study will evaluate the relevance of *SMB* and *HML* factors using the CDS returns, and aim to provide clarification on whether *SMB* and *HML* actually captures the default risk. This is done by adding a pure measure of credit risk to check if it substantially alters the explanatory power of *SMB* and *HML* factors. This study tests if the augmented version of the FF model does a better job in explaining daily CDS returns which will help in concluding the preferred model for asset pricing test for the CDS market.

The main finding of this study supports the generalizability of the FF factor models, both the 3F and 5F model, in explaining daily excess portfolio returns. This study finds, the 5F model offers significant improvement over the 3F model especially for portfolios with extreme tilts of size, book-to-market, operating profitability and investment quintiles.

Moreover, the improvement provided by the 5F model over the 3F model is mostly evident in the crisis and post-crisis period, while for pre-crisis period the improvement is marginal at its best. Augmenting the FF models with distance-to-default factor, suggests that it is unlikely that *SMB* and *HML* are proxying for default risk. Moreover, augmenting FF models with *DTD* factor, leads to marginal improvement in model's explanatory power and therefore for reasons of parsimony, this paper suggest the FF 5F model to be a preferred model for explaining daily CDS returns.

The remainder of this paper is as follows. Section 4.2 provides a brief literature review of the asset pricing models. Section 4.3 details the estimation process which specifies the CDS return estimation, calculation of FF factors and FF 3F and 5F model estimation process. Section 4.4 details the empirical results and compares the 3F model to 5F model results. This study also augments both the 3F and 5F model using distance-to-default measure and compares the improvement in model explanatory power. Section 4.5 concludes with discussion of the main results and highlights scope for further research.

4.2 Literature Review

Sharpe (1964) and Lintner (1965) pioneered the literature on capital asset pricing models and their CAPM was considered the most favoured until the late 1970 and early 1980's. Mis-specification of the CAPM; specifically the positive connection between stock returns and earning to price ratio (Basu, 1977), higher risk adjusted returns for small firms compared to large firms (Banz, 1981), positive connection between debt to equity and stock returns even after controlling for systemic risk, firm size and January effect (Bhandari, 1988), positive connection between expected returns and book-to-market and cash flow yields (Chan, Hamao and Lakonishok, 1991) paved the way for Fama and French (1992, 1993) asset pricing model. Fama and French (1993) developed the asset pricing model that explained stock excess returns using market excess returns, and two additional variables namely, firm size and book-to-market ratio.

The FF 3F model creates two mimicking portfolios *SMB* (formed based on market capitalisation as a proxy for firm size) to capture the return premium that small firms receive over large firms and *HML* (formed based on book-to-market ratio) to capture the return premium high book-to-market firm receive over low book-to-market firms. However, as claimed in Gharghori, Chan and Faff (2007) there is a lack of clarity on the type of risk *SMB* and *HML* captures and the economic significance of these factors has been fiercely debated in academic literature. Fama and French (1996) themselves claim *SMB* and *HML* as proxies for firm distress. Alves (2013) claims size to be associated with firm profitability whereas the book-to-market ratio to be associated with the financial distress problem. These studies rationalises that small stocks leads to lower earning than larger stocks and consequently to a higher expected return, after controlling for book-to-market. On the other hand, firms with higher book-to-market systematically presents lower earning on book equity, indicating signals of financial distress problem. Lakonishok, Shleifer and Vishny (1994) argues that book-to-market proxies for investor bias in earning growth extrapolation while Daniel and Titman (1997) find *SMB* and *HML* pick up co-movement of stocks with similar characteristics and hence conclude that it is the characteristics and not the co-movement that explains cross sectional returns. Liew and Vassalou (2000) claim that both *SMB* and *HML* contain important information about future GDP growth which is further supported by Vassalou (2003) that suggests these factors proxy for risk associated with future GDP growth. Studies by Rolph (2003) and Ferguson and Schokley (2003) argue that Fama French factors proxy for leverage effects, Chung, Johnson and Schill (2006) argue that *SMB* and *HML* proxy for measures of market risk that are not captured by the CAPM while Berk (1995), Kothari, Shanken, and Sloan (1995), and Ferson, Sarkissian, and Simin (1999) argue that the explanatory power of *SMB* and *HML* are spurious. Further studies by Bondt and Thaler (1987), Lakonishok *et al.*, (1994), and Haugen (1995) hypothesise that book-to-market explanatory ability is a product of investor's overreaction to both good and bad news and rationalises a behavioural explanation whereby, investors extrapolate past performance and become overly pessimistic for value stocks and overly optimistic for growth stocks. Consequently, when the overreaction is eventually corrected, value stocks outperform while growth stocks underperform. Despite the ongoing debate on the type of risk captured by the three-factor model, FF asset-pricing model have achieved increasing applicability to many academic and real-world problems.

The underlying theme of majority of these studies reflects that *SMB* and *HML* factors capture some element of (if not exactly) the default risk. The first study to explore the default risk and return relationship in the Fama and Macbeth (1973) regression framework was undertaken by Dichev (1998). Their study used both the Z-score (Altman, 1968) and the O-score (Ohlson, 1980) as proxies for firm default risk and find a negative relationship between default risk and return after controlling for size and book-to-market value. This negative relationship implies, when default risk is higher the returns are lower and vice versa which is inconsistent with the risk-based explanation of default. Similar study by Griffin and Lemon (2002) investigated the relationship between book-to-market, default risk and returns and find book-to-market effect to be mainly concentrated in high default risk stocks. This is supported by Vassalou and Xing (2004) who examined default risk in the context of the Fama French model and find that default risk is priced in the cross section of equity returns concluding default risk is systematic in nature. Their study also concludes that *SMB* and *HML* contain some element of default related information. However, Gharghori *et al.*, (2007) consider their outcomes to be misleading and suggest the findings to be inconsistent with the risk-based explanation of default. All these studies inspire an interesting line of inquiry; specifically, If *SMB* and *HML* does indeed capture default related information, the CDS market where returns are driven by default risk expectations should be an ideal testing ground for the Fama French asset pricing model.

Recently studies by Novy-Marx (2013) conclude that profitability has roughly the same predictive power as book-to-market in predicting the cross section of average returns thereby contributing economically significant information to the asset pricing framework. A positive (albeit weak) relationship between profitability and average returns was also found by Fama and French (2008). Fama and French (2006) conclude that current earning (as a proxy for future profitability) have explanatory power in the Fama and MacBeth (1973) cross sectional regression framework and Novy-Marx (2013) extends this by claiming gross profitability to have far more explanatory power than current earning. Novy-Marx (2013) extends the risk based pricing argument between book-to-market and returns and claim that firms with productive assets should yield more than firms with unproductive assets. Therefore, productive firms where investors demand high average returns to hold should be priced accordingly to less productive firms where investors demand lower returns. Consequently, sorting portfolios based on profitability should exhibit large variations in returns where more profitable firms earn higher average returns than unprofitable firms. The intuition behind considering profitability is the same as strategies devised based on valuation ratios. Novy-Marx (2013) claims both strategies are designed to acquire productive assets cheaply. Valuation strategies do this by financing the purchase of inexpensive assets by the sale of expensive assets, while profitability strategies achieve the same end by financing the purchase of productive assets through the sale of unproductive assets. Studies by Haugen and

Baker (1996) and Cohen, Gompers and Vuolteenaho (2002) further support that controlling for book-to-market equity average returns are positively related to profitability.

Further Titman, Wei, and Xie (2004), documents a negative relationship between abnormal capital investment and future stock returns. Specifically they find that firms that increase their level of capital expenditure the most tend to achieve lower stock returns for five subsequent years. Similarly, studies by Fairfield, Whisenant, and Yohn (2003), Richardson and Sloan (2003) find a negative relationship between average return and investment concluding firms that invest more have lower average returns. Penman (1991), Lakonishok *et al.*, (1994), Fama and French, (1995) reports book-to-market value to be negatively related to profitability and investment (growth stocks tend to be more profitable and to invest more) and both profitability and investment are known to be persistent. Fama and French (2015) also acknowledges that much of the variation in average returns related to profitability and investment is left unexplained by the 3F model of Fama and French (1993) and suggest adding the profitability and investment factor to the 3F model. This led to the development of 5F model which they claim to be a better asset pricing model compared to the 3F model.

The past few decades have generated a wealth of literature on asset pricing models and majority of these studies broadly revolve around the following three strands. Firstly, studies that support the Fama and French factor model as a better asset pricing model compared to CAPM (Chan, Hamao and Lakonishok, 1991; Fama and French, 1996; Chui and Wei, 1998; Fama and French, 1998; Griffin, 2002; Aksu and Onder, 2003; Faff, 2004; Gaunt, 2004; Cao, Leggio and Schniederjans, 2005; Moerman, 2005; Nartea, Gan and Wu, 2008; Fama and French, 2015 among other). Secondly, studies that reject the Fama and French factor model for traditional CAPM (Daniel and Titman, 1997; Bruner, Eades, Harris, and Higgins, 1998; Graham and Harvey, 2001 among others). Finally, studies that support the FF factor model but suggest an augmented version by adding additional factors to improve the pricing model (Jegadeesh and Titman, 1993; 2001; Carhart, 1997, Pástor and Stambaugh, 2003; Gómez-Biscarri and López-Espinosa, 2008 among others). All these studies have focussed on return dynamics in the equity markets both for developed and developing economies. To the best of the author's knowledge, there is no study that tests the generalizability of the FF factor models to the CDS markets and remains a pristine area of exploration. Estimation of CDS returns and modelling FF factors and portfolios from the CDS returns is elaborated in the following section.

4.3 Estimation Process

The 5 year constant maturity CDS spreads used in the analysis is extracted from Markit dataset. Markit collates an extensive record of single name CDS spreads on a daily frequency. This study extracts 652,729 daily CDS spreads belonging to 968 US corporates from the period 1st January 2005 till 30th June 2014. The reported CDS spreads are at-market spreads for newly issued default swap contracts with constant maturity and no time series data on actual transaction price for a specific CDS contract is available. As such, spreads do not represent the actual transaction price for the specific CDS contract and using it directly into calculating return will result in an incorrect estimation of the underlying firm's credit dynamics and so requires computation of CDS returns. To convert CDS spreads into daily returns, this study follows the procedure detailed in Berndt and Obreja (2010). The estimation process and assumptions are as below and is similar to Section 3.3.1,

4.3.1 CDS return estimation

Consider a 100% leveraged portfolio, made up of long position of T-years defaultable bond, issued by a firm i, trading at par value and short position in a T-years par value riskless bond. Berndt and Obreja (2010) argues that this portfolio will generate cash-flows that are similar to those from selling credit protection on firm i, via a T-years CDS contract with a nominal value at par[51]. The initial value of both the CDS contract and the long-short portfolio position is zero. Over some time interval the change in the value of the CDS contract to the investor ΔV_{CDS} will be equal to the change in the value of the long-short bond position, i.e.

$$\Delta V_{CDS} = \Delta P_D - \Delta P_{RF} \tag{4.1}$$

Where, ΔP_D and ΔP_{RF} denotes the changes in the value of the risky and risk-free bond. On dividing each side of the Eqn. (4.1) by the par value, the CDS implied excess return on defaultable debt, r_D^e could be represented as,

$$r_D^e = \Delta V_{CDS} \tag{4.2}$$

[51] This assumption ignores the possibility that the fixed rate Treasury bond may not be selling at par value in an event of default.

The above equation indicates that the rate of return on the defaultable bond is equal to the rate of return on the riskless bond plus the change in value of the CDS contract divided by par. Over a short interval, the change in the value of the CDS contract to the investor is equal to minus the change in the CDS rate, i.e. - ΔCDS multiplied by the value of a defaultable T-year annuity, A (T)

$$\Delta V_{CDS} = -\Delta CDS * A(T) \tag{4.3}$$

Where,

$$A(T) = \frac{1}{4}\sum_{j=1}^{4T} \delta\left(\frac{j}{4}\right) q\left(\frac{j}{4}\right) \tag{4.4}$$

In the above equation δ (s) denotes the risk free discount rate for s years out, and q (s) denotes the risk neutral survival probability of firm i, over the next s years. The discount factors are interpolated using standard cubic spline algorithm using daily generic government bond yields[52] downloaded from Bloomberg. To obtain estimates for $q(s)$, this study assumes a constant risk neutral default intensity λ for firm (i)[53]. The survival probability simplifies to,

$$q(s,\lambda) = e^{-\lambda s} \tag{4.5}$$

Which allows to express the annuity factor $A(T)$ as a function of λ, where λ can be computed directly from observed CDS rates by solving for equation,

$$CDS\ A(T,\lambda) = L\sum_{j=1}^{4T} \delta\left(\frac{j}{4}\right) [q\left(\frac{j-1}{4},\lambda\right) - q\left(\frac{j}{4};\lambda\right)] \tag{4.6}$$

Where L, represents the risk neutral expected fraction of notional lost in the event of default. We assume a constant L of 60%[54]. The right hand side of the equation represents the value of the protection seller leg at initiation of the default swap contract, whereas $CDS\ A(t)$ equals the value of the protection buyer leg. Equality holds since at-market CDS rates are set so that both of these values agree. Using Eqn. (4.5) to solve for Eqn. (4.6) gives,

52 Generic government bonds yields with maturity ranging from 3m, 6m, 1y, 2y, 3y and 5y are used to interpolate the corresponding risk free discount function

53 This simplifying assumption represents a trade-off between a loss of generality on the one side and a potentially incorrect measurement of λ due to model misspecification error on the other.

54 Our assumption of L is similar to the one used by Berndt and Obreja (2010) and considers a constant recovery rate of 40% across all CDS in our sample

$$\lambda = 4\log(1 + \frac{CDS}{4L}) \tag{4.7}$$

Unlike Berndt and Obreja (2010), who use weekly CDS rates to estimate r_D^e, this study uses daily CDS spreads to estimate daily CDS returns for all firms in US that have CDS spreads data available in Markit dataset. The estimation process considers a constant L of 60%, and estimates daily risk neutral default intensity for each firm i, using Eqn. (4.7). The risk free discount rate for each period (as above) is interpolated using cubic spline algorithm from daily generic government bond yields obtained from Bloomberg. Next, the value of the defaultable 5 year annuity, $A(5, \lambda)$ is estimated using Eqn. (4.6). Finally, the CDS implied excess daily returns is estimated as given in Eqn. (4.3). In all we are able to estimate 612,724 daily CDS returns belonging to 850 unique US corporates.

4.3.2 Fama French Model Estimation

To estimate the FF factors for the CDS markets, CDS data obtained from Markit is matched with the underlying firm to extract accounting and market data from Bloomberg. The portfolio construction process follows the series of steps as detailed below,

Step 1, Constructing Size based portfolios: Portfolios are constructed based on Size. June month end market capitalisation (*MC*) for the year (*t*) is used as proxy for firm size in year (*t*). The sample for each year is split into three groups; bottom 30 percentile value of *MC* categorised as '*Small*', top 30 percentile as '*Big*' and middle 40 percentile as '*Medium*'. *MC* <0 is not used. Fama French (1993) splits firms into '*Small*' and '*Big*' using the median NYSE *MC* value, this study follows the three group percentile splitting approach as detailed in Fama and French website[55]. Moreover, rather than depending on an external breakpoint[56] to split the size categories, this study employs in-sample breakpoints for the ease of categorising size groups that are not plagued by missing observation bias. The portfolios are constructed at the end of each June using the June *MC* values downloaded from Bloomberg and categorised based on year (*t*) in-sample breakpoints.

[55] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[56] Fama French employ NYSE breakpoints to split the firm size categories

Step 2, Constructing Book-to-market portfolios: Portfolios are constructed based on book-to-market (*B/M*), estimated as the June month end book value of equity (*BE*) for year (*t*) over the market capitalisation (*MC*) as of December (*t-1*). The sample for each year (*t*) is split into three groups; bottom 30 percentile value of *B/M* categorised as '*Value*', top 30 percentile as '*Growth*' and middle 40 percentile as '*Neutral*'. Again, this study employs in-sample breakpoints for the ease of categorising *B/M* groups that are not plagued by missing observation bias. The portfolios are constructed at the end of each June using the June market equity values downloaded from Bloomberg and categorised based on year (*t*) in-sample breakpoints.

Step 3, Constructing Profitability portfolios: Portfolios are constructed based on Operating profitability (*OP*) for each June month end for year (*t*), estimated as the annual revenue (*t*) minus the (Cost of goods sold + interest expense + selling general and administrative expense) over the book value of equity for year (*t-1*). The sample for each year (*t*) is split into three groups; bottom 30 percentile value of *OP* categorised as '*Weak*', top 30 percentile as '*Robust*' and middle 40 percentile as '*Neutral*'. The portfolios are constructed at the end of each June using the data downloaded from Bloomberg and categorised based on year (*t*) in-sample breakpoints.

Step 4, Constructing Investment portfolios: Portfolios are constructed based on Investment (*Inv*) for each June month end for year (*t*), estimated as the change in total assets for fiscal year ending in June (*t-2*) and total asset in June (*t-1*) over the total assets in year (*t-2*). The sample for each year (*t*) is split into three groups; bottom 30 percentile value of *Inv* categorised as '*Conservative*', top 30 percentile as '*Aggressive*' and middle 40 percentile as '*Neutral*'. The portfolios are constructed at the end of each June using the data downloaded from Bloomberg and categorised based on year (*t*) in-sample breakpoints.

Step 5, Constructing 6 portfolio formed on Size and Book-to-market: The portfolios constructed at the end of each June are the intersection of the two portfolios formed on Size (*MC*) i.e. '*Small*' and '*Big*' and three portfolios formed on ratio of book equity to market capitalisation (*B/M*) i.e. '*Value*', '*Neutral*' and '*Growth*'. The six portfolios formed are - '*Small Value*', '*Small Neutral*', '*Small Growth*', '*Big Value*', '*Big Neutral*' and '*Big Growth*'.

Step 6, Constructing 6 portfolio formed on Size and Profitability: The portfolios constructed at the end of each June are the intersection of the two portfolios formed on Size (*MC*) i.e. '*Small*' and '*Big*' and three portfolios formed on Operating Profitability (*OP*) i.e. '*Robust*', '*Neutral*' and '*Weak*'. The six portfolios formed are - '*Small Robust*', '*Small Neutral*', '*Small Weak*', '*Big Robust*', '*Big Neutral*' and '*Big Weak*'.

Step 7, Constructing 6 portfolio formed on Size and Investment: The portfolios constructed at the end of each June are the intersection of the two portfolios formed on Size (*MC*) i.e. '*Small*' and '*Big*' and three portfolios formed on Investment (*Inv*) i.e. '*Conservative*', '*Neutral*' and '*Aggressive*'. The six portfolios formed are - '*Small Conservative*', '*Small Neutral*', '*Small Aggressive*', '*Big Conservative*', '*Big Neutral*' and '*Big Aggressive*'.

Step 8, Constructing Fama French 3 factors: The Fama French three-factors are constructed using the six equal weighted portfolios formed on Size and book-to-market value (*B/M*) from Step 5. SMB^3 (Small minus Big) is the average return on the three small CDS portfolio minus the average return on the three big CDS portfolios. Fama and French (1993) claims this difference between return on Small and Big stock portfolio to be largely free of the influence of *B/M*, focussing instead on the different return behaviour of Small and Big stocks.

$$SMB^3 = Avg(Small\ Value, Small\ Neutral, Small\ Growth) - Avg\ (Big\ Value, Big\ Neutral, Big\ Growth) \quad (4.8)$$

HML (High minus Low) is the average return on the two value portfolio minus the average return on the two growth portfolios. Fama and French (1993) claims this difference between return on High and Low *B/M* portfolios to be largely free of the influence of Size factor in returns, focussing instead on the different return behaviour of High and Low *B/M* firms.

$$HML = Avg(Small\ Value, Big\ Value) - Avg\ (Small\ growth, Big\ Growth) \quad (4.9)$$

Step 9, Constructing Fama French 5 factors (2X3 sorts): The Fama French five-factors are constructed using the six equal weighted portfolios formed on Size and book-to-market value (B/M) from Step 5, the six equal weighted portfolios formed on Size and operating profitability (OP) from Step 6 and the six equal weighted portfolio formed on Size and Investment (Inv) from Step 7. SMB^5 (Small minus Big) is the average return on the nine small CDS portfolio minus the average return on the nine big CDS portfolios and is estimated as,

$$SMB^5 = Avg\left(SMB_{(B/M)}, SMB_{(OP)}, SMB_{(INV)}\right) \tag{4.10}$$

Where,

$$SMB_{(B/M)} = Avg(Small\ Value, Small\ Neutral, Small\ Growth) \\ - Avg\ (Big\ Value, Big\ Neutral, Big\ Growth) \tag{4.11}$$

$$SMB_{(OP)} = Avg(Small\ Robust, Small\ Neutral, Small\ Weak) \\ - Avg\ (Big\ Robust, Big\ Neutral, Big\ Weak) \tag{4.12}$$

$$SMB_{(INV)} = Avg(Small\ Conservative, Small\ Neutral, Small\ Aggressive) \\ - Avg\ (Big\ Conservative, Big\ Neutral, Big\ Aggresive) \tag{4.13}$$

HML (High minus Low) is the average return on the two value portfolio minus the average return on the two growth portfolios and is similar to *HML* constructed for the three-factor model as given in Eqn. (4.9);

RMW (Robust minus Weak) is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios,

$$RMW = Avg(Small\ Robust, Big\ Robust) - Avg\ (Small\ Weak, Big\ Weak) \tag{4.14}$$

CMA (Conservative minus Aggressive) is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios,

$$CMA = Avg(Small\ Conservative, Big\ Conservative) \\ - Avg\ (Small\ Aggressive, Big\ Aggressive) \tag{4.15}$$

Step 10, Estimating market excess return: Market return (R_M) is estimated as the equal weighted (average) return for all US firms that have daily CDS return available for the period of analysis. Risk free rate (R_f) is the one month bill rate, estimated on a daily basis. The market risk premium ($R_M - R_f$) is estimated on a daily basis.

Step 11, Estimating 25 *Size-B/M*, 25 *Size-OP* and 25 *Size-Inv* Portfolios: 25 *Size-B/M* portfolios is constructed similar to the six *Size-B/M* portfolios as detailed in Step 5. The *Size* and *B/M* values for each year is sub-divided into five equal quintiles and the intersection of the five *Size* and five *B/M* portfolios produce 25 *Size-B/M* portfolios. Similarly, the 25 *Size-OP* (*Size-Inv*) portfolios are constructed similar to the six *Size-OP* (*Size-Inv*) portfolio as detailed in Step 6 (Step 7) and is formed from the intersection of five *Size* and five *OP* (*Inv*) portfolios. The excess returns on the 25 portfolios from 1st January 2005 till 30th June 2014 is the dependent variables for portfolio returns in the regression model.

The details for portfolio composition are similar to as elaborated in Kenneth Fama website. However, considering the nature of the CDS market and dynamics of CDS return data, this study employs minor adjustments to the FF model construction methodology. These differences are elaborated as follows; firstly contrary to Fama and French who employ a value weighted technique for estimating stock portfolios, this study employs equal weightings for portfolio construction. Fama and French (1993) claims value weighted components of return minimises variance and captures return behaviour in a way that corresponds to realistic investment opportunities. However, since CDS spreads are available on an ad-hoc basis, the daily returns are unavailable for all days and the missing returns data would skew the portfolio return dynamics for firms that have more spreads/returns data available. This study employs equal weighted approach to ensure the data is not plagued by missing values. Secondly, Fama and French estimates $R_M - R_f$ (excess return on the market) using value-weighted return for all firms in CRSP (Centre for research in Security Prices) database, incorporated in the US and listed on the NYSE, AMEX or NASDAQ exchange. This study estimates R_M as the equal weighted (average) return for all US firms that have daily CDS return available for the period of analysis. Employing these two changes means the dataset is subject to survival bias and missing observations bias, with CDS spreads/returns only available for firms that are active and not defaulted. Apart from these two deviations, the estimation procedure used in this study entirely replicates the portfolio construction logic as proposed in Fama and French (1993, 2015).

4.3.3 The three-factor and five-factor Models

The FF 3F model (1993) was designed to capture the relationship between average equity returns and *Size* and the average equity return and *B/M*. Test on the three factor model centres on the time series regression,

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i(SMB_t^3) + h_i(HML_t) + e_{it} \quad (4.16)$$

This study motivates from this same logic and estimate the three factor regression such that, R_{it} is the average CDS returns on portfolio *i* for period *t*, $R_{Ft}$is the risk free return, R_{Mt} is the return on the equal weighted market portfolio, SMB_t^3 is the return on the diversified portfolio of small firms minus the return on the diversified portfolio of big firms. HML_t is the difference between the return on the diversified portfolios of high and low *B/M* firms and e_{it} is the zero mean residual. This study follows the time series regression approach by Jensen Black and Scholes (1972), where daily returns on portfolios of stocks are regressed on the return to the market portfolio of stocks and mimicking portfolios for *Size* and *B/M* equity. Jensen, Black and Scholes (1972) claims that undertaking a cross-sectional regression to portfolios return rather than to underlying individual securities (virtually and entirely) eliminates the measurements error bias.

Studies by Novy-Marx (2013), Titman, Wei and Zie (2004) claims the FF 3F model is an incomplete model for expected return as the three-factors miss the variation in average returns related to profitability and investment. Motivated by these evidences, Fama and French (2015) propose the FF 5F model as below to incorporate the effect of profitability and investment.

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i(SMB_t^5) + h_i(HML_t) + r_i(RMW_t) + c_i(CMA_t) + e_{it} \quad (4.17)$$

In the above equation, RMW_t is the difference between the return on a diversified portfolio of firms with robust and weak profitability, and CMA_t is the difference between the return on a diversified portfolio of low and high investment firms, referred to as conservative and aggressive. Fama and French (2015) claims if the exposure to the five factors (i.e. b_i, s_i, h_i, r_i, c_i) captures all variations in the expected returns, the intercept a_i will be zero for all portfolios.

4.4 Empirical results

4.4.1 The playing field

The empirical tests examine whether FF 3F and FF 5F model explains average return on portfolios formed to produce large spreads in *Size, B/M, OP* and *Inv* respectively. This study examines the *Size, B/M, OP* and *Inv* pattern in average CDS returns. Panel A of Table 4.1 shows the average daily excess returns for 25 equally weighted portfolios from independent sorts of firms into five *Size* groups and five *B/M* groups. Although employing daily data increases the number of data points and should help capture more variations in returns, it does not come without a cost. Specifically, this study acknowledges that the book-to-market factor which is commonly viewed as a proxy for a relative distress factor (or some other similar fundamental characteristic) that evolves slowly over time. As such, high frequency data intuitively will be unlikely to capture such fundamental features in a totally reliable manner. However, this study motivates from Iqbal and Brooks (2007) that claim daily data provides more reliable and informative risk-return relationship compare to the monthly and weekly data for the Fama and French factors. Unlike Fama and French (1993, 2015) this study draws conclusion based on daily CDS returns. The observations are grouped based on three separate period of analysis; Pre-Crisis from 1st January 2005 till 30th June 2007, Crisis period from 1st July 2007 to 30th June 2009 and Post-Crisis period from 1st July 2009 till 30th June 2014. Similar to Kahle and Stulz (2013) other studies propose a modified version of the period of analysis further splitting the crisis period. However, the choice of period used in this study is based on the ease of comparing CDS return dynamics across the major economic conditions in US. The sample splitting approach is based on periods as defined in Breitenfellner and Wagner (2012). It is worth noting that the post-crisis period has a longer time horizon (about 50% of the full sample) compared to the pre-crisis and crisis period. Consequently the full sample will be highly biased towards observations in the post-crisis era. Hence, we refrain from drawing any conclusions based on the full sample and focus on observations within the period context. The start and end date is based on the sample availability and with an intention to keep the findings and observations recent and up to date as of writing this paper.

From Panel A of Table 4.1, the 25 portfolios formed on *Size* and *B/M* produces a wide range of average excess returns, from 0.01 bp to -2.32 bp daily in the pre-crisis, -0.45 bp and -9.16 bp in the crisis period and 3.20 bp and -0.04 bp in the post crisis period. In each *B/M* column of Panel A of Table 4.1, the average return typically falls from small stocks to big stocks – Size effect. Thus the portfolios confirm the Fama French (1992) evidence of negative relationship between size and average returns more so in the post-crisis period. Also unlike observations on Fama French (1992) there is no positive relationship between average return and book-to-market equity for any of the sub-periods. Contrary to expectation, the relationship between average returns and *B/M* – value effect, is stronger among big stocks and shows the reverse effect especially during the crisis period. For the microcap portfolio in the first row, average excess returns decreases across all sub-periods. For the megacap firms, the increase is very marginal from -1.62 to -1.54 in pre-crisis period and 0.44 to 0.54 in the post-crisis period. Contrary to expectations, in the crisis period average return decreases with *B/M*, falling from -1.20 to -2.45 bp.

Panel B of Table 4.1 shows average excess returns for 25 equally weighted portfolios from independent sort of stocks into *Size* and *OP* quintiles. The details of the 5x5 sorts are similar to Panel A, but the second sort is on *OP* rather than *B/M*. The pattern in the average returns for the 25 *Size-OP* portfolios is Table 4.1, are as expected. Holding operating profitability roughly constant, average return typically falls as Size increases mainly for the pre-crisis and post-crisis period. The average returns mostly increases with increase in *OP* and this effect is more evident especially during the crisis period.

From Panel C of Table 4.1, in most size quintiles, the average return on the portfolio in the lowest *Inv* quintile is higher than the return on the portfolio in the highest *Inv* quintile. Portfolios of small stocks have higher average returns than the big stocks in the post-crisis period, while the results are mixed for other sub-periods. Overall, from Table 4.1, it can be concluded that the average daily excess portfolio returns are not perfectly aligned as expected to the book-to-market, operating profitability and investment factors and expose variations in average returns sufficient to provide strong challenges in asset pricing tests. Moreover, the relationship between the portfolio type and average excess return trend fluctuates based on the period of analysis. The average excess returns across the three sets of 25 portfolios are negative in the pre-crisis and crisis period, while it is positive in the post-crisis period.

Table 4.1: Average daily excess returns in basis points for portfolios formed on *Size and B/M, Size and OP, Size and Inv* from 1st January 2005 to 30th June 2014. At the end of each June, stocks are allotted to five *Size* groups (Small to Big), using in-sample break points. Stocks are allotted independently to five *B/M* groups (Low to High). The intersections of the two stocks produce 25 equally weighted *Size-B/M* portfolios. In the sort of June for year *t*, *B* is the book equity at the end of the fiscal year ending in year *t-1* and *M* is the market capitalisation at the end of December of year *t-1*. The *Size-OP* and *Size-Inv* portfolios are formed in the same way, except that the second sort variable is operating profitability or investment. Operating profitability, *OP*, in the sort for June for year *t* is measured using accounting data for the fiscal year ending in *t-1* and is revenue minus the Cost of goods sold, minus interest expense, minus selling general and administrative expense all divided by book value of equity. Investment, *Inv* is the change in total assets from the fiscal year ending in year *t-2* to the fiscal year ending in *t-1*, divided by *t-2* total assets. The table shows the averages of daily CDS returns in excess of one month Treasury bill rate. The observations are grouped based on three separate period of analysis; Pre-Crisis from 1st Jan 2005 till 30th June 2007, Crisis period from 1st July 2007 to 30th June 2009 and Post-Crisis period from 1st July 2009 till 30th June 2014.

Panel A: Size-B/M Portfolios

		Pre-Crisis					Crisis						Post-Crisis					
Mean		B/M Quintiles						B/M Quintiles						B/M Quintiles				
		L	2	3	4	H		L	2	3	4	H		L	2	3	4	H
Size	S	0.01	-1.32	-2.02	-1.93	-1.84	S	-0.45	-2.41	-2.50	-1.37	-5.22	S	3.20	1.54	0.47	0.62	0.78
	2	-2.32	-1.62	-1.52	-1.84	-1.82	2	-2.63	-2.50	-4.50	-1.80	-3.04	2	1.00	0.70	0.81	0.84	0.85
	3	-1.63	-1.55	-1.59	-1.66	-2.06	3	-1.45	-1.91	-0.61	-1.12	-9.16	3	0.13	0.33	0.34	-0.04	0.40
	4	-1.84	-1.68	-1.52	-1.64	-1.30	4	-2.80	-3.69	-2.22	-0.62	-4.45	4	0.22	0.27	0.28	0.39	1.02
	B	-1.62	-1.61	-1.71	-1.71	-1.54	B	-1.20	-2.87	-1.80	-5.26	-2.45	B	0.44	0.21	0.52	0.24	0.54

Panel B: Size-OP Portfolios

		Pre-Crisis					Crisis						Post-Crisis					
Mean		OP Quintiles						OP Quintiles						OP Quintiles				
		L	2	3	4	H		L	2	3	4	H		L	2	3	4	H
Size	S	-1.81	-1.26	-2.84	-0.73	-0.20	S	-4.04	-4.37	-2.97	-0.03	-2.65	S	0.62	0.47	1.15	3.03	2.03
	2	-2.02	-1.63	-1.85	-1.64	-2.10	2	-2.22	-2.47	-3.29	-1.60	-1.10	2	0.38	0.74	1.31	2.37	0.38
	3	-1.84	-1.63	-1.86	-1.64	-1.52	3	-3.21	-0.83	-1.03	-3.93	-1.07	3	0.34	0.36	0.09	0.20	0.06
	4	-1.58	-1.49	-1.63	-1.21	-2.02	4	-3.12	-1.52	-0.61	-5.17	-1.71	4	0.73	0.15	0.12	0.20	0.89
	B	-1.83	-1.67	-1.45	-1.55	-1.66	B	-3.04	-1.97	-2.13	-2.93	-2.01	B	0.49	0.69	0.24	0.29	0.38

Panel C: Size-Inv Portfolios

		Pre-Crisis					Crisis						Post-Crisis					
Mean		Inv Quintiles						Inv Quintiles						Inv Quintiles				
		L	2	3	4	H		L	2	3	4	H		L	2	3	4	H
Size	S	-1.53	-1.93	-2.15	-3.03	-1.05	S	-2.49	-5.17	-3.94	-0.92	-3.14	S	1.81	0.87	1.86	1.02	1.10
	2	-1.98	-1.47	-1.97	-1.79	-1.83	2	-4.09	-2.11	-1.40	-5.61	-1.50	2	0.81	0.78	0.94	0.89	0.49
	3	-1.82	-1.68	-1.43	-1.75	-2.13	3	1.75	-2.75	-1.20	-4.11	-2.11	3	0.42	-0.22	0.39	0.42	0.75
	4	-1.63	-1.87	-1.55	-1.60	-1.52	4	-2.82	-1.21	-2.54	-5.12	-3.99	4	0.30	0.44	0.61	0.08	0.48
	B	-1.58	-1.56	-1.77	-1.53	-1.63	B	-3.58	-2.06	-1.97	-1.04	-2.16	B	0.07	0.18	0.31	0.42	1.03

4.4.2 Fama French five-factor (2x3 sorts) model

The three factor model of Fama and French (1993) is augmented with profitability and investment factor defined like the value factor for that model. The *Size* and *Value* factors use independent sort of stocks into two *Size* groups and three *B/M* groups (i.e. independent 2x3 sorts). The details for portfolio construction are as given earlier. The choice of 2x3 sorts is arbitrary and follows Fama and French (2015). Although, they do present alternative (2x2 and 2x2x2x2) sorts, this study limits the analysis to 2x3 sorts considering the results will not be too dependent on the choice of alternative version of sorts. Moreover, Fama and French (2015) also claim that since multivariate regressions slopes capture the marginal effect, the five factor slope produced by the factors from 2x3 sorts may isolate exposure to value, profitability and investment effects in returns as the factors from the alternative sorts. Nevertheless, it will be interesting to check if the results hold for alternative definitions of sorts and could be an avenue for further exploration.

4.4.3 Summary Statistics for Factor returns

Panel A, of Table 4.2 displays the summary statistics of factor returns for each sub-period of analysis. The average *SMB*[5] returns across the sub-period ranges from -0.34bp in crisis and 0.55bp in the post-crisis period. A similar trend can be noticed across the other factors and high variation and standard deviation can be noted in the crisis and post-crisis period. The 2x3 sorts does not use the middle 40% of the *Size, B/M, OP* and *Inv*, focussing more on the extreme of the four factor variables and is expected to produce large averages than the 2x2 or other sorting alternatives. Each factor from the 2x3 sort controls for *Size* and one other variable (*HML, OP* and *Inv*). As expected the *Rm-Rf* mean is negative during the crisis period denoting the stress in the CDS market. Panel B of Table 4.2 shows the correlation matrix for each set of factors across the three sub-periods and some interesting trends are visible. The value factor is negative correlated to market factor and the investment factor is negative correlated to size factor across the three sub-periods. Profitability factor is negatively correlated to market but this relationship becomes positive and significant in the post-crisis period. Similarly the relationship between value and size factor, size and profitability factor, investment and market factor, profitability and investment factor switches sign based on the period of analysis. Since small stocks tend to have higher market betas than big stocks, *SMB* shows positive and significant correlation with excess market return.

However, during the crisis period this relationship tends to be negative and significant, which could be attributed mostly to the negative excess return during the crisis period. The negative correlation between *HML* and *CMA* for the crisis period supports the assumption, that high *B/M* firms tends to be low investment firms, while this relationship is surprisingly positive and significant in the post-crisis period. The negative and significant correlation between *RMW* and *HML* for the post-crisis period, suggesting less profitable firms tend to have high *B/M* value. However, this relationship fluctuates based on period of analysis and is positive and significant for the pre-crisis period. A positive and significant correlation between SMB^5 and *HML* factor (r=0.53) can be noted in the crisis period which does not hold in the pre-crisis period and switches sign in the post-crisis period. The independent sorts on size and book-to-market value was design to isolate the size effect from book-to-market effect and vice versa indicating this may not have always worked across the three sub-periods. Similarly, a higher and significant correlation between SMB^5 and *RMW* (r=0.53) in the post-crisis period also suggest that the independent sorts on size and profitability may not be clearly distinguishable and hence the component of CDS return each factor aims to explain may be somewhat overlapping.

Table 4.2: Descriptive statistics for daily factor returns in basis points, from 1st January 2005 to 30th June 2014. *Rm-Rf* is the equal weighted returns on the CDS market portfolio of all stocks minus the one-month-Treasury bill rate (adjusted for daily returns). At the end of each June, stocks are assigned to two size groups (30th and 70th percentile) using in-sample breakpoints. Stocks are also assigned independently to three book-to-market equity (*B/M*), Operating profitability (*OP*) and Investment (*Inv*) groups using the 30th and 70th percentile. The *B/M* factor, *HML* uses the equal weighted portfolio formed from the intersection of *Size* and *B/M* sorts (2x3 = six portfolios) and the profitability and investment factors, *RMW* and *CMA* respectively uses six equal weighted portfolios from the intersection of *Size* and *OP* or *Inv* sorts. The observations are grouped based on three separate period of analysis; as defined in Table 4.1. Panel A shows the descriptive statistics for the five factors in basis points. Panel B shows the correlation for each set of factor across each sub-period of analysis. * denotes significance at 5% level.

Panel A	Pre-Crisis							
	N	**Mean**	**Median**	**Min**	**Max**	**Stdev**	**Skew.**	**Kurt.**
Rm-Rf	636	-1.66	-1.28	-44.40	24.24	4.20	-1.81	23.08
SMB[5]	636	0.10	0.50	-44.72	40.15	5.94	-0.59	15.51
HML	636	0.31	0.03	-36.55	53.55	6.05	1.12	16.09
RMW	636	0.47	0.13	-30.30	46.23	6.72	1.20	13.20
CMA	636	0.02	-0.07	-23.06	24.94	5.47	0.09	6.04
	Crisis							
	N	**Mean**	**Median**	**Min**	**Max**	**Stdev**	**Skew.**	**Kurt.**
Rm-Rf	504	-2.78	-1.99	-147.94	95.82	20.41	-0.66	11.24
SMB[5]	504	-0.34	0.10	-126.18	128.33	16.97	-0.54	17.46
HML	504	2.03	1.06	-155.23	132.76	22.56	0.30	13.22
RMW	504	0.99	0.67	-68.30	92.21	14.05	0.47	10.67
CMA	504	-0.99	-0.24	-114.68	118.27	18.08	-0.85	16.10
	Post-Crisis							
	N	**Mean**	**Median**	**Min**	**Max**	**Stdev**	**Skew.**	**Kurt.**
Rm-Rf	1159	0.45	0.91	-110.85	79.85	13.93	-0.77	12.54
SMB[5]	1157	0.55	0.71	-121.30	89.16	17.07	-0.60	10.85
HML	1159	-0.07	0.06	-93.20	114.52	14.47	0.31	13.37
RMW	1159	0.41	0.44	-96.05	173.16	14.10	1.42	26.54
CMA	1159	-0.66	-0.43	-114.01	98.33	14.35	-0.55	14.35

Panel B	Pre-Crisis					Crisis					Post-Crisis				
	Rm-Rf	*SMB*[5]	*HML*	*RMW*	*CMA*	*Rm-Rf*	*SMB*[5]	*HML*	*RMW*	*CMA*	*Rm-Rf*	*SMB*[5]	*HML*	*RMW*	*CMA*
Rm-Rf	1					1					1				
SMB[5]	0.69*	1				-0.41*	1				0.72*	1			
HML	-0.06	0.003	1			-0.79*	0.53*	1			-0.31*	-0.22*	1		
RMW	-0.14*	0.06	0.48*	1		-0.15*	-0.17*	-0.02	1		0.31*	0.53*	-0.22*	1	
CMA	-0.43*	-0.47*	0.02	-0.14*	1	0.32*	-0.25*	-0.31*	0.23*	1	-0.37*	-0.25*	0.11*	-0.49*	1

4.4.4 Regression Details

For insights into model performance, the regression details, specifically the intercepts and the pertinent slopes are examined. Regression intercepts and pertinent slopes from FF 5F model as given in Eqn. (4.17) for the 25 *Size-B/M*, 25 *Size-OP* and 25 *Size-Inv* portfolios are shown. For perspective on the FF 5F model result, the regression intercept for the FF 3F model as given in Eqn. (4.16) is shown along with the significance.

25 Size-B/M portfolios:

Panel A, of Table 4.3 shows intercept for the 3F regressions for the 25 *Size-B/M* portfolios across the three sub-period of analysis. Contrary to observations by Fama and French (2015), the portfolio of smallest extreme growth stock produces positive and significant 3F intercepts in the post-crisis period while the portfolios of large extreme growth stocks produce negative intercepts which are significant in the pre-crisis period. The 5F model does not reduce these issues (Panel B of Table 4.3). Across all *B/M* quintiles, big firms in the pre-crisis period retain their negative and significant intercepts with almost no reduction in the value of the intercept. Overall, the intercepts for the 5F model is comparable to the 3F model and retains their significance. Moreover, the pattern (sign) in the intercepts survives in the 5F model across the sub-periods. The intercepts are mostly positive (wherever significant) for the crisis and post-crisis period and negative and significant for the pre-crisis period across both the 3F and 5F models which implies that for the portfolios in questions, the 3F and 5F model significantly overstates the returns in the pre-crisis period. Significant intercepts across the 3F and 5F models (14 out of 25 portfolios) in the pre-crisis period compared to the crisis (2 out of 25 portfolio) and post-crisis period (3 out of 25 portfolios) indicate the factors do a good job in predicting the variability across the *Size-B/M* portfolio returns especially during the crisis and the post-crisis period. Next, the slopes of the five factors are explored. The market and *SMB* slopes are not shown here following Fama and French (2015), who note these slopes, are similar for different models. Hence, they cannot account for changes in the intercepts observed when additional factors are added. Instead, the focus is on *HML*, *RMW* and the *CMA* slopes to save space. Given the second pass sort variable is *B/M*, the *HML* slope for the *Size-B/M* portfolios show the expected pattern i.e. positive for overvalued (Growth or Low *B/M)* portfolios and negative for undervalued (Value or High *B/M*) portfolios. This effect is consistent across the three sub-period of analysis. Across the *Size* quintiles, the *HML* slope reduces across *Big* to *Small* firms for Low *B/M* portfolios. For the megacap portfolio in the pre-crisis period across the *B/M* quintiles, the strong positive *HML* and negative *RMW* slopes imply that the portfolio contains stocks whose return 'behave like' those of unprofitable firms that are overvalued. Similarly for the smallest *B/M* quintile microcap portfolio, the strong positive *HML* and negative *CMA* slope imply that the portfolio contains stocks whose returns behave like those of overvalued firms that have grown aggressively. The loadings on *HML* are significant for 14/25 in the pre-crisis, for 14/25 in crisis and 17/25 portfolios in the post-crisis period. The loadings on *RMW* are significant for 8/25 in the pre-crisis, for 16/25 in crisis and 17/25 portfolios in the post-crisis period whereas the loading for *CMA* are significant for 8/25 in the pre-crisis, for 13/25 in crisis and 12/25 portfolios in the post-crisis period. Thus, it can be concluded that over the three sub-periods of analysis, the factors become significance predictors of portfolio returns for the 25 *Size-B/M* portfolios in the crisis and the post-crisis periods.

Table 4.3: Regression output for 25 equal weighted *Size-B/M* portfolios starting from 1st January 2005 to 30th June 2014. At the end of June each year, stocks are allotted to five *Size* groups (Small to Big) using in-sample breakpoints. Stocks are allotted independently to five *B/M* groups (Low *B/M* to High *B/M*), again using in-sample breakpoints. The intersection of the two sorts produces 25 *Size-B/M* portfolios. The LHS variables in each set of 25 regressions are daily excess CDS returns on 25 *Size-B/M* portfolios. The RHS variables are the excess market return *(Rm-Rf)*, the Size factor *(SMB)*, the value factor *(HML)*, the profitability factor *(RMW)*, and the investment factor *(CMA)*, constructed using independent 2x3 sorts on *Size* and each of *B/M*, *OP* and *Inv*. Panel A shows 3F intercepts produced by the *Mkt*, SMB^3 and *HML*. Panel B shows 5F intercepts, slopes for *HML*, *RMW* and *CMA* as well as the significance of these coefficients. The observations are grouped based on three separate period of analysis as defined in Table 4.1. The 3F and 5F regression equations are,

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i(SMB_t^3) + h_i(HML_t) + e_{it}$$

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i(SMB_t^5) + h_i(HML_t) + r_i(RMW_t) + c_i(CMA_t) + e_{it}$$

Panel A: 3 factor model $R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i(SMB_t^3) + h_i(HML_t) + e_{it}$

	Pre-Crisis					Crisis					Post-Crisis				
	a					a					a				
B/M→	**L**	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**
S	-0.03	-0.76	-1.03***	-0.37	-0.48	0.25	-0.45	-0.89	0.35	-0.08	0.98**	0.4	-0.67	-0.11	-0.31
2	-0.4	-0.55***	-0.6***	-0.32	-0.74***	-0.86	-0.59	-0.57	0.75	0.33	0.18	0.38	0.51	0.34	0.33
3	-0.28	-0.16	-0.42***	-0.13	-0.8***	0.89	0.12	2.29	1.47**	-3.72	-0.16	0.17	0.06	-0.48**	-0.18
4	-1.03***	-0.9***	-0.13	-0.52***	0.18	0.69	-1.31	0.38	3.26**	-0.75	-0.13	0.06	-0.04	0.13	0.73***
B	-1.22***	-1.02***	-0.41**	-0.75***	-0.86***	-0.03	0.05	0.86	-1	0.41	0.22	0.05	0.28	-0.15	-0.09

Panel B: 5 factor model $R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i(SMB_t^5) + h_i(HML_t) + r_i(RMW_t) + c_i(CMA_t) + e_{it}$

	Pre-Crisis					Crisis					Post-Crisis				
	a					a					a				
B/M→	**L**	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**
S	0.57	-0.7*	-1.51***	0.2	-0.38	0.28	-0.39	-0.91	0.31	0.02	1.07**	0.29	-0.73	0.02	-0.42
2	-0.24	-0.55***	-0.63***	-0.24	-0.63**	-0.76	-0.22	-0.67	0.85	0.4	0.11	0.39	0.49	0.3	0.31
3	-0.34	-0.13	-0.39***	-0.05	-0.81***	0.92	0.16	2.26	1.51**	-4.31	-0.19	0.15	0.04	-0.46**	-0.15
4	-1.02***	-0.91***	-0.03	-0.55***	0.2	0.76	-1.49*	0.48	3.55**	-0.7	-0.13	0.06	-0.05	0.11	0.73***
B	-1.21***	-1.03***	-0.4**	-0.79***	-0.86***	0.01	-0.04	0.81	-1.02	0.47	0.17	0.05	0.26	-0.15	-0.05

	Pre-Crisis					Crisis					Post-Crisis				
	h					h					h				
	L	2	3	4	H	L	2	3	4	H	L	2	3	4	H
S	1.94***	0.16**	0.15***	-0.54***	-0.37***	0.24***	0.56***	-0.01	-0.07	-0.73***	1.39***	0.33***	-0.08	-0.31***	-0.54***
2	0.38***	0.05	0.09***	0.05	-0.05	0.09	0.09*	0.03	0.22***	-0.34***	0.24***	0.08***	0.09***	0.03	-0.19***
3	0.04	0.04	0.1***	0.04	0.05*	0.05	0.06	-0.54***	0.11**	0.3	0.01	0.06***	0.07**	0.04*	-0.03
4	0.05*	0.04	-0.19***	0.07**	-0.12**	-0.02	0.56***	0.13***	-0.58***	-0.22***	0.03	0.05***	-0.02	0.03***	-0.07***
B	0.07***	0.04***	0.01	-0.03	0.03**	0.09***	0.15**	-0.08	-0.06	-0.78***	0.03**	-0.01	0.04***	-0.07***	-0.13***

	Pre-Crisis					Crisis					Post-Crisis				
	r					r					r				
	L	2	3	4	H	L	2	3	4	H	L	2	3	4	H
S	-0.01	0.64***	-0.19***	0.13***	-0.35***	-0.04	0.2***	-0.04	-0.03	-0.03	0.01	-0.21***	0.22***	-0.49***	0.49***
2	-0.1	-0.02	-0.07**	-0.01	-0.01	-0.09	-0.19***	-0.06	0.05	-0.25***	-0.17	-0.1***	0.07	-0.17***	-0.36***
3	-0.05	0.02	-0.06**	-0.01	-0.07***	-0.2***	-0.13**	0.26**	-0.14***	0.9***	-0.06***	-0.02	-0.1**	-0.09***	0.05
4	-0.01	-0.04	0.05*	-0.06*	-0.08*	-0.3***	0.15**	-0.11**	-0.76***	-0.37***	-0.12***	0.04***	-0.03*	-0.04**	0.08***
B	-0.08***	-0.02*	0.05	0.03	-0.02	-0.06***	0.06	0.22***	0.17	0.15**	-0.02	0.02**	-0.02	0.1***	0.22***

	Pre-Crisis					Crisis					Post-Crisis				
	c					c					c				
	L	2	3	4	H	L	2	3	4	H	L	2	3	4	H
S	-0.36***	-0.24***	0.27***	0.2***	-0.4***	0.02	0.19***	-0.21***	-0.18***	-0.07	-0.12**	-0.38***	0.06	0.05	-0.01
2	-0.01	0.01	0.01	0.04	-0.04	0.01	0.41***	-0.24**	0.1*	-0.12***	-0.05	-0.01	-0.02	-0.16***	-0.16***
3	-0.11	-0.06*	-0.01	0.16***	0.06*	-0.11**	-0.02	0.13	-0.03	-0.4*	-0.07***	-0.04*	-0.08*	0.01	0.09***
4	0.01	-0.03	-0.24***	-0.07**	0.01	-0.07	-0.17***	0.11***	0.24**	-0.13*	-0.07***	0.02	-0.04***	-0.05***	0.01
B	0.01	-0.02	0.05	0.04	-0.02	0.01	0.08	0.15***	0.48***	0.33***	-0.1***	-0.01	-0.07***	0.02	0.12***

Note: ***, ** and * denote significance at 1%, 5% and 10% levels

25 Size-OP portfolios:

Panel A, of Table 4.4 shows intercept for the 3F regressions on 25 *Size-OP* portfolios for the three sub-periods of analysis. Similar to the observations from Table 4.3, for *Size-B/M* portfolios, the portfolio of big firms irrespective of the *OP* quintiles produce negative and significant intercepts in the pre-crisis period. This is evident both for the 3F and 5F models, indicating the 5F model does not reduce these issues (Panel B of Table 4.4). The 5F model intercepts show no reduction and are comparable to the 3F model while retaining their significance and pattern (sign). The intercepts are mostly negative (wherever significant) for the pre-crisis period across the 3F and 5F model models which implies that for the portfolios in questions, the 3F and 5F model significantly overstates the returns in the pre-crisis period. Similar to earlier observations, significant intercepts across the 5F models (for 16/25 portfolios) in the pre-crisis period compared to the crisis (for 3/25 portfolio) and post-crisis period (for 4/25 portfolios) indicate the factors do a good job in predicting the variability across the *Size-OP* portfolio returns especially during the crisis and the post-crisis period. Next turning to the slopes of the 5F models, the focus of the interpretation is on *HML*, *RMW* and the *CMA* slopes to save space. Given the second pass sort variable is *OP*, the *RMW* slope for the *Size-OP* portfolios show the expected pattern i.e. negative for less profitable (Low *OP)* portfolios and positive for more profitable (High *OP*) portfolios. This effect is consistent across the three sub-period of analysis. For the megacap portfolio (smallest *OP* quintiles) in the pre-crisis period, the strong positive *HML* and negative *RMW* slopes imply that the portfolio contains stocks whose return 'behave like' those of unprofitable firms that are overvalued consistent to the findings in Table 4.3. However, this relationship does not hold for other sub-periods. For the megacap portfolio (highest *OP* quintiles) in the pre-crisis period, the strong positive *HML* and positive *RMW* slopes imply that the portfolio contains stocks whose return 'behave like' those of profitable firms that are overvalued. This relationship is not consistent and switches sign in the crisis and post-crisis period, *HML* switches sign to negative and significant while *RMW* maintains the positive and significant relationship, indicating the portfolio contains stocks whose return 'behave like' those of profitable firms that are undervalued. For the microcap portfolio (largest *OP* quintiles) across all sub-period, the strong positive *HML*, positive *RMW* and negative *CMA* slopes imply that the portfolio contains stocks whose return 'behave like' those of overvalued and profitable firms that have grown aggressively. The loadings on *HML* are significant for 15/25 in the pre-crisis, for 12/25 in crisis and 12/25 portfolios in the post-crisis period. The loadings on *RMW* are significant for 11/25 in the pre-crisis, for 18/25 in crisis and 16/25 portfolios in the post-crisis period whereas the loading for *CMA* are significant for 8/25 in the pre-crisis, for 12/25 in crisis and 15/25 portfolios in the post-crisis period. Thus this study concludes that over the three sub-periods of analysis, the *RMW* and *CMA* factors become significance predictors of portfolio returns for the 25 *Size-OP* portfolios in the crisis and the post-crisis periods unlike *HML* factors where they are more significant predictors in the pre-crisis period.

Table 4.4: Regression output for 25 equal weighted *Size-OP* portfolios starting from 1st January 2005 to 30th June 2014. At the end of June each year, stocks are allotted to five *Size* groups (Small to Big) using in-sample breakpoints. Stocks are allotted independently to five *OP* groups (Low to High), again using in-sample breakpoints. The intersection of the two sorts produces 25 *Size-OP* portfolios. The LHS variables in each set of 25 regressions are daily excess CDS returns on 25 *Size-OP* portfolios. The RHS variables are the excess market return *(Rm-Rf)*, the *Size* factor *(SMB)*, the value factor *(HML)*, the profitability factor *(RMW)*, and the investment factor *(CMA)*, constructed using independent 2x3 sorts on *Size* and each of *B/M*, *OP* and *Inv*. Panel A shows 3F intercept produced by the *Mkt*, SMB^3 and *HML* and their significance. Panel B shows 5F intercepts, slopes for *HML*, *RMW* and *CMA* as well as the significance of these coefficients. The observations are grouped based on three separate period of analysis as defined in Table 4.1. The 3F and 5F regression equations are,

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i(SMB_t^3) + h_i(HML_t) + e_{it}$$

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i(SMB_t^5) + h_i(HML_t) + r_i(RMW_t) + c_i(CMA_t) + e_{it}$$

Panel A: 3 factor model $R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i(SMB_t^3) + h_i(HML_t) + e_{it}$															
	Pre-Crisis					Crisis					Post-Crisis				
	a					a					a				
OP→	L	2	3	4	H	L	2	3	4	H	L	2	3	4	H
S	0.99*	-0.75	-2.54**	0.87*	-1.09*	-0.22	-1.59	0.91	1.13*	-0.81	-0.03	-0.55	0.83	2.58***	0.81
2	-0.63***	-0.9***	-0.6***	0.01	-0.58	1.24	-0.62	-0.34	1.01*	0.97	-0.24	0.39	1***	1.62***	0.12
3	-0.11	-0.21	-0.95***	-0.42***	-0.08	0.98	1.55*	0.66	-1.3	1.2	-0.08	0.07	-0.21	-0.29	-0.45
4	0.12	-0.74***	-0.53***	-0.33	-0.74**	0.64	1.12*	0.67	-1.18	1.16	0.4**	-0.14	-0.25	-0.09	0.62**
B	-0.93***	-0.77***	-1***	-1.08***	-0.75***	0.28	-0.48	-0.04	-0.42	0.74	0.14	0.38	-0.09	0.04	-0.01

Panel B: 5 factor model $R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i(SMB_t^5) + h_i(HML_t) + r_i(RMW_t) + c_i(CMA_t) + e_{it}$															
	Pre-Crisis					Crisis					Post-Crisis				
	a					a					a				
OP→	L	2	3	4	H	L	2	3	4	H	L	2	3	4	H
S	-0.63	-0.24	-3.88***	1.17**	-0.76**	-0.05	-1.58	1.09	1.12*	-1.01	0.04	-0.34	0.82	2.72***	0.45
2	-0.51**	-0.89***	-0.55***	-0.05	-0.6	1.48**	-0.57	-0.08	1.01	0.81	-0.21	0.37	0.98***	1.65***	0.11
3	-0.02	-0.12	-0.96***	-0.38***	-0.07	1.03	1.61**	0.66	-1.52	1.19	-0.06	0.05	-0.22	-0.25	-0.38
4	0.09	-0.71***	-0.57***	-0.21	-0.53**	0.86	1.35**	0.6	-1.33	1.1	0.37*	-0.13	-0.26	-0.09	0.62**
B	-0.95***	-0.74***	-1.02***	-1.1***	-0.75***	0.49	-0.38	0.04	-0.44	0.57	0.13	0.28	-0.07	0.04	0.01

	Pre-Crisis					Crisis					Post-Crisis				
	h					h					h				
	L	2	3	4	H	L	2	3	4	H	L	2	3	4	H
S	0.3***	-0.45***	-0.07	-0.37***	0.35***	-0.13***	-0.44***	-0.56***	-0.09*	0.2***	-0.07***	-0.35***	-0.14**	-0.49***	-0.02
2	0.07	0.07**	0.11***	0.09*	0.07	-0.01	0.07*	0.24**	-0.07	-0.36***	-0.03	0.02	-0.01	0.04	0.03
3	0.07*	-0.03	0.06**	0.11***	0.05	0.08	0.04	0.04	0.11	-0.15*	0.04**	0.05***	0.02	-0.06*	0.06**
4	0.01	0.05***	0.06**	-0.15***	-0.31***	-0.09	0.1**	-0.01	0.32***	-0.24***	0.05***	0.03***	0.01	0.02	0.02
B	0.11***	-0.06*	0.03*	0.03***	0.05***	-0.19**	-0.03	0.1**	-0.04	-0.21***	-0.03	0.08***	-0.03*	-0.05***	-0.03**

	Pre-Crisis					Crisis					Post-Crisis				
	r					r					r				
	L	2	3	4	H	L	2	3	4	H	L	2	3	4	H
S	-1.37***	-0.4***	-0.23	0.38***	1.46***	-0.41***	-0.38***	0.2	0.18***	0.78***	-0.49***	-0.23***	-0.06	-0.28***	1.16***
2	-0.05	-0.05*	-0.06**	-0.04	0.04	-0.43***	-0.12***	0.02	-0.08	0.19*	-0.34***	-0.02	-0.1***	0.05	-0.03
3	-0.01	-0.03	-0.07***	-0.07***	-0.01	-0.28*	-0.25***	-0.13***	0.37***	0.21**	-0.09***	-0.06**	-0.04*	-0.07	0.04
4	-0.05	-0.02	-0.09***	-0.07	0.18***	-0.78***	-0.53***	-0.07	0.04	0.19**	-0.14***	-0.08***	-0.07***	0.05**	0.15***
B	-0.14***	0.04	-0.01	-0.02	0.03**	-0.79***	-0.23***	-0.08**	0.44***	0.33***	-0.19***	-0.03	-0.01	0.11***	0.12***

	Pre-Crisis					Crisis					Post-Crisis				
	c					c					c				
	L	2	3	4	H	L	2	3	4	H	L	2	3	4	H
S	-0.51***	-0.11	1.07***	0.42***	-0.58***	-0.1**	-0.3***	0.06	-0.02	0.05	-0.04	0.43***	0.01	0.3***	-0.18***
2	0.03	0.04	-0.07*	0.02	-0.02	0.05	0.01	0.28***	-0.07*	-0.25***	-0.07**	-0.04	-0.05	0.08	-0.02
3	0.05	0.22***	0.09***	-0.03	-0.07	-0.16	-0.05	-0.08**	-0.13*	0.11	0.01	-0.06***	-0.05**	0.04	0.14***
4	-0.02	-0.04**	-0.05*	-0.06	-0.38***	-0.18**	0.18***	-0.15***	-0.15**	-0.06	-0.12***	-0.04***	-0.05***	0.03	0.06***
B	0.02	0.07*	-0.02	-0.01	0.03	-0.04	0.08***	0.18***	0.53***	-0.01	-0.12***	-0.22***	0.01	0.04***	0.04**

Note: ***, ** and * denote significance at 1%, 5% and 10% levels

25 Size-Inv portfolios:

Panel A, of Table 4.5 shows intercept for the 3F regressions on 25 *Size-Inv* portfolios for the three sub-periods of analysis. Similar to earlier observations, for *Size-Inv* portfolios, the portfolio of big firms regardless of the *Inv* quintiles produces negative and significant 3F intercepts which are significant in the pre-crisis period. The 5F model does not reduce these issues (Panel B of Table 4.5). Across all *Inv* quintiles, big firms in the pre-crisis period retain their negative and significant intercepts with almost no reduction in the value of the intercept. Overall, the intercepts for the 5F model is comparable to the 3F model and retains their significance. Moreover, the pattern (sign) in the intercepts survives in the 5F model. The intercepts are mostly positive (wherever significant) for the crisis and post-crisis period and negative and significant for the pre-crisis period across both the 3F and 5F models which implies that for the portfolios in questions, the 3F and 5F model significantly overstates the returns in the pre-crisis period similar to our earlier observations. Similar to earlier observations, significant intercepts across the 5F models (for 16/25 portfolios) in the pre-crisis period compared to the crisis (for 2/25 portfolio) and post-crisis period (for 2/25 portfolios) indicate the factors do a good job in predicting the variability across the *Size-Inv* portfolio returns especially during the crisis and the post-crisis period. Next turning to the slopes of the 5F models, the focus is on *HML*, *RMW* and the *CMA* slopes as discussed earlier and to save space. The slopes for *HML* are mostly significant in the pre-crisis period, and are negative for small firms and positive for big firms across *Inv* quintiles. Given the second pass sort variable is *Inv*, the *CMA* slope for the *Size-Inv* portfolios show the expected pattern i.e. positive for Low investment (Low *Inv)* portfolios and negative for high investment (High *Inv*) portfolios. This effect is consistent across the three sub-period of analysis. For the megacap portfolio (smallest *Inv* quintile) in the pre-crisis period, the strong positive *HML*, negative *RMW* and positive *CMA* slopes imply that the portfolio contains stocks whose return 'behave like' those of overvalued and unprofitable firms, that have low investment growth consistent to the findings in Table 4.3. The megacap portfolio (biggest *Inv* quintile) in the pre-crisis period displays a similar relationship. For the other sub-periods, the variables switches sign and become insignificant. The difference across periods could be explained using the *HML*, *RMW* and *CMA* slopes. In crisis period, the strong positive *RMW* and *CMA* slope imply that the megacap portfolio (with lowest *Inv* quintile) contains stocks whose returns 'behave like' those of profitable firms that have low investment growth, while the megacap portfolio (with highest *Inv* quintile) contains stocks whose returns 'behave like' those of unprofitable firms that have grown aggressively. The loadings on *HML* are significant for 15/25 in the pre-crisis, for 10/25 in crisis and 8/25 portfolios in the post-crisis period. The loadings on *RMW* are significant for 10/25 in the pre-crisis, for 20/25 in crisis and 10/25 portfolios in the post-crisis period whereas the loading for *CMA* are significant for 7/25 in the pre-crisis, for 15/25 in crisis and 11/25 portfolios in the post-crisis period. Thus this study conclude that over the three sub-periods of analysis, the *RMW* and *CMA* factors become significance predictors of portfolio returns for the 25 *Size-Inv* portfolios especially in the crisis periods unlike *HML* factors where they are more significant predictors in the pre-crisis period.

Table 4.5: Regression output for 25 equal weighted *Size-Inv* portfolios starting from 1st January 2005 to 30th June 2014. At the end of June each year, stocks are allotted to five *Size* groups (Small to Big) using in-sample breakpoints. Stocks are allotted independently to five *Inv* groups (Low *Inv* to High *Inv*), again using in-sample breakpoints. The intersection of the two sorts produces 25 *Size-Inv* portfolios. The LHS variables in each set of 25 regressions are daily excess CDS returns on 25 *Size-Inv* portfolios. The RHS variables are the excess market return *(Rm-Rf)*, the Size factor *(SMB)*, the value factor *(HML)*, the profitability factor *(RMW)*, and the investment factor *(CMA)*, constructed using independent 2x3 sorts on *Size* and each of *B/M*, *OP* and *Inv*. Panel A shows 3F intercept produced by the *Mkt*, SMB^3 and *HML* and their significance. Panel B shows 5F intercepts, slopes for *HML*, *RMW* and *CMA* as well as the significance of these coefficients. The observations are grouped based on three separate period of analysis as defined in Table 4.1. The 3F and 5F regression equations are,

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i(SMB_t^3) + h_i(HML_t) + e_{it}$$

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i(SMB_t^5) + h_i(HML_t) + r_i(RMW_t) + c_i(CMA_t) + e_{it}$$

Panel A: 3 factor model $R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i(SMB_t^3) + h_i(HML_t) + e_{it}$

	Pre-Crisis					Crisis					Post-Crisis				
	a					a					a				
Inv→	L	2	3	4	H	L	2	3	4	H	L	2	3	4	H
S	-0.01	-0.97***	-1.06	-1.11*	-0.59	-0.63	0.36	-1.14	0.24	0.28	0.27	-0.51	-0.7	0.41	0.2
2	-0.08	-0.56	-0.9***	-0.66***	-0.08	-1.67**	1.21	0.29	-0.91	0.58	0.38	0.4	0.57	0.47	0.05
3	-0.14	-0.4	-0.45	-0.97***	0.14	5.06***	-0.3	0.88**	-1.02	0.46	0.01	-0.51**	0.1	0.03	0.23
4	-0.83***	-1.26***	-0.82***	-0.51***	0.66**	1.39	0.83	1.45	-0.98	-1.71	0.05	0.23	0.3	-0.15	0.04
B	-0.99***	-0.85***	-0.86***	-0.96***	-0.7***	0.04	0.36	-0.51	0.12	0.01	-0.23*	-0.09	0.06	0.07	0.59**

Panel B: 5 factor model $R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i(SMB_t^5) + h_i(HML_t) + r_i(RMW_t) + c_i(CMA_t) + e_{it}$

	Pre-Crisis					Crisis					Post-Crisis				
	a					a					a				
Inv→	L	2	3	4	H	L	2	3	4	H	L	2	3	4	H
S	0.16	-1.11***	-1.03	-1.73***	-0.88**	-0.25	0.25	-1.1	0.19	0.27	0.32	-0.21	-0.65	0.15	-0.13
2	-0.06	-0.62*	-0.95***	-0.52***	-0.12	-1.26*	1.38	0.32	-1.3	0.67	0.43	0.38	0.54	0.42	0.01
3	-0.03	-0.35	-0.5	-0.97***	0.37	4.83***	-0.46	0.96**	-0.74	0.55	0.02	-0.51**	0.1	0.03	0.25
4	-0.86***	-1.24***	-0.8***	-0.57***	0.78***	1.81	0.98*	1.47	-0.89	-2.12*	0.06	0.22	0.28	-0.16	0.05
B	-0.99***	-0.84***	-0.88***	-0.98***	-0.76***	0.12	0.35	-0.52	-0.03	-0.05	-0.21	-0.08	0.06	0.03	0.57**

	Pre-Crisis					Crisis					Post-Crisis				
	h					h					h				
	L	2	3	4	H	L	2	3	4	H	L	2	3	4	H
S	-0.23***	0.04	-0.52***	-0.03	-0.16***	0.38***	-0.74***	-0.04	0.09*	-0.34***	-0.4***	-0.13*	0.26***	-0.04	-0.21***
2	0.06	0.1	0.05	0.07**	0.22***	-0.05	-0.08	-0.09**	0.73***	0.04	-0.01	0.01	0.06*	0.04	-0.14***
3	0.08**	0.07	0.03	0.04**	-0.03	-0.19*	0.1	0.03	-0.12	0.03	0.04*	0.02	0.04	0.06*	0.03
4	0.05**	0.01	0.06**	0.08***	-0.27***	0.09	0.1**	-0.31***	-0.1	0.56***	0.01	0.04***	0.01	0.02	0.01
B	0.05***	-0.02	0.05***	0.07***	0.06***	0.05	-0.26***	-0.01	0.12***	0.06	-0.01	-0.04**	-0.03***	0.02	-0.07***

	Pre-Crisis					Crisis					Post-Crisis				
	r					r					r				
	L	2	3	4	H	L	2	3	4	H	L	2	3	4	H
S	0.14***	-0.2***	-0.23**	-0.72***	-0.15***	0.21**	0.81***	-0.27***	0.14***	-0.27***	-0.12*	0.21***	0.19*	0.02	0.07**
2	-0.05	-0.03	-0.02	-0.01	-0.13***	-0.28***	-0.34***	0.02	0.45*	-0.17***	-0.07*	-0.17***	-0.06	0.02	-0.32***
3	-0.05	-0.05	-0.02	-0.03	-0.06	0.28**	0.26***	-0.16***	-0.26	-0.29***	-0.04	0.02	-0.1***	-0.11***	-0.1***
4	-0.03	-0.01	0.03	-0.09***	-0.02	-0.54***	-0.16***	-0.36***	-0.79***	0.08	-0.03	-0.02	-0.02	0.01	-0.01
B	-0.03**	0.03	0.02	-0.05***	-0.05**	0.38***	0.06*	-0.12**	0.09**	-0.21***	0.04***	0.04**	-0.02	0.08***	0.02

	Pre-Crisis					Crisis					Post-Crisis				
	c					c					c				
	L	2	3	4	H	L	2	3	4	H	L	2	3	4	H
S	1.12***	-0.12*	0.04	0.05	-1.33***	0.76***	-0.02	-0.12**	-0.09***	-0.35***	1.53***	0.84***	0.11	-0.47***	-0.67***
2	0.1*	0.03	-0.01	0.02	-0.1**	0.39***	0.03	-0.01	-0.49**	-0.06	0.08**	-0.07**	-0.03	-0.09**	-0.2***
3	0.12***	0.12**	-0.15	0.03	0.06	0.06	-0.11*	0.03	0.02	-0.07*	0.01	-0.02	-0.03	-0.06	-0.02
4	0.02	-0.03	-0.03	-0.05	-0.25***	0.5***	0.14***	-0.12**	-0.32***	-0.52***	0.01	-0.03	-0.05**	-0.03*	-0.01
B	0.04**	0.04*	-0.03	-0.01	-0.02	0.72***	0.11***	-0.06	-0.14***	-0.18***	0.02	0.01	-0.01	-0.06***	-0.08***

Note: ***, ** and * denote significance at 1%, 5% and 10% levels

4.4.5 FF 5F model improvement over FF 3F model

Overall from the above set of analysis, purely based on the regression intercepts alone, it can be noted that the 5F do not provide a clear consistent improvement on the 3F model in explaining the portfolio returns across the 25 *Size-B/M*, 25 *Size-OP* and 25 *Size-Inv* portfolios. Moreover, the returns across these portfolios vary based on the sub-period of analysis. However, based on the significance of the factors across the sub-periods of analysis, the 5F model's ability to explain portfolio's return dynamics cannot be ignored. This study proceeds to test how well the 5F model performs in comparison to the 3F model and employ Cohen (1988) size effect measure. The model's *Adj.* R^2 value from the 3F regressions is compared to the model's *Adj.* R^2 for the 5F regressions using the formulae,

$$f^2 = \frac{R_{5F}^2 - R_{3F}^2}{1 - R_{5F}^2} \tag{4.18}$$

Where, R_{5F}^2 is the proportion of variance accounted for by the 5F regressors (jointly) and R_{3F}^2 is the proportion of variance accounted for by the 3F regressors (jointly). Thus the numerator reflects the proportion of variance uniquely accounted by the *RMW* and the *CMA* factors over and above that of all other variables.

Panel A of Table 4.6, reports the Cohen's f^2 statistics for the 25 *Size-B/M* portfolios. The effect size of adding *RMW* and *CMA* factors to the 3F model increases the model's *Adj.* R^2 value and this effect is mostly small *(r<0.1)* across all sub-periods of analysis; except for small size firms in the low *B/M* quintiles in the pre-crisis period, where the effect size is medium. A medium effect size *(>0.1 r <0.3)* for the portfolio of *Small* size firms in the post-crisis period can be noted regardless of the *B/M* quantiles. Except for the smallest firm in the lowest *B/M* quintile, the addition of *RMW* and *CMA* factor generally increases the models *Adj.* R^2 value. The 3F model regression explains on an average 39% of the variation in the pre-crisis period, 50% of variation in crisis period and 67% of variation in the post-crisis period. Whereas, the 5F model regression explains on an average 41% of the variation in the pre-crisis period, 52% of variation in crisis period and 67% of variation in the post-crisis period for the 25 *Size-B/M* portfolios. For both the models, the explanatory power increases over the sub-periods of analysis. Overall the 5F model does a good job in explaining the return variability especially for the microcap firms in the pre-crisis and post-crisis period whereas for the crisis period the effect size is mostly small.

Panel B of Table 4.6, reports the Cohen's f^2 statistics for the 25 *Size-OP* portfolios. The effect size of adding *RMW* and *CMA* factors to the 3F model increases the model's *Adj.* R^2 value and this effect is mostly small *(r<0.1)* across most portfolios for each sub-periods of analysis. However, a large effect size *(r>0.3)* for *Small* size firms with extreme tilts of profitability can be noted across the three sub-period of analysis; except for microcap lowest profitability quintiles where the effect is medium. Contrary to observations for the 25 *Size-B/M* portfolios, the 25 *Size-OP* portfolios for the lowest profitability quintile in the crisis period show a medium effect regardless of the *Size* of the portfolio. The proportion of variance accounted for by the 5F is higher (based on medium to large effect size) in the 25 *Size-OP* portfolios compared to the 25 *Size-B/M* portfolios. The 3F model regression explains on an average 33% of the variation in the pre-crisis period, 49% of variation in crisis period and 62% of variation in the post-crisis period. Whereas the 5F model regression explains on an average 37% of the variation in the pre-crisis period, 52% of variation in crisis period and 64% of variation in the post-crisis period for the 25 *Size-OP* portfolios. Similar to observations for 25 *Size-B/M* portfolios, both the 3F and 5F model explanatory power increases over the sub-periods of analysis.

Panel C of Table 4.6, reports the Cohen's f^2 statistics for the 25 *Size-Inv* portfolios. The effect size of adding *RMW* and *CMA* factors to the 3F model increases the model's *Adj.* R^2 value and this effect is mostly small *(r<0.1)*. Similar to observations drawn from the 25 *Size-OP* portfolios, a large effect size *(r>0.3)* for *Small* size firms with extreme tilts of Investment can be observed across the three sub-period of analysis; except for the crisis period where the effect is medium. In line with the observations from 25 *Size-OP* portfolios, the extreme tilts in the investments quintile in the crisis period show a medium effect regardless of the *Size* of the portfolio. The proportion of variance accounted for by the 5F is higher (based on medium to large effect size) in the 25 *Size-Inv* portfolios compared to the 25 *Size-B/M* portfolios and is in agreements with the observations drawn based on the 25 *Size-OP* portfolios. The 3F model regression explains on an average 36% of the variation in the pre-crisis period, 49% of variation in crisis period and 63% of variation in the post-crisis period. Whereas the 5F model regression explains on an average 39% of the variation in the pre-crisis period, 53% of variation in crisis period and 65% of variation in the post-crisis period for the 25 *Size-Inv* portfolios. Similar to observations for 25 *Size-B/M* and 25 *Size-OP* portfolios, both the 3F and 5F models explanatory power increases over the sub-periods of analysis.

Taken as a whole, the findings indicate that the 5F model offers significant improvement over the 3F model, especially for portfolios with extreme tilts on *Size, B/M, OP* and *Inv*. These improvements are mostly evident in the crisis and post-crisis period. For the pre-crisis period, the improvement provided by the 5F model over the 3F model is marginal at the best.

Table 4.6: Cohen's f^2 statistics comparing the *Adj.* R^2 values for the 3F model and the 5F model for each of the 25 equally weighted portfolios formed of *Size-B/M* in Panel A, *Size-OP* in Panel B and *Size-Inv* in Panel C. The analysis covers the periods starting from 1st January 2005 to 30th June 2014. The observations are grouped based on three separate period of analysis as defined in Table 4.1. The $f^2<0.1$ indicate small effect, $0.1< f^2 < 0.3$ indicate medium effect while $f^2 > 0.3$ indicate large effect. The Cohen's f^2 statistics is obtained from the *Adj.* R^2 for the 3F model compared to the *Adj.* R^2 for 5F models using the formulae,

$$f^2 = \frac{R_{5F}^2 - R_{3F}^2}{1 - R_{5F}^2}$$

Panel A - Size-B/M portfolios

	Pre-Crisis					Crisis					Post-Crisis				
B/M→	**L**	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**
S	-0.16	0.28	0.20	-0.06	0.02	-0.01	0.05	0.02	0.01	-0.01	-0.17	0.04	0.07	0.14	0.14
2	-0.01	0.00	0.01	0.01	-0.01	0.00	0.36	0.01	0.02	0.02	0.01	0.02	0.00	0.02	0.06
3	0.00	0.01	0.00	0.01	0.02	0.03	0.01	0.01	0.02	0.02	0.01	0.00	0.00	0.02	0.01
4	-0.01	0.00	0.13	0.01	0.00	0.07	0.02	0.02	0.08	0.06	0.02	0.00	0.01	0.01	0.01
B	0.06	0.01	0.00	-0.01	0.01	0.00	-0.01	0.04	0.05	0.04	0.04	-0.02	0.01	0.05	0.08

Panel B - Size-OP portfolios

	Pre-Crisis					Crisis					Post-Crisis				
OP→	**L**	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**
S	0.81	-0.05	0.26	0.08	1.51	0.15	0.05	0.02	0.03	0.37	0.30	0.09	0.01	0.07	1.81
2	-0.01	0.01	0.02	0.00	0.00	0.10	0.01	0.03	-0.03	0.01	0.09	0.00	0.01	0.00	0.00
3	0.00	0.01	0.04	0.03	0.00	0.01	0.03	0.05	0.03	0.02	0.03	0.00	0.00	0.01	0.02
4	0.00	0.01	0.03	-0.01	0.16	0.16	0.31	0.02	0.01	0.01	0.07	0.04	0.02	0.01	0.00
B	0.06	0.01	0.00	0.00	0.00	0.25	0.10	0.01	0.17	0.18	0.04	0.07	0.03	0.07	0.08

Panel C - Size-Inv portfolios

	Pre-Crisis					Crisis					Post-Crisis				
Inv→	**L**	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**
S	0.92	0.03	0.03	0.14	0.68	0.25	0.10	0.01	0.02	0.19	0.82	0.25	0.00	0.13	0.66
2	0.01	0.00	0.00	-0.01	0.02	0.26	0.01	0.00	0.01	0.02	0.01	0.02	0.01	0.01	0.03
3	0.03	0.01	0.00	0.01	0.00	0.02	0.02	0.04	0.00	0.09	0.00	0.00	0.00	0.01	0.02
4	0.00	0.00	0.00	0.03	0.03	0.13	0.05	0.07	0.15	0.15	0.00	-0.01	-0.01	0.00	0.02
B	0.02	0.01	0.00	0.02	0.00	0.30	-0.02	0.02	0.07	0.20	0.05	0.03	0.01	0.04	0.02

4.4.6 Augmenting the FF model with distance-to-default factor

Gharghori *et al.*, (2007) claims that the type of risk *SMB* and *HML* factors capture is not clear, whereas Fama and French (1996) claims these factors capture some element of default risk. This section queries whether the *SMB* and *HML* factors are proxying for default risk in the CDS returns. If truly *SMB* and *HML* are proxies for default risk, their explanatory power would be a result of these factors capturing priced default risk. Consequently, in the presence of a superior proxy for default risk, *SMB* and *HML* should lose their ability to explain CDS returns. Moreover, CDS returns are implied excess return derived from CDS spreads which in turn are considered a pure measure of corporate credit risk. Therefore, the variability in CDS returns theoretically could be explained using a measure of corporate credit risk. Motivated from this, this section estimates the distance-to-default (*DTD*) as a measure of corporate credit risk and query if the addition of *DTD* can improve in explaining the CDS return dynamics. *DTD* are considered a good estimation of corporate credit risk and has been used widely both in academic literature as well as in the industry on a commercial basis (*KMV CreditMonitor*^{TM}). The improvement to the asset pricing model is tested both on the 3F model and the 5F model to check for model parsimony. The estimation of *DTD* measure is as detailed below and is similar to as elaborated in section 2.3.2.

This study employs Merton (1974) model based on the assumption that the firm has a simple capital structure comprising of just debt and equity. Merton interprets the equity of the firm as a call option on the firm's asset and debt as strike price on that call option. The starting point of the Merton model is the assumption that the total value of firm V follows a geometric Brownian motion;

$$dV = \mu_v V dt + \sigma_v dW \tag{4.19}$$

Where μ_V is the expected return on V, σ_V is the volatility of the firm value V and W is the standard Wiener process. X is the book value of debt at time t, with maturity of duration T. The market value of equity E based on the Black-Scholes-Merton (BSM) model is then:

$$E = VN(d_1) - Xe^{-rt}N(d_2) \tag{4.20}$$

Where,

$$d_1 = \left. ln\left(\frac{V}{X}\right) + \left(r + \frac{1}{2}\sigma_v^2\right)T \middle/ \sigma_v^2\sqrt{T} \right. \tag{4.21}$$

$$d_2 = d_1 - \sigma_v\sqrt{T} \tag{4.22}$$

r is risk-free interest rate and N is the cumulative density function of standard normal distribution.

The key to estimating *DTD* is the estimation of V and σ_V in the BSM model. To estimate these two variables, this study follows the approach as detailed in Vassalou and Xing (2004). Assuming a forecasting horizon of 1 year, i.e. ($T = 1$) or 250 trading days in a year, firstly σ_V and μ_V are estimated iteratively using the estimated equity volatility from the past year as a starting value. Using BSM and for each trading day, V is computed using E as the market value of equity for that day. The estimation procedure is repeated for the remaining 250 trading days in that year. The standard deviation of the return in V during that period becomes the new starting value for σ_V for the next iteration. If the difference in σ_V between two successive iterations is less that 10^{-4}, the iteration procedure is discontinued and the values are inserted in the BSM equation to obtain V. The resulting values of V, σ_V and μ_V are then used to calculate the firm-specific *DTD* over a horizon T as,

$$DTD = \frac{\ln\left(\frac{V}{X}\right) + \left(\mu_v - \frac{1}{2}\sigma_v^2\right)T}{\sigma_v^2\sqrt{T}} \tag{4.23}$$

Default occurs when the ratio of the value of assets to debt is less than one, (i.e. its log is negative). The exogenous default boundary is set as book value of short term liabilities plus one half of the long term liability and is similar to the one used by *KMV CreditMonitor*^{TM} and considered to be relatively more realistic. The *DTD* measures the number of standard deviation this ratio needs to deviate from its mean for default to occur. Average annualised equity return *(ret)* is estimated using the last 250 trading day market capitalization value of the equity and volatility *(σret)*, the annualized standard deviation is estimated from prior 250 trading days daily stock price return.

The sample of each year (t) is split into three groups; bottom 30 percentile value of *DTD* categorised as 'Vulnerable', top 30 percentile as 'Stable' and middle 40 percentile as 'Neutral'. Again this study employs in-sample breakpoints for the ease of categorising *DTD* groups that are not plagued by missing observation bias. The portfolios are constructed at the end of each June using the June market equity and Debt values downloaded from Bloomberg and categorised based on year (t) in-sample breakpoints.

Next, 6 portfolios are formed on *Size* and *DTD*. The portfolios constructed at the end of each June are the intersection of the two portfolios formed on *Size* i.e. '*Small*' and '*Big*' and three portfolios formed on *DTD* i.e. '*Vulnerable*', '*Neutral*' and '*Stable*'. The six portfolios formed are - '*Small Vulnerable*', '*Small Neutral*', '*Small Stable*', '*Big Vulnerable*', '*Big Neutral*' and '*Big Stable*'.

The FF 3F model is augmented with the *DTD* factor. The model construction process is similar to as given in Step 7 except for adjustment in the *SMB* variable. SMB^4 (Small minus Big) is the average return on the six small CDS portfolio minus the average return on the six big CDS portfolios and is estimated as,

$$SMB^4 = Avg(SMB_{(B/M)}, SMB_{(DTD)}) \tag{4.24}$$

Where,

$$SMB_{(B/M)} = Avg(Small\,Value, Small\,Neutral, Small\,Growth) \\ - Avg\,(Big\,Value, Big\,Neutral, Big\,Growth) \tag{4.25}$$

$$SMB_{(DTD)} = Avg(Small\,Vulnerable, Small\,Neutral, Small\,Stable) \\ - Avg\,(Big\,Vulnerable, Big\,Neutral, Big\,Stable) \tag{4.26}$$

The fourth factor *DTD;* measured as *VMS* (Vulnerable minus Stable) is the average return on the two '*Vulnerable*' portfolios minus the average return on the two '*Stable*' portfolios. Similar to the other factors estimated, the difference between return on '*Vulnerable*' and '*Stable*' portfolios is expected to be largely free of the influence of Size factor in returns, focussing instead on the different return behaviour of Vulnerable and Stable firms.

$$VMS = Avg(Small\,Vulnerable, Big\,Vulnerable) - Avg\,(Small\,Stable, Big\,Stable) \tag{4.27}$$

The augmented FF 3F model regression equation is given as,

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i(SMB_t^4) + h_i(HML_t) + v_i(VMS_t) + e_{it} \tag{4.28}$$

Next, the FF 5F model is augmented with the *DTD* factor. The model construction process is similar to Step 8 with the adjustment on *SMB* variable. SMB^6 (Small minus Big) is the average return on the twelve small CDS portfolio minus the average return on the twelve big CDS portfolios,

$$SMB^6 = Avg(SMB_{(B/M)}, SMB_{(OP)}, SMB_{(INV)}, SMB_{(DTD)}) \tag{4.29}$$

Where,

$$\begin{aligned} SMB_{(B/M)} = {} & Avg(Small\,Value, Small\,Neutral, Small\,Growth) \\ & - Avg\ (Big\,Value, Big\,Neutral, Big\,Growth) \end{aligned} \tag{4.30}$$

$$\begin{aligned} SMB_{(OP)} = {} & Avg(Small\,Robust, Small\,Neutral, Small\,Weak) \\ & - Avg\ (Big\,Robust, Big\,Neutral, Big\,Weak) \end{aligned} \tag{4.31}$$

$$\begin{aligned} SMB_{(INV)} = {} & Avg(Small\,Conservative, Small\,Neutral, Small\,Aggressive) \\ & - Avg\ (Big\,Conservative, Big\,Neutral, Big\,Aggresive) \end{aligned} \tag{4.32}$$

$$\begin{aligned} SMB_{(DTD)} = {} & Avg(Small\,Vulnerable, Small\,Neutral, Small\,Stable) \\ & - Avg\ (Big\,Vulnerable, Big\,Neutral, Big\,Stable) \end{aligned} \tag{4.33}$$

The *HML, RMW, CMA* and *VMS* factors are as estimated in Eqn. (4.9), Eqn. (4.14), Eqn. (4.15) and Eqn. (4.26) respectively. The augmented FF 5F model regressions is given as,

$$\begin{aligned} R_{it} - R_{Ft} = {} & a_i + b_i(R_{Mt} - R_{Ft}) + s_i(SMB_t^6) + h_i(HML_t) + r_i(RMW_t) + c_i(CMA_t) + v_i(VMS_t) \\ & + e_{it} \end{aligned} \tag{4.34}$$

Next, the 25 *Size-DTD* portfolios are estimated by dividing the *Size* and *DTD* for each year into five equal quintiles. The intersection of the five *Size* and five *DTD* portfolios produce 25 *Size-DTD* portfolios.

Panel A of Table 4.7, shows the average daily excess returns for 25 equally weighted portfolios formed from independent sorts of firms into five *Size* groups and five *DTD* groups. The details of the 5x5 sorts are similar to Table 4.1, except that the second sort is on *DTD*. From Panel A of Table 4.7, the 25 portfolios formed of *Size* and *DTD* produce a wide range of average excess returns, from -2.69 bp to -1.09 bp in the pre-crisis, -10.4 bp to -0.51 bp in the crisis period and -0.7 bp to 1.9 bp in the post-crisis period. Across most *DTD* quintile the average return typically falls from small stocks to big stocks in the pre-crisis and post-crisis period indicating a negative relationship between size and average returns. Across each *Size* group the average returns in the crisis period increases with increase in *DTD*. In the crisis period, a huge negative excess returns can be noticed for small stocks in the lowest *DTD* quintile, for the microcap firms in the smallest *DTD* quintile the excess return goes to -6.22 bp daily. Similar to earlier observations the average daily excess returns are not perfectly aligned as expected, with average excess returns across portfolio types changing based on the period of analysis. The average excess returns across the 25 *Size-DTD* portfolios are negative in the pre-crisis and crisis period, while it is positive in the post-crisis period.

Panel B of Table 4.7, displays the summary statistics for *VMS* factor across the three sub-periods of analysis. The average *VMS* returns ranges from -2.71bp in the crisis period to 0.97 in the post-crisis period. Huge variation is also evident from higher standard deviations across the crisis and post-crisis period. Panel C reports the correlation of *VMS* across the other factors in the augmented 5F model for each sub-period of analysis. *VMS* is positively correlated with the market across the sub-periods while it is positively correlated to *SMB* in the pre-crisis and negatively correlated in the crisis and post-crisis period. This indicates small firms tend to be more credit risky in the pre-crisis period while the opposite i.e. big firms tend to be more vulnerable to credit risk in the crisis and post-crisis period. *HML* is negative correlated to *VMS* in the pre-crisis and crisis period, indicating high *B/M* firms tends to be more vulnerable to credit risk although this relationship does not tend to hold in the post-crisis period. *CMA* is negative correlated to *VMS* in the pre-crisis and post-crisis period while positively correlated in the crisis period indicating, low investment firm tend to be more vulnerable to credit risk in the crisis period while the opposite is true before and after the crisis period. A negative and significant correlations can be observed between *HML* and *VMS* particularly in the crisis period (r=-0.71) and *SMB*[6] and *VMS* in the pre-crisis period (r=0.63). The independent sorts on *B/M* and *DTD* and *Size* and *DTD* were designed to isolate the *B/M* effect from credit risk effect and *Size* effect from credit risk effect indicating they may have not worked in the crisis and pre-crisis period respectively. The strong correlation between *VMS* and *HML* in the crisis period (r=-0.71) may point towards some element of overlap in distress risk captured by these two factors.

Table 4.7: Panel A, reports the average daily excess returns in basis points for portfolios formed on *Size and DTD* from 1st January 2005 to 30th June 2014. At the end of each June, stocks are allotted to five *Size* groups (Small to Big) and five *DTD* groups (Low to High), using in-sample break points. The intersections of the two stocks produce 25 equally weighted *Size-DTD* portfolios. The observations are grouped based on three separate period of analysis as defined in Table 4.1. Panel B reports the descriptive statistics for daily factor returns in basis points. The *VMS* factor uses equal weighted portfolio formed from the intersection of *Size* and *DTD* sorts (2x3 = six portfolios). Panel C shows the correlation for each set of factor with *VMS* across each sub-period of analysis. * denotes significance at 5% level.

Panel A: Size-DTD Portfolios																			
	Pre-Crisis						**Crisis**						**Post-Crisis**						
Mean		**DTD Quintiles**						**DTD Quintiles**						**DTD Quintiles**					
		L	**2**	**3**	**4**	**H**		**L**	**2**	**3**	**4**	**H**		**L**	**2**	**3**	**4**	**H**
Size	**S**	-1.71	-1.47	-1.80	-1.34	-1.79	**S**	-6.12	-2.29	-2.28	-1.67	-0.83	**S**	1.61	1.90	0.49	0.04	1.69
	2	-2.58	-1.55	-1.67	-1.69	-1.70	**2**	-5.02	-3.74	-1.99	-1.62	-2.00	**2**	1.85	1.85	0.78	-0.70	-0.24
	3	-2.69	-1.09	-1.55	-1.64	-2.02	**3**	-5.99	-1.87	-0.99	-1.17	-0.78	**3**	1.50	0.98	0.02	0.36	0.39
	4	-1.54	-1.60	-1.40	-1.58	-1.71	**4**	-2.90	-3.37	-1.66	-0.51	-10.38	**4**	1.80	0.97	0.54	0.14	0.15
	B	-1.89	-1.62	-1.69	-1.64	-1.48	**B**	-3.10	-3.39	-1.29	-1.19	-0.97	**B**	0.41	1.60	0.48	0.42	0.24

Panel B	***Descriptive statistics for VMS***							
VMS	**N**	**Mean**	**Median**	**Min**	**Max**	**Stdev**	**Skew.**	**Kurt.**
Pre-Crisis	636	-0.21	0.07	-49.85	35.24	6.84	-0.49	9.86
Crisis	504	-2.71	-0.78	-220.20	170.01	28.53	-0.82	16.16
Post-Crisis	1159	0.97	0.56	-128.12	340.02	22.29	3.16	53.95

Panel C	***Correlation with VMS across sub-periods***		
VMS	**Pre-Crisis**	**Crisis**	**Post-Crisis**
Rm-Rf	0.76*	0.83*	0.23*
SMB[6]	0.63*	-0.36*	-0.19*
HML	-0.28*	-0.71*	0.05
RMW	-0.16*	0.01	-0.04
CMA	-0.39*	0.49*	-0.46*
VMS	1	1	1

25 Size-DTD portfolios

Panel A, of Table 4.8 shows intercept for the augmented version of 3F model on 25 *Size-DTD* portfolios for the three sub-periods of analysis. Similar to earlier observations, the portfolio of both big and small firms irrespective of the *DTD* quintiles produce negative and significant intercepts in the pre-crisis period. This is evident both for the augmented 3F and 5F models, indicating the augmented 5F model does not reduce these issues (Panel B of Table 3). The augmented 5F model intercepts show no reduction and are comparable to the augmented 3F model while retaining their significance and pattern (sign). The intercepts are mostly positive (wherever significant) for the crisis and post-crisis period and negative and significant for the pre-crisis period across both the 3F and 5F models which implies that for the portfolios in questions, the 3F and 5F model significantly overstates the returns in the pre-crisis period. Significant intercepts across the augmented 5F models (for 18/25 portfolios) in the pre-crisis period compared to the crisis (for 2/25 portfolio) and post-crisis period (for 8/25 portfolios) indicate the factors do a good job in predicting the variability across the *Size-DTD* portfolio returns especially during the crisis period.

Next turning to the slopes of the augmented 5F models, the focus is on *HML, RMW, CMA* and the *VMS* slopes and to save space. Given the second pass sort variable is *DTD*, the *VMS* slope for the *Size-DTD* portfolios show the expected pattern i.e. positive for Vulnerable (Low *DTD*) portfolios and negative for Stable (High *DTD*) portfolios. This effect is consistent across the three sub-period of analysis. For the microcap portfolio (smallest *DTD* quintiles) across the sub-periods, the strong negative *HML, RMW* and *CMA* slopes along with the strong positive *VMS* slopes imply that the portfolio contains stocks whose return 'behave like' those of unprofitable, undervalued firms that have grown aggressively and are vulnerable to credit risk shocks. For the microcap portfolio (highest *DTD* quintiles) in the pre-crisis period, the strong positive *HML* and negative *RMW, CMA* and *VMS* slopes imply that the portfolio contains stocks whose return 'behave like' those of unprofitable, overvalued firms that have grown aggressively but have a stable credit risk profile. This relationship is not consistent and switches in the crisis and post-crisis period, where *HML, RMW and CMA* switches sign and is significant while *VMS* maintains the positive and significant relationship, indicating the portfolio contains stocks whose return 'behave like' those of profitable firms which are undervalued and have low investment growth yet a stable credit risk profile. Compared to the other portfolios analysed earlier, both the augmented version of 3F and 5F models still produce positive and significant intercepts for higher proportion of 25 *Size-DTD* portfolios in the post-crisis period. The loadings on *HML* are significant for 16/25 in the pre-crisis, for 14/25 in crisis and 10/25 portfolios in the post-crisis period. The loadings on *RMW* are significant for 11/25 in the pre-crisis, for 17/25 in crisis and 12/25 portfolios in the post-crisis period whereas the loading for *CMA* are significant for 6/25 in the pre-crisis, for 14/25 in crisis and 9/25 portfolios in the post-crisis period. For the *VMS* factor the loading are significant for 15, 12 and 14 out of 25 portfolios in the pre-crisis, crisis and post-crisis period respectively. Thus the findings conclude that, over the three sub-periods of analysis, the *RMW* and *CMA* factors become significance predictors of portfolio returns for the 25 *Size-DTD* portfolios in the crisis and the post-crisis periods unlike *HML* factors where they are more significant predictors in the pre-crisis period. The *VMS* factor is significant for higher proportion of the 25 *Size-DTD* portfolios and across each sub-period of analysis.

The *VMS* factor is added to both the 3F model and the 5F model to note the change in the *SMB* and *HML* coefficient significance across the 25 *Size-B/M*, 25 *Size-OP*, 25 *Size-Inv* and 25 *Size-DTD* portfolios. Overall, across the 4 sets of 25 portfolios, the coefficient of *SMB* and *HML* retain their significance across each sub-period of analysis. If *SMB* and *HML* were truly capturing default risk in CDS returns then their coefficients should have become insignificant in the presence of *VMS*. This finding indicates that it is unlikely that *SMB* and *HML* are proxying for default risk. Gharghori *et al.*, (2007) drew a similar conclusion using Australian equity returns, the findings in this section supplements their conclusion but in the context of US CDS market and across the three sub-period of analysis.

Table 4.8: Regression output for 25 equal weighted *Size-DTD* portfolios starting from 1st January 2005 to 30th June 2014. At the end of June each year, stocks are allotted to five *Size* groups (Small to Big) using in-sample breakpoints. Stocks are allotted independently to five *DTD* groups (Low to High), again using in-sample breakpoints. The intersection of the two sorts produces 25 *Size-DTD* portfolios. The LHS variables in each set of 25 regressions are daily excess CDS returns on 25 *Size-DTD* portfolios. The RHS variables are the excess market return *(Rm-Rf)*, the *Size* factor *(SMB)*, the value factor *(HML)*, the profitability factor *(RMW)*, the investment factor *(CMA)* and credit risk factor *(VMS)*, constructed using independent 2x3 sorts on *Size* and each of *B/M*, *OP*, *Inv* and *DTD*. Panel A of table shows the augmented 3F intercept produced by the *Mkt*, *SMB*, *HML* and *DTD* and their significance. Panel B shows the augmented 5F intercepts, slopes for *HML*, *RMW*, *CMA* and *DTD* as well

as the significance of these coefficients. The observations are grouped based on three separate period of analysis as defined in Table 4.1. The augmented 3F and 5F model regression equations are,

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i(SMB_t^4) + h_i(HML_t) + v_i(VMS_t) + e_{it}$$

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i(SMB_t^6) + h_i(HML_t) + r_i(RMW_t) + c_i(CMA_t) + v_i(VMS_t) + e_{it}$$

Panel A: 3F + DTD model $R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i(SMB_t^4) + h_i(HML_t) + v_i(VMS_t) + e_{it}$

	Pre-Crisis					Crisis					Post-Crisis				
	a					a					a				
DTD→	L	2	3	4	H	L	2	3	4	H	L	2	3	4	H
S	-0.63***	-2.17***	-0.63**	-0.28	-1.23***	-0.41	-0.46	-0.64	0.26	0.57	0.31	1.25**	0.33	0.59	2.06
2	0.79	0.1	-1.03***	-1.21***	-0.33	2.27	-1.48	0.12	-0.52	0.09	1.48***	1.47***	0.55	-0.73	-0.33
3	0.79*	1.19	-0.91***	-1.19***	-1.48***	0.42	0.92	1.26***	0.22	0.7	1.04**	0.72**	-0.21	0.21	0.3
4	0.5	-0.31**	-0.5***	-0.91***	-0.89***	1.92*	0.76	0.54	1.35	-5.99*	1.37***	0.68**	0.39*	0.05	0.06
B	-0.47	-0.89***	-1.04***	-0.85***	-1.13***	0.55	-0.19	0.61	0.44	-0.14	0.04	1.32***	0.35**	0.26	0.14

Panel B: 5F +DTD model $R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i(SMB_t^6) + h_i(HML_t) + r_i(RMW_t) + c_i(CMA_t) + v_i(VMS_t) + e_{it}$

	Pre-Crisis					Crisis					Post-Crisis				
	a					a					a				
DTD →	L	2	3	4	H	L	2	3	4	H	L	2	3	4	H
S	-0.52**	-2.23***	-0.7***	-0.45	-1.06***	-0.56	-0.44	-0.79	0.6	0.73	0.2	1.28**	0.14	0.24	2.13
2	0.95*	0.09	-1.01***	-1.25***	-0.26	1.94	-0.96	0.31	-0.48	0.13	1.49***	1.46***	0.51	-0.76	-0.35
3	1.01**	1.11	-0.9***	-1.2***	-1.49***	0.32	0.98	1.26***	0.24	0.69	1.01**	0.7**	-0.23	0.21	0.3
4	0.49	-0.33**	-0.52***	-0.93***	-0.92***	1.84*	0.98	0.62	1.76**	-6.01*	1.35***	0.66**	0.39*	0.04	0.04
B	-0.17	-0.91***	-1.05***	-0.89***	-1.13***	0.5	-0.19	0.67	0.42	-0.13	0.03	1.3***	0.35*	0.25	0.13

	Pre-Crisis					Crisis					Post-Crisis				
	h					h					h				
	L	2	3	4	H	L	2	3	4	H	L	2	3	4	H
S	-0.18***	-0.32***	0.18***	-0.06	0.15**	-0.26***	0.26***	-0.16***	0.13	-0.48***	-0.09***	-0.22***	-0.13*	0.21	-0.54***
2	0.13	0.12**	0.01	0.06***	-0.03	0.24*	0.15	-0.04	0.04	-0.29***	-0.12***	-0.03	-0.03	0.01	0.03
3	-0.1	-0.06	0.07***	0.07***	0.01	-0.27*	-0.03	0.07**	0.06	-0.01	-0.05	-0.03	0.01	-0.02	0.01
4	-0.13**	0.15***	0.04	0.08***	0.02	-0.12	0.07	-0.3***	0.2***	2.44***	-0.07*	-0.01	-0.02	0.02	0.01
B	0.19*	0.06***	0.05***	0.05**	0.02*	-0.04	-0.3***	-0.32***	0.05	0.06***	-0.1**	-0.12***	-0.04***	-0.05***	-0.01

	r					r					r				
	L	2	3	4	H	L	2	3	4	H	L	2	3	4	H
S	-0.21***	0.67***	-0.18***	-0.13**	-0.19***	-0.38***	0.12*	0.25***	-0.06	0.39***	0.21***	-0.21***	0.12	1.29***	-0.14
2	0.02	-0.02	-0.01	-0.07***	0.1*	-0.2	-0.17*	-0.23***	-0.01	0.01	-0.09	0.03	0.11**	0.08	0.06**
3	-0.02	-0.02	-0.02	-0.02	-0.04	0.38**	-0.2**	-0.08**	-0.19***	-0.14***	0.11**	0.01	0.02	0.03	0.01
4	-0.01	-0.07**	-0.01	-0.05***	-0.07***	-0.3***	-0.21***	-0.22***	-0.68***	1.17***	0.13***	0.04	-0.04	0.06**	0.05***
B	0.2**	-0.02	-0.02	-0.07***	-0.01	0.43***	-0.15*	-0.1**	-0.08**	-0.05***	0.31***	0.19***	0.07***	0.03	0.01

	c					c					c				
	L	2	3	4	H	L	2	3	4	H	L	2	3	4	H
S	-0.31***	0.18*	0.01	-0.04	-0.19***	-0.31***	0.01	-0.17***	0.37***	0.31***	-0.22***	-0.06	-0.21**	-0.08	2.11***
2	0.11	-0.05	0.03	0.01	-0.14**	-0.43***	0.57***	0.13**	0.04	0.14***	0.1*	0.02	0.05	-0.01	0.02
3	0.31***	-0.17	0.01	-0.01	0.03	-0.01	-0.02	-0.01	-0.06	-0.01	0.11**	-0.05	-0.03	0.05**	0.02
4	-0.44***	-0.03	-0.04	0.01	-0.06*	-0.27***	0.18***	0.04	0.45***	-2.03***	-0.02	-0.04	-0.05**	0.04	-0.01
B	0.38***	0.03*	0.01	-0.01	-0.02	0.19***	-0.05	0.06*	-0.07**	-0.01	0.13**	0.06*	0.04**	0.02	-0.04***

	v					v					v				
	L	2	3	4	H	L	2	3	4	H	L	2	3	4	H
S	0.62***	0.28**	0.02	-0.37***	-1.06***	0.9***	0.09	0.01	-0.45***	-0.79***	0.29***	0.23***	0.22***	-0.15	-0.73***
2	-0.14	0.06	-0.02	0.04	-0.57***	0.86***	0.09	0.04	-0.01	-0.57***	0.23***	0.1***	0.11***	0.01	0.02
3	0.15	-0.18	0.08***	0.04**	-0.05	-0.34**	-0.09	-0.09***	0.08	0.07*	0.13***	0.04**	0.02	0.05***	0.01
4	0.69***	0.16***	0.13***	0.07***	-0.09**	0.04	0.05	-0.18***	-0.34***	-0.47	0.05*	0.01	0.04***	0.01	-0.01
B	1.07***	0.1***	0.03	-0.07***	-0.02	0.75***	0.14**	-0.01	-0.05	-0.05***	0.13***	0.07***	0.02	0.04***	-0.01

Note: ***, ** and * denote significance at 1%, 5% and 10% levels

If *DTD* factor truly helps in explaining higher variation in portfolio returns the *Adj.* R^2 for the augmented model (both 3F and 5F) should be significantly higher than the original 3F and 5F models. Table 4.9 and Table 4.10 reports the effect size of adding the *DTD* factor to the 3F and 5F model respectively. For both the tables, the Cohen's f^2 effect size for 25 *Size-B/M* portfolios is noted in Panel A, 25 *Size-OP* portfolios in Panel B, 25 *Size-Inv* portfolios in Panel C and 25 *Size-DTD* portfolios in Panel D. From Panel A of Table 4.9, the effect of adding *DTD* factor to the 3F model is mostly small expect for the megacap portfolio with highest *B/M* quintile where the effect is medium. Panel A of Table 4.10, also reports the effect size to be mostly small across the three sub-periods. From Panel B for both Table 4.9 and Table 4.10, a medium effect size can be observed for the microcap portfolio in the smallest *OP* quintile but this is only evident in the crisis period. From Panel C for both Table 4.9 and Table 4.10, large to medium effect size can be noted for the megacap portfolio in the smallest *Inv* quintile in the crisis period. Majority of the effect could be noted in the 25 *Size-DTD* portfolios especially those with extreme tilts of Size and Credit risk. From Panel D across both tables, medium effect can be noted in the pre-crisis period across the lowest *DTD* quintile, whereas large effect can be observed for the smallest firm in the largest *DTD* quintile. For the crisis period, across portfolios with extreme tilts of *DTD* quintiles and size groups the effect size of adding *DTD* to both the 3F and 5F model shows a large effect. In the post-crisis period, medium to large effect could be noted for the smallest size firm and across extreme *DTD* quintiles.

Table 4.9 and Table 4.10: Table 4.9 reports the Cohen's f^2 statistics comparing the *Adj.* R^2 values for the 3F model and the augmented version of 3F model adding the *DTD* factor for each of the 25 equally weighted portfolios formed of *Size-B/M* in Panel A, *Size-OP* in Panel B, *Size-Inv* in Panel C and *Size-DTD* in Panel D. Table 4.10 reports the Cohen's f^2 statistics comparing the *Adj.* R^2 values for the 5F model and the augmented version of 5F model adding the *DTD* factor for the same 4 set of 25 portfolios. The analysis covers the periods starting from 1st January 2005 to 30th June 2014. The observations are grouped based on three separate period of analysis as defined in Table 4.1. The f^2<0.1 indicate small effect, $0.1 < f^2 < 0.3$ indicate medium effect while $f^2 > 0.3$ indicate large effect. The Cohen's f^2 statistics in Table 4.9 (Table 4.10) is obtained from the *Adj.* R^2 for the 3F (5F) model compared to the *Adj.* R^2 for 3F+*DTD* (*5F+DTD*) models using the formulae,

$$f_4^2 = \frac{R^2_{3F+DTD} - R^2_{3F}}{1 - R^2_{3F+DTD}} \; , \; f_6^2 = \frac{R^2_{5F+DTD} - R^2_{5F}}{1 - R^2_{5F+DTD}}$$

Table 4.9:

Panel A - 25 Size-B/M portfolios

	Pre-Crisis					Crisis					Post-Crisis				
B/M→	**L**	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**
S	-0.05	0.13	0.10	-0.04	0.00	-0.01	0.18	-0.02	-0.01	0.03	-0.07	0.07	0.18	0.01	0.04
2	0.00	0.01	0.00	0.01	0.00	0.00	0.03	0.01	0.01	0.05	0.00	0.00	0.00	0.02	0.05
3	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02
4	0.03	0.00	0.11	0.02	0.01	0.02	0.05	0.04	0.06	0.01	0.02	0.00	0.01	0.00	0.01
B	0.00	0.00	0.14	0.01	0.00	0.00	-0.07	0.03	0.12	0.13	-0.02	-0.02	0.01	0.03	0.02

Panel B - 25 Size-OP portfolios

	Pre-Crisis					Crisis					Post-Crisis				
OP→	**L**	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**
S	-0.01	0.00	0.10	0.00	0.04	0.11	0.01	0.10	-0.04	0.01	0.00	0.59	0.01	-0.02	0.05
2	0.00	0.00	0.01	0.00	0.00	-0.05	0.02	0.00	-0.02	0.11	0.00	0.00	0.01	-0.01	0.00
3	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.01	-0.01	0.00	0.01	0.00	0.00	0.01	0.01
4	0.01	0.01	0.00	0.00	0.09	0.04	0.08	0.01	0.02	0.04	0.02	0.00	0.00	0.00	-0.02
B	0.00	0.03	0.00	0.01	0.09	-0.02	0.00	-0.02	0.35	0.06	-0.01	0.00	0.01	0.00	0.01

Panel C - 25 Size-Inv portfolios

	Pre-Crisis					Crisis					Post-Crisis				
Inv→	**L**	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**
S	0.02	0.00	0.04	-0.01	0.03	0.00	0.11	-0.01	-0.03	-0.04	0.05	0.07	0.02	0.11	0.03
2	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.05	0.01	0.01	0.00	0.01	0.01	0.00	0.00
3	0.00	0.00	0.00	0.00	-0.01	0.00	-0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00
4	0.01	0.02	0.03	0.01	0.08	0.00	0.05	0.04	0.06	0.09	0.00	0.00	0.01	0.00	0.00
B	0.00	0.02	0.06	0.00	0.01	0.39	0.12	0.01	0.05	-0.03	-0.01	0.01	0.01	-0.01	0.01

Panel D - 25 Size-DTD portfolios

	Pre-Crisis					Crisis					Post-Crisis				
Inv→	**L**	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**
S	-0.05	0.09	0.01	0.04	0.52	0.51	-0.05	0.00	0.01	0.46	0.30	0.04	0.05	0.01	0.26
2	0.00	0.00	0.00	0.00	0.15	0.10	0.04	0.01	0.00	0.39	0.02	0.01	0.01	0.00	0.00
3	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.03	0.00	-0.04	0.02	0.01	0.00	0.00	0.00
4	0.10	0.06	0.02	0.01	0.01	-0.01	0.00	0.06	0.03	0.02	0.00	0.00	0.01	0.00	0.00
B	0.13	0.04	0.00	0.02	0.01	0.79	0.00	0.01	0.02	0.05	0.01	0.01	0.00	0.01	-0.01

Table 4.10:

Panel A - 25 Size-B/M portfolios															
	Pre-Crisis					**Crisis**					**Post-Crisis**				
B/M→	**L**	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**
S	0.09	0.10	0.05	0.01	0.03	0.00	0.11	-0.01	0.00	0.05	0.01	0.04	0.14	0.05	0.03
2	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.01	0.04
3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01
4	0.03	0.00	0.13	0.02	0.01	0.00	0.02	0.04	0.07	0.00	0.01	0.00	0.00	0.00	0.01
B	0.00	0.00	0.12	0.01	0.00	0.01	0.01	0.02	0.10	0.07	0.00	-0.01	0.00	0.02	0.00
Panel B - 25 Size-OP portfolios															
	Pre-Crisis					**Crisis**					**Post-Crisis**				
OP→	**L**	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**
S	-0.05	0.02	0.03	-0.01	-0.01	0.24	0.00	0.09	-0.02	0.00	0.04	0.54	0.00	-0.01	0.00
2	0.00	0.00	0.00	0.00	0.00	-0.03	0.01	0.01	0.01	0.10	0.01	0.00	0.01	0.00	0.00
3	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00
4	0.01	0.01	0.00	0.01	0.11	0.01	0.10	0.01	0.01	0.04	0.00	0.00	0.00	0.00	0.00
B	0.00	0.02	0.00	0.02	0.10	0.04	0.01	0.02	0.23	0.02	0.00	0.00	0.00	0.01	0.00
Panel C - 25 Size-Inv portfolios															
	Pre-Crisis					**Crisis**					**Post-Crisis**				
Inv→	**L**	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**
S	0.01	0.00	0.04	-0.02	0.01	-0.01	0.07	0.01	-0.01	0.09	-0.02	0.00	0.01	0.03	0.06
2	0.00	0.00	0.00	0.00	0.01	0.02	0.00	0.07	0.01	0.01	0.01	0.01	0.01	0.00	0.00
3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
4	0.01	0.02	0.03	0.01	0.10	0.01	0.04	0.01	0.02	0.02	0.00	0.00	0.01	0.00	0.00
B	0.00	0.01	0.06	0.00	0.01	0.28	0.11	0.01	0.02	0.00	-0.02	0.00	0.00	-0.01	0.01
Panel D - 25 Size-DTD portfolios															
	Pre-Crisis					**Crisis**					**Post-Crisis**				
Inv→	**L**	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**
S	0.21	-0.01	0.00	0.03	0.47	0.49	-0.02	0.00	0.03	0.51	0.10	0.03	0.04	0.00	0.07
2	0.00	0.00	0.00	0.00	0.16	0.11	0.00	0.00	0.00	0.38	0.02	0.01	0.02	0.00	0.01
3	0.00	0.00	0.01	0.01	0.00	0.01	0.00	0.02	0.00	-0.02	0.03	0.01	0.00	0.01	0.00
4	0.13	0.06	0.02	0.01	0.01	0.00	0.00	0.04	0.06	0.01	0.01	0.00	0.01	0.00	0.00
B	0.13	0.04	0.00	0.01	0.00	0.52	0.01	0.01	0.01	0.03	0.02	0.01	0.01	0.02	0.00

4.5 Conclusion

One of the main aims of this paper was to test the external validity of the Fama French (3F and 5F) models and its application to the CDS market. This is the first paper to test the application of FF factor models to explain daily CDS returns. As such, this study limits the analysis to test the generalizability of FF model in explaining daily CDS returns for US firms that has active CDS trading data available in Markit. Unlike Fama and French (1993, 2015) who used monthly returns, this study draws observation based on daily CDS returns covering a period from 1st January 2005 till 30th June 2014. This study motivates from Iqbal and Brooks (2007), who claims daily data provides more reliable and informative risk-return relationship compare to monthly and weekly data for the FF factors. The timeline of analysis used in this study is based on the sample availability and with an intention to keep the findings and observations recent and up to date as of writing this paper. The sample is split into three separate period of analysis; pre-crisis, crisis and post-crisis based on the ease of comparing CDS return dynamics across the major economic conditions in US.

Overall, this study finds that the average daily excess portfolio returns are not perfectly aligned as expected to the book-to-market, operating profitability and investment factors and expose variations in average returns sufficient to provide strong challenges in asset pricing tests. Moreover, the relationship between the portfolio type and average excess returns trend changes based on the period of analysis, where average excess returns across the three sets of 25 portfolios (*Size-B/M, Size-OP and Size-Inv*) are negative in the pre-crisis and crisis period, while it is positive in the post-crisis period. Value factor is found to be negatively correlated to market premium and the investment factor to be negatively correlated to size factor across the three sub-periods. However, the relationship between other factors switches sign based on the period of analysis further supporting the choice of splitting the sample into sub-periods and refraining from drawing conclusions based on full sample. From analysing the three sets of portfolios, it can be concluded that over the three sub-periods of analysis, the factors become significance predictors of portfolio returns for the 25 *Size-B/M, Size–OP* and *Size-Inv* portfolios in the crisis and the post-crisis periods. Moreover, significant intercepts across the 3F and 5F models in the pre-crisis period compared to the crisis and post-crisis period indicates, the factors do a good job in predicting the variability of returns especially during the crisis and the post-crisis period. For each set of portfolios, the intercepts are mostly negative (wherever significant) for the pre-crisis period across the 3F and 5F models, which implies that for the portfolios in questions, the 3F and 5F model significantly overstates the returns in the pre-crisis period. Across the three sets of portfolios, it can also be noted that *RMW* and *CMA* factors become significance predictors in the crisis and the post-crisis periods unlike *HML* factors where they are more significant predictors in the pre-crisis period.

Purely on the basis of the regression intercepts alone, 5F model do not provide a clear consistent improvement over the 3F model. However, *RWM* and *CMA* factor significance do signal some value in 5F over 3F model. Both the 3F and 5F models' explanatory power increases over the sub-periods of analysis. Taken as a whole, the findings indicate that the 5F model offer significant improvement over the 3F model, especially for portfolios with extreme tilts on *Size, B/M, OP* and *Inv*. These improvements are mostly evident in the crisis and post-crisis period. For the pre-crisis period, the improvement provided by the 5F model over the 3F model is marginal at the best.

This study also access the external validity of the default risk hypothesis, by testing whether default risk is priced in the cross section of CDS returns and whether the *SMB* and *HML* factors are proxying for default risk in the CDS market. Distance-to-default is estimated as a measure of corporate credit risk and this study queries if the addition of *DTD* factor to the 3F and 5F model improves in explaining CDS return variability. This study also creates 25 portfolios from independent sorts of *Size* and *DTD* to test the model performance across portfolios with extreme tilts in Size and credit risk. A strong correlation can be noted between *VMS* and *HML* factor in the crisis period, pointing towards some level of overlap in distress risk captured by these two factors. Similar to earlier observations, the average daily excess returns for the 25 *Size-DTD* portfolios are not perfectly aligned as expected, with returns across portfolio changing based on the period of analysis. Again, the average excess returns across the 25 *Size-DTD* portfolios are found to be negative in the pre-crisis and crisis period, and positive in the post-crisis period. The loadings on *HML, RMW and CMA* are found to be significant especially for the crisis and post-crisis period and *VMS* factor to be significant for higher proportion of 25 *Size-DTD* portfolios and across each sub-period of analysis. Overall, adding the *VMS* factor across the 4 sets of 25 portfolios, does not lead to loss of significance for *SMB* and *HML* coefficients across each sub-period of analysis. These findings indicate, it is unlikely that *SMB* and *HML* are proxying for default risk.

This study also tests if an augmented version of the Fama French model provide a better explanation of CDS return that the factor model developed by Fama and French (1993, 2015). This study augments both the 3F and 5F models with *DTD* factor and tests the improvement over both the 3F and 5F model to check for model parsimony. The augmented 5F model intercepts show no reduction and are comparable to the augmented 3F model while retaining their significance and sign. Overall, the findings suggest that the 5F model is superior to the 3F model especially for portfolios that have extreme tilts of *Size* and *B/M, OP, Inv* and *DTD.* In addition, augmenting the FF 3F and FF 5F model with a default risk factor, results in at best a marginal improvement to the model's explanatory power. Therefore for reasons of parsimony, this paper concludes Fama and French 5F model as a preferred model for explaining CDS returns.

The author believes this study the first of its kind; will provide useful insights on the generalizability of the Fama French models to the CDS market. This study lends itself to testing for robustness of results under various different specifications. This study is limited in terms of the 2x3 sorts employed which controls for Size and one other variable within the set of 25 portfolios. Fama and French (2015) present alternative specifications of sorts (2x2 and 2x2x2x2) using both the 25 and 32 portfolio sets controlling for all four factors simultaneously. It will be interesting to check if the results hold for alternative definitions of sorts and could be an avenue for further exploration. This study employs daily returns for estimating the models while Fama and French (1993, 2015) use monthly returns. It would be interesting to check if the results hold for monthly return frequency. Similarly the sample and analysis can be extended to non US firms CDS returns to check if the model stands the test across these different specifications. Moreover, Fama and French website collates the factors for the 3F and 5F model estimated for the US equity market. It will be interesting to test if the factor important in stock returns estimation helps us in explaining the CDS returns and vice versa considering financial markets are global and interlinked and could be an avenue for further exploration. The author expects this study to trigger intellectual discussions and further research avenues on the pricing model for CDS market with an aim of improvising on the existing idea and building towards the goal of achieving a preferred model for asset pricing test for the CDS market.

CHAPTER 5

CONCLUSION AND DISCUSSION

CHAPTER 5 – CONCLUSION AND DISCUSSION

This chapter provides an overall summary of the findings and conclusions drawn from each of the earlier chapters. The summary of the main findings are provided at the concluding section of each chapter and this chapter revisits the main research findings and provides discussion of the key results. This chapter also provides a synthesis of the policy implications drawn from the research findings and highlights how each chapter and the overall thesis adds to a better understanding of the CDS market. The findings are grouped based on each chapter and discussed in the following section.

Using 5 year constant maturity quarterly spread data obtained from Bloomberg for corporates across all GICS sectors in US, UK and for 12 EU countries, the collective CDS spread behaviour could be seen to follow an interesting trend. The full sample ranging from Q1 2005 to Q4 2012 is split into sub-periods and observations drawn based on the three major economic conditions before, during and after the global financial crisis of 2007-2008. Across US and UK markets, the median CDS spreads seems to follow a similar trend. The pre-crisis period can be characterised with extremely low median spreads signalling very low credit risk environment for corporates. This period also represents the infancy stage in the development and growth of the CDS market and lower representation by market participants both from the buy and sell-side. The start of the financial crisis triggered by Lehman collapse, witnessed a sudden upswing in median spreads as well as higher variability in spreads across corporates. The median spread for US corporates was in the range of 160bp while for UK it was around 136bp; indicating the stress in the CDS market at the start of the financial crisis. The post-crisis period, starting mid 2009 witnessed a steady decrease in median spreads across both the markets but the effect of the Greek sovereign default drama does seem to have a negative influence in the post-crisis period. The CDS market in the post-crisis period has also come under intense scrutiny and witnessed a myriad of changes introduced by regulators to increase the transparency and reduce counterparty risk in the CDS market. Median spreads in post-crisis period are although comparatively lower than the crisis period, they are still high and nowhere comparable to the pre-crisis levels. This could be attributed both to the increasing involvement of financial market participants, better transparency and faster absorption of price and risk related information resulting for increased liquidity in the CDS market. The counterparty risk in a CDS contract has a major influence in CDS pricing and effort by regulators to introduce standardisation across contracts, encouraging central counterparty clearing and setting restrictions on 'naked' CDS contracts (only in EU) seems to have stabilised the counterparty risk in the post-crisis period. Market level counterparty risk measured using LIBOR-OIS spreads have reverted back closer to pre-crisis levels after the upsurge witnessed in the crisis period across the three markets. The EU corporate CDS spreads also witnessed the upsurge following the credit crisis where the median spread was in the range of 134bp comparable to US and UK. However, as evident during the post-crisis period, the sovereign default episodes and related triggers caused median spreads in EU to increase comparatively higher and reaching its peak of 185bp in 2011 mostly driven by corporate in Portugal, Ireland, Greece and Spain (PIGS). A stark contrast in aggregate country level corporate spreads could also be witnessed with Germany, France, Netherland and Austria being at the lower end of the scale compared to corporates in the so called PIGS economy at the higher end in the post-crisis period. Sector level aggregate CDS spreads across the US, UK and EU samples highlight the strain in the 'Financial' and 'Consumer cyclical' GICS sectors during the crisis and the post-crisis period. It indicates corporates in these sectors were driving the higher credit riskiness in the CDS market. This does not come in as a surprise as financial institutions were making headlines during the crisis and post-crisis period with a series of Government and Central bank policy interventions aimed at stabilising the financial system and its spillover to other sectors in the economy. 'Consumer cyclical' sector are more correlated with the general business environment and consumption so the higher risk associated with corporates in these sectors reflect more of the credit risk arising from fall in consumer demand and spending.

Chapter Two, provides a contribution to the literature on pricing of CDS spreads across a wider sample domain encompassing US, UK and EU corporate CDS for which spread data is available on Bloomberg. This chapter tests the determinants of CDS spread with a focus on pricing across three main periods of analysis namely; pre-crisis, crisis and post-crisis. CDS spreads are modelled using accounting based, market based and macroeconomic variables. Firstly, 10 accounting based ad-hoc measures that proxy for size, profitability, liquidity, trading account activity, sales growth and capital structure are used to model spreads. Although, there is no theoretical rational for the use of these variables in modelling spreads, past studies have found these variables to have crucial information and better proxies for corporate credit risk. Secondly, we estimate the distance to default measure drawing from the Black-Scholes-Merton option pricing theory and use theses inputs to model spreads. Macro-economic variables that proxy for economic condition, market return and GICS sector returns acts as time dummies accounting for time clustering in the dataset. Using fixed effect panel data regression, both the accounting and market based variables are modelled individually as well as collectively in a single combined model. This chapter documents the changing nature of spread predictor variables based on the sub-period analysed. Overall, for accounting variables, the significance and the sign of variables change based on the period of analysis and the sample analysed. Some accounting variables lose their significance at certain sub-periods indicating during certain periods these variables are more closely related to CDS spreads or capturing credit risk more effectively than at other times. The significance of the variables also switches based on the sample analysed, with most variables being significant in the US sample as compared to UK and EU[57]. This is interesting as across the three samples most companies follow the International Financial Reporting Standards (IFRS) or very closely related reporting standards[58] that does not seems to significantly change the measurement of the variables analysed in this study. The market based variables are more significant predictors of spreads across the three samples and the sub-periods analysed with most variables being statistically significant at 1% level across sub-periods analysed. Unlike Das *et al.*, (2009), this study notes market based variables to be more closely aligned to spreads than their accounting counterparts.

Chapter Two, also evaluates each variable set individually as well as in a combined model to ascertain the improvement in CDS pricing across the sub-periods of analysis using a hierarchical fixed effect regression function. This study run the panel data regression using only accounting variables and then using market based variables within the same regression model to note the improvement in model explanatory power by the addition of the new information set. The effect size estimates the magnitude of improvement in model explanatory power by the addition of the new set of variables. The process is repeated by adding market based variables set to accounting variables set and vice versa to ensure the results are not biased based on the order on entering the variables set. This study notes a variables effect across the sub-periods analysed. Specifically, a large effect could be noticed in the post-crisis period for the EU sample, while medium effect in the crisis period for US and UK samples. This points towards significant explanatory power of market based variables over and above accounting variables especially during the crisis and post-crisis period. By reversing the process, i.e. adding accounting variable set to market based variables, suggest accounting variables increases noise in the model with very small

[57] The author acknowledges that this could also be driven by the sample size used across the three markets, with US sample size being much higher than UK and EU samples.
[58] US follows IFRS and US-GAAP, while UK follows IRFS and UK-GAAP

increment in model's explanatory power. However, across samples analysed and for all sub-periods collectively, the comprehensive model performs better than each of the variables sets individually. Das *et al.*, (2005) also advocates the use of both information set as additive rather than substitutive within CDS pricing framework. This study supports this viewpoint and proposes the use of accounting variables in combination with market based variables when modelling spreads. However, it is worth highlighting that by virtue of parsimony, the set of three market based variables tend to be more closely aligned in describing CDS spreads dynamics than the set of 10 accounting variables analysed in this study.

Chapter Two, also notes an interesting trend in modelling CDS spreads in the post crisis period. Across the three samples analysed, the comprehensive set of variables are better able to model spreads more so in the crisis period than the pre-crisis and post-crisis period. Using the same set of predictor variables, the explanatory power of the comprehensive model drops in the post-crisis period across the three samples analysed. This denotes that either the variables are not doing a good job in explaining spreads or CDS spreads have deviates from their regular credit risk signalling characteristics and may be plagued by other elements which are not only capturing the credit risk dynamics of the underlying firm. Across the three markets, the higher model explanatory power in the crisis period; when the credit risk within the financial system was at its peak; hints that the variables in the comprehensive model are doing a good job in capturing spreads if spreads are in effect capturing credit risk information. The sharp fall in model explanatory power in the post-crisis period using the same set of variables may be signalling more of a problem in CDS spreads than the variables used to model them. The substantial portion of spreads that could not be accounted for by the comprehensive model maybe in effect signalling presence of the non-default elements driving CDS spreads in the post-crisis period across the three markets. This observation does not harmonise with the system wide effort introduced by regulators in the aftermath of the financial crisis to enhance liquidity and transparency in the CDS market. Understanding what drives CDS spreads and the basis of CDS pricing is crucial as regulators and market participants consider CDS spreads as an important signal for system wide credit risk.

Chapter Two, also examines the dynamics of monthly corporate bond yield spreads for those corporate that have active CDS contract trading in the market. This study splits the bond yields spreads into default and non-default element using one of the earliest studies on CDS pricing by Longstaff *et al.*, (2005). The CDS spreads for a referenced entity is taken as the default component of bond yield spread under the notion they are representing the pure measure of credit risk. The remaining proportion of bond yield spreads is attributed as non-default component. This provide crucial data on the percentage split of default and non-default component of bond yield spreads that has important implications for both the CDS and bond pricing literature. It can be noted that, default risk only partially explains bond yield spreads and non-default component is a key additional explanatory factor and is in line with findings by Longstaff *et al.*, (2005). However, the observation drawn in this study is based on larger sample size and evident across the three markets more so for the post-crises period. Across the three market, higher proportion of non-default component (>50%) of bond yield spreads points towards bond yield spreads being affected by market microstructure and not representing the default risk as they were earlier attributed to capture before the introduction of the CDS market. This finding is in agreement with past studies that attribute bond yield spreads as not capturing default risk adequately and being plagued by non-default related information. However, the conclusion drawn above assumes that CDS spreads as pure measures of credit risk. As noted earlier CDS spreads themselves are plagued by non-default elements in the post-crisis period, the value relevance of bond yield spreads in capturing default related information further drops corroborating the previous findings on inadequacy of bond yields spreads in capturing default risk.

Past studies have well documented bond yield spreads to be plagued by non-default elements; specifically bond market liquidity and a similar effect is tested for CDS spreads. Tan and Yan (2006) claims that illiquidity in bond market affects dealer's hedging capabilities and increases the premium embedded in CDS spreads. This is tested by regressing bond market liquidity proxies on CDS spreads which are found to be significant across the three samples and more so in the post-crisis period for US and EU samples. These observations point towards some level of liquidity spillover from the bond market to the CDS market in the post-crisis period. This provides a possible explanation for the higher level of CDS spreads in the post-crisis period across the three markets and the possibility that CDS spreads are plagued by bond market liquidity dynamics. Next, this study also tests the effect of liquidity dynamics in the CDS market on CDS pricing, to note if these liquidity dynamics are driving spreads more than the credit risk of the underlying reference entity. Fixed effect panel data regressions are run using two proxies of CDS market liquidity and controlling for firm specific credit risk using the variables from the comprehensive model. The results indicate a significant effect of CDS liquidity on CDS spreads across the three markets and supports the notion that CDS spreads may be driven by liquidity and other non-default element and may not be capturing the true credit riskiness of the underlying corporate. A variety of robustness checks are undertaken to validate the finding from this study and these point towards consistency and reliability of the model estimates used in the study. In effect, it can be concluded that CDS pricing in the post-crisis period are signalling some level of haphazardness and possibility of it being plagued by financial market dynamics. Hence their use as pure measure of credit risk would lead to wrong estimates. Consequently, the signals from CDS market may not entirely reflect the credit risk within the financial system and policy makers and market participants should be careful in interpreting these signals when drawing policy implications or making credit risk decision. Recently, few studies have also provided evidence on the notion that CDS spreads are not reflecting the true credit risk inherent in the CDS market. However, none of these studies have explored such a wider sample domain across such a longer timeline as this study and so the findings from this study provide stronger evidence of CDS spreads being plagued by non-default element. The findings from this study is also significant as it is drawn from a large sample set covering three major developed economies where CDS are extensively traded. Moreover, a longer period of evaluation covering the three major economic conditions highlights the variability based on the period of analysis. Individually each set of CDS spreads predictor variables set and their extent of variability in CDS pricing provides a glimpse into the reliability of these information set in CDS pricing. This study highlights that policy makers need to be aware of the context in which the policies are made and if the context changes or the estimation period is too long, the re-estimation of model estimated should be mandatory. Due to the possibility of CDS spreads being driven by liquidity spillover effect from the bond market and liquidity in the CDS market, the signals coming from the CDS market may be not completely accurate and should be considered in conjunction with other financial market indicators before drawing a policy to address the issues in the CDS market.

In Chapter Three, the focus is on the effect of the policy announcements during the crisis period on the corporate CDS market for the US and UK economies. Instability in the financial system and threat of insolvency of large SIFIs prompted policy makers across these two economies to announce a series of measures to stabilise the flailing financial system. These measures ranged from reduction in the base rate; with an aim to kick start consumer spending, quantitative easing; by increasing the money supply in the system to encourage more lending and borrowing activity as well as fiscal policy initiatives primarily in the form of adjustment to tax rates, economic and fiscal stimulus initiatives etc. These unprecedented interventions were aimed at reducing the credit risk inherent in the financial system and to provide liquidity at a time when the extent of crisis was considered as the worst since the economic depression of 1930s. The policy interventions were aimed at stabilising the financial markets and the series of announcements should have helped reduce the system wide credit risk if they were successful in achieving their intended goal. Moreover, the literature on the type of policy intervention is broadly divided into two main camps; proponents of monetary policy believe it to be the best tool to stem a crisis, while proponents of fiscal policy argue against it. Both camps realise that a particular policy, be it monetary or fiscal have aftereffects. Specifically, monetary policy is criticised to create liquidity trap, zero bound interest rate and asset bubble while fiscal policy is believed to lead to inflation, crowding-out effect and inefficient use of resources. However, it is important to note these tools are at the disposal of the Government and Central banks and are implemented as seemed appropriate for the economic environment. This presents an interesting scope of inquiry in the effectiveness of the policy announcements in general and the effectiveness of the type of policy intervention announced during the recent financial crisis. The extant of interventional in terms of the monetary cost to the economy provides the motivation for this study and it extends the work of Greatrex and Rengifo (2010) by accessing the impact of policy intervention on the business sector. This chapter explores the following line of inquiry. Firstly, this study questions if policy announcements were effective in reducing system wide credit risk. Next, is there is a variable effect on system wide corporate credit risk based on the type of policy intervention announced or is the effect similar across the different policy types? This study further queries if the type of policy announcement has similar effect across corporates in the US and UK economy. Lastly, if the effect of a policy announcement was similar across all firms or were there firm specific differences that lead to differential effect following a policy announcement. The findings and discussion of the results are as elaborated in the following section.

The financial crisis of 2007-2008 is also referred to as the 'credit crunch' or 'the crisis of credit' as witnessed by large scale bankruptcies and default of SIFIs triggering a systemic collapse. To measure the effect of policy intervention and gradual recovery in the financial market in the form of reduction in system wide corporate credit risk, CDS market presents the optimal testing ground. As detailed earlier, CDS spreads provides more reliable, cross-sectional and time series indicator of credit risk and a vast number of studies have employed CDS spreads as a pure measure of credit risk. The findings from the Chapter Two also corroborate this view and the movement in CDS spreads; at least during the crisis period can be seen to provide useful signals about the credit risk inherent in the financial system. During the crisis period, CDS spreads witnessed a steady upsurge signalling extreme credit risk environment before stabilising in the post-crisis period for both the US and UK corporates. However, changes in spreads over time do not accurately indicate the change in credit riskiness of the underlying reference entity over time. Hence, using spreads to estimating the change in credit risk will lead to an incorrect estimation of underlying firm's credit dynamics. This study estimates daily CDS returns from CDS spreads using the procedure as detailed in Brendt and Obreja (2010). Thus this study improves on the work of King (2009), Xiao (2009) and Greatrex and Rengifo (2010) that have used changes in default risk premium i.e. CDS spreads by providing a better measure of corporate credit risk in the event study context. CDS returns estimated individually for each firm on a daily basis provides the flexibility of aggregating returns over sector, quality, firm size and liquidity. As detailed earlier, CDS returns estimated on a daily basis is the return for the insuring party in a CDS contract given the change in the value of the risky and risk-free bonds long - short portfolio position. A fall in CDS return following the announcement would indicate the losses arising to the insuring party resulting from credit deterioration of the underlying firm. This study is the first to estimate the effect of announcement on CDS returns estimated and aggregated independently for corporates in the US and UK economy.

To address the research questions in Chapter Three, this study uses the well establish event study methodology to estimate abnormal return following an event announcement. Smaller event windows are employed as policy announcement are bound to be complex and unprecedented without any apparent benchmark to evaluate their effects. Moreover, this study expects the announcement effect to be short-lived similar to the effect as noted in the equity market. A range of parametric and non-parametric test statistic is employed to access the significance of the abnormal return for the event windows following the policy announcements. However, in order to draw statistically significant outcomes, this study expects at least one variant of the non-parametric test to be significant. This is driven by the dynamics of CDS returns which this study notes to be widely dispersed evident from high kurtosis and skewness pointing towards non-normal distribution of returns. Addressing the research question, this study finds that cumulative average abnormal returns following the policy announcement were mostly positive and significant. However, the cumulative abnormal return shows variations based on the type of policy intervention announced. This study also notes a difference between the US and UK samples for the same type of policy announcements. Returns' following the interest rate announcement is small but positive, following quantitative easing announcement is large and positive and following fiscal policy announcement is small and positive in the US sample. While for UK sample, returns following the interest rate announcements are small but negative, following quantitative easing announcement is large and positive and following fiscal policy announcement is small and negative. However, the results only hold up for smaller event windows and become unclear for the larger event window analysed, highlighting the effect of announcement may be fading out faster lasting for very small time period. This finding is similar to Brendt *et al.*, (2005) and King (2005) who notes a modest gain in stock returns immediately following the announcement followed by resumption to pre-announcement downward trend a few days after the announcement. This lends further support to the notion that policy announcement effects are short-lived with results corroborated across both the equity and the CDS market.

A positive abnormal return in the US sample, following interest rate announcement which are significant across the three event windows analysed in this study, points towards support for past studies that claim credit risk transfer mechanism is sensitive to changes in short term interest rate. Thus the findings are in line with Dunbar (2008), Houweling and Vorst (2005), Jarrow and Turnbull (1995). This effect could be attributed to the improvement in the environment for debt financing and cash flow financing needs of the firms following favourable announcement regarding interest rate which were crucial during the crisis period. A lower effect in CDS abnormal returns for financial sector firms following interest rate announcement compared to non-financial sector firms supports Ricci (2014) that suggest financial firms to be less sensitive to traditional monetary policies like interest rate cuts. Similarly, a higher and positive effect following interest rate announcement could be noted for small size firms as well as speculative grade firms in the US sample. This could be attributed to the improvement in firm credit profile which varies based on the degree of financial dependence as rationalised in Laeven and Tong (2012). Speculative grade firms as well as small firms tend to be more dependent on external financing needs and announcement pertaining to lower interest rate are bound to increase the credit profile of these firms more than others. The negative effect following interest rate announcement in UK, could be attributed to past studies including Andersen, Bollersev, Diebold and Vega, 2007; Bernanke and Kuttner, 2005; Chuliá Martens and van Dijk, 2010; Guo, 2004; Gurkaynak Sack and Swanson, 2005; Wongswan, 2009 that suggest financial markets do not respond to anticipated monetary policy changes. This could also be attributed to the interest rate announcement that were too little and too late compared to market expectations or being already anticipated by financial markets without any surprise element attached to the interest rate announcement. Across both the sample, abnormal returns following the quantitative easing announcements, for the full sample and across the three event windows increased comparatively more compared to the interest rate and fiscal policy announcements. This finding points towards the popularity of quantitative easing announcements in calming the financial markets during the crisis period. Across both samples the CDS return increasing highlighting improvement in corporate credit risk profile. This is crucial to note as it implies financial markets responded more favourably to quantitative easing than other policy initiatives. It is important to note here that this study does not justify, whether QE measures are better for the ailing economy during crisis period. All this study does is, it provides an indication that the announcement pertaining to QE had a favourable effect on corporate CDS market, something that the policy makers could note for handling future crisis situations. Following fiscal policy announcements, the abnormal returns in smaller event windows across the US and UK sample, show a small upsurge. However, the effect is small and short lived. Across sub-samples the effect are inconclusive and at times contradictory supporting past studies that note contradicting effect of fiscal policy on consumption. The inconclusive evidence following fiscal policy announcements across both the samples, could be attributed to the varying perception of market participants depending on whether they perceive the benefit in the short run to outweigh the effects in the long run.

This study also splits the full sample based on firm idiosyncratic characteristics namely; sector, quality, size and CDS liquidity and notes that the effect following a policy announcement is not always consistent across these different sample categories. This is true across all policy types and event windows analysed. Barring very few studies, e.g. Aït-Sahalia *et al.,* (2012) and Greatrex and Rengifo (2010), most studies do not measure the impact across the different policy types i.e. between fiscal and monetary policy interventions. Moreover, majority of the studies assume one single effect of policy intervention which could be challenged on the grounds of firm specific heterogeneity. The finding from this study provides evidence in support of firm specific heterogeneity and thus the differential effect across both the type of policy intervention and the firm idiosyncratic characteristics. This has important policy implications as policy makers could be able to access firstly; the reduction in credit risk attributable to different policy intervention and the magnitude of effect across the different types of underlying referenced entity that display a specific characteristics. This differential effect could have been overlooked without the sample splitting approach undertaken in this study and provides a strong support to the different effect based on policy type and firm specific differences.

This study also undertaken comparison of mean and median abnormal returns for pre and post policy announcement days and note the differences to be mostly significant across sub-samples for the US. While median abnormal returns is mostly higher in the post announcement days, in the US sample the effect is opposite in the UK sample across the three policy types. This may points towards a possible effect of policy announcements leading to reduction in corporate credit risk for the US sample while an opposite effect pointing towards increase in credit risk can be noted for the UK sample. These results were tested across alternative specification of pre and post event windows and found to be consistent.

The findings from this study suggest that following certain policy announcement, firms with certain idiosyncratic characterises may be showing more reduction/increase in credit risk than others. To further disentangle this effect, this study tests if the abnormal return following the announcement is a function of firm specific characteristics. Since event study methodology does not lend itself to causality i.e. the effect on CDS returns following the announcement could not be attributed to the effect of the announcement and is a design specific challenge that event study methodology is unable to address. This study attempts to infer the abnormal return following the announcement on firm specific characteristics by regressing firm specific variables on abnormal returns following the policy announcements. The regression results indicate that following monetary policy announcements less profitable firms tends to display more reduction in credit risk. For the US sample following interest rate announcements more liquid contracts tend to adjust to the new policy information more quickly showing greater reduction in credit risk evident from higher abnormal returns. The above finding is also true for quantitative easing announcements in the US sample. The opposite effect in the UK sample indicates, on the flip side interest rate announcements lead to quicker absorption of policy information leading to faster assimilation of credit risk evident from negative abnormal returns. This study also notes that large firms as well as less profitable firms record a higher abnormal return following monetary policy announcements indicating a reduction in credit risk for the underlying firms which could be attributed to the positive effect of monetary interventions especially in the US sample. To further validate the research findings, the process is reversed and firm's abnormal return following policy announcements are categorised into high and low quintiles and firm idiosyncratic characteristics across the two groups tested for significant differences. Similar to earlier observations, for the US sample firms grouped into higher ARs following the announcements are found to have significantly higher liquidity and gearing for interest rate announcements, higher liquidity and larger size for the quantitative easing announcements and higher capitalisation following the fiscal policy announcements. However, for the UK sample, firms grouped into higher ARs following the policy announcements are found to have significantly lower liquidity for interest rate announcements and smaller size following the fiscal policy announcements. Although it is difficult to draw a theoretical justification for the difference observed in US and UK corporates. Nevertheless, it does strengthen the firm specific idiosyncratic differenced playing a role in differential effect of policy announcements on corporate credit risk across the two samples analysed.

The opposite effect between the two samples following the three policy types analysed in this study could be potentially attributed to the ineffectiveness of UK policy interventions in calming the CDS market compared to the policy interventions in US which had a positive impact on corporate credit risk environment in the CDS market. Another possible reason could be attributed to the extent of policy interventions carried out by US is more, not only in terms of the number of announcements but also in terms of the scope of impact. Similarly, majority of the policy interventions in UK were mostly lagging US interventions. This could potentially be conceived as a situation where market participants expected the UK government and BOE to follow suit in case of a major announcement in US. The mix of expected policy initiatives which did not surprise the market or did not exceed the market expectation of policy initiative may be a crucial factor in explaining the differential effect across the policy interventions in the two samples. The author also acknowledges that the extent of credit risk; gauged on the basis of median CDS spreads in the crisis period for the UK corporates were not as high as the US corporate. Hence, the effect may be higher in US sample compare to the UK sample. However, from the point of view of magnitude of credit risk reduction effect following the policy interventions, US corporates show a higher reduction in credit risk compared to UK corporates.

From the perspective of policy implications, this study provides some important findings that require some serious considerations. The type of policy announcement during a crisis period is not bound to have the same effect on the corporate credit risk environment. Some policies especially; quantitative easing has a higher effect than fiscal policy. This provides an indication of the kind of policy interventions that could be ideal for addressing the credit risk in corporate CDS market for a similar situation in the future. This could help policy makers decide on the use of the right tool for achieving the right kind of outcomes. The differential effect of policy announcement based on firm idiosyncratic characterises point towards a differential effect based on the types of corporates, gives an indication of the corporates that would benefit the most following a certain policy intervention. The differential effect across US and UK for the three policy type analysed in this study, points towards the ineffective nature of trailing policy announcements. Market participants react favourably to policy initiatives that were unexpected rather than those that are already anticipated by the market. In such circumstances, policy intervention does not provide any economic benefits and fails to deliver the desired results. Lastly, a policy intervention that has worked in the past or in a different economy may not guarantee the same results and the possibility of a variable effect has to be taken into consideration when deciding on the type and the timing of policy interventions.

Chapter Four, attempts to provide evidence on the generalizability of the well-known Fama and French asset pricing model to the CDS market. The asset pricing literature has evolved since the introduction of CAPM pioneered by Sharpe (1964), Lintner (1965) and the subsequent misspecification of the model is widely documented in the past studies. Motivated from these, Fama and French (1993) developed the three-factor model which has received a lot of attention in asset pricing literature and continues to be the most well-known and widely adopted asset pricing model among academics and industry practitioners. Majority of studies have used the FF model and provided its application to the equity market. None of the studies till date have attempted to test the generalizability of the FF model to the CDS market. The availability of large amount of CDS spreads data and the ease of estimating returns from spreads, provides an interesting avenue for exploration. With the development and growth of the CDS market, market participants can now access corporate credit risk information which is more reliable and robust than the bond yield spread used in past studies. Chapter Two provided some indication on the drivers of corporate CDS spreads and Chapter Three estimated CDS returns from spreads rationalising the returns to capture the time series dynamics of credit risk evolution over time. This Chapter queries if the CDS returns dynamics can be modelled within an asset pricing framework. This is an interesting avenue to explore not only from an academic perspective but also from the regulation and policy viewpoint. This Chapter tests the external validity of the FF model and its application to the

CDS market, with an aim to test if the model works for the CDS market. In doing so, this study follows the estimation procedure used by FF to estimate portfolios using daily CDS returns. The model is tested across all US corporate CDS for which spread data is available in Markit dataset. A longer time horizon of analysis spanning the last 10 years provides the flexibility of splitting the sample into sub-period of analysis namely; pre-crisis, crisis and post-crisis to test the model performance across the three main economic situations in US.

The findings from the portfolios returns indicate the average daily excess returns are not perfectly aligned as expected to the book-to-market, operating profitability and investment factors and expose variations in average return sufficient to provide strong challenges in asset pricing tests. The relationship between the portfolio type and average excess return trend fluctuates based on the sub-period of analysis. Moreover, the average excess CDS returns across the three sets of portfolios are found to be negative in the pre-crisis and crisis period, while positive in the post-crisis period. Negative average returns in the crisis period across portfolio is indicative of the higher credit risk in the CDS market and without splitting the effect across sub-periods this would have been ignored. For insights into model performance, the regression details specifically the intercepts and the pertinent slopes are examined both for the FF 3F and FF 5F model. Across the set of 25 portfolios formed on *Size-B/M*, *Size-OP* and *Size-Inv*, the intercepts for both the 3F and the 5F model are found to be positive for the pre-crisis period while it is negative for the crisis and the post-crisis period. This indicates that the 3F and 5F model significantly overstates the returns in the pre-crisis period. Moreover, based on the significance of the regression intercepts, the factors collectively for the 3F and the 5F model seem to do a good job in explaining variability in excess CDS returns in the crisis and the post-crisis period. The pre-crisis period represents a time when the CDS market was in its infancy stage and low market participation evident from missing observations and low liquidity could be a potential reason why the FF models do not adequately capture the dynamics of CDS excess returns in the pre-crisis period. However, it is important to note the factor models become more relevant in the crisis and the post-crisis period when it matters the most. Similarly, it can be observed that the models predictive power increases over the sub-period of analysis, indicating the FF model is better able to capture CDS excess returns recently, when the CDS market witnessed greater market participation and higher liquidity.

Across the set of portfolios formed on *Size-B/M*, *Size-OP* and *Size-Inv*, the regression intercept alone does not provide a clear consistent improvement of the 5F model over the 3F model. Effect size is estimated for each set of portfolios and for each sub-period of analysis to evaluate the improvement in 5F model over the 3F model that could be attributed to the addition of profitability and investment factor. Overall, the findings indicate that the 5F model offers significant improvement over the 3F model, especially for portfolios with extreme tilts on *Size*, *B/M*, *OP* and *Inv*. These improvements are mostly evident in the crisis and post-crisis period. For the pre-crisis period, the improvement provided by the 5F model over the 3F model is marginal at the best. The finding indicates the FF models; both the 3F and 5F help in explaining average CDS returns for portfolios formed as per FF approach. This provides proof on the generalizability of the FF model to the CDS market. This is an important conclusion not only for the CDS market but it also lends further support to the value relevance of the FF model itself. Moreover, Fama and French (2015) proposes the 5F model to be better than the 3F model and this study finds evidence in support of 5F model being a better asset pricing model than 3F. However, where Fama and French (2015) provides evidence using equity returns across the sample of analysis, this study draws a similar outcome based on the CDS returns and across all sub-periods of analysis.

Vassalou and Xing (2004) examined default risk in the context of Fama and French model and find that default risk is priced in the cross-section of equity returns concluding default risk is systemic in nature. For the CDS market, where returns are derived based on changes in the risky and risk-free bond long and short portfolio position, the change in CDS returns are bound to be credit risk driven and thus presents an interesting avenue for exploring the default risk and return relationship for the CDS market. Chapter Four, examines the 25 *Size-DTD* portfolios formed from the intersection of the five *Size* and five *DTD* portfolios. The average excess returns for the portfolios are mostly negative for the pre-crisis and crisis period, while it is positive for the post-crisis period. Overall, across the three sub-period of analysis in general, average excess portfolio return decreases across the *DTD* quintiles, indicating a positive relationship between default risk and returns. Dichev (1998) also explored the default risk and return relationship in the Fama and Macbeth (1973) regression framework and found a negative relationship between default risk and return. However, the findings from this chapter points towards consistency with the risk based explanation of default compared to previous studies like Dichev (1998) and Griffin and Lemon (2002). This provides further support to the model estimation and the portfolio construction process used in this study.

Overall, the findings from this Chapter indicates the FF 3F and FF 5F model can be generalised to the CDS market. It also notes that between the 3F and 5F model, the 5F model is a better asset pricing model for the CDS market. This study goes a step further and queries if the FF factor model for the CDS market can be improved on by augmenting it with a default driven factor. This study estimates distance-to-default measure and builds a new factor *VMS*; estimated as a difference between the aggregate CDS returns for the two vulnerable portfolios minus the two stable portfolios. This study expects the CDS excess returns to be closely related to a pure measure of firm credit risk. DTD is also widely used both in academic literature and well as in the industry on a commercial level. The augmented 3F and 5F model is tested across each of the 4 sets of 25 *Size-B/M*, 25 *Size-OP*, 25 *Size-Inv* and 25 *Size-DTD* portfolios. Augmenting both the 3F and 5F model with the *VMS* factor results in at best a marginal improvement to the model's explanatory power across the sub-periods analysed in this study. Hence for reasons of parsimony, this study suggest the FF 5F model to be preferred asset pricing model for the CDS market

Apart from testing the external validity of the FF model, this study also aims to access the external validity of the default risk hypothesis, by testing if the default risk is priced in the cross section of CDS returns and if the FF factors; *SMB* and *HML* factors are proxying for default risk in the CDS returns. The CDS market provides an ideal testing ground for the default risk hypothesis and this study augments both the 3F and 5F model with distance-to-default factor by creating a new factor; *VMS* and notes the change in the *SMB* and *HML* coefficient significance across the 25 *Size-B/M*, 25 *Size-OP*, 25 *Size-Inv* and 25 *Size-DTD* portfolios. Overall, across the 4 sets of 25 portfolios, the coefficient of *SMB* and *HML* retain their significance across each sub-period of analysis. This study concludes that if *SMB* and *HML* were truly capturing default risk in CDS returns then their coefficients should have become insignificant in the presence of a superior measure of credit risk; *VMS*. This finding indicates that it is unlikely that *SMB* and *HML* are proxying for default risk. The findings in this study supplements that of Gharghori *et al.*, (2007) who drew a similar outcome for the Australian equity returns. However, it is worth noting that the *VMS* factor estimated using distance-to-default measure is highly correlated to the *HML* factor for the crisis period. This may indicate that although *HML* is not capturing the default risk but there is some overlap in the type of risk captured by *HML* and *VMS* especially in the crisis period. Past studies on stock returns, have widely debated about the type of risk captured by the *SMB* and *HML* factors and the findings in this study provide further fuel to this debate lending some clarity and insight into the kind of risk dynamic captured by the *SMB* and *HML* factors.

Overall, the thesis presented herein; draws key observations on CDS spreads and returns and contributes to the growing literature on corporate credit risk. With the increasing participation and adoption of CDS by financial market participants along with the improved transparency and standardisation ushered by increasing regulatory actions, the extent of studies exploring the dynamics of the CDS market is bound to increase. Moreover, new information on trade and trading frequency is being tracked on a daily as well as intraday frequency by Markit and other data providers. This will further enhance the transparency and the dynamics of this market in the near future and trigger a wave of academic research as witnessed in the equity and bond markets. The findings from this thesis provide important contribution towards a better understanding of the CDS market highlighting central outcomes for policy implication. The author acknowledges that the analysis done, outcomes drawn and recommendations made may be subject to certain limitations as elaborated in each Chapter individually. The complexities in the CDS market provides for an interesting avenue for further research exploration and this thesis will serve as an important step to build on further complex investigations. The author concludes by emphasizing that further research in the CDS market is warranted both for the financial and academic community at large to be able to keep up with this intricate, enigmatic, dynamic yet fascinating market.

REFERENCES

A

Abid, F. and Naifar, N. (2006) 'The determinants of credit default swap rates: an explanatory study', *International Journal of Theoretical and Applied Finance*, 9(1), pp.23-42.

Acharya, V. and Johnson, T. (2007) 'Insider trading in credit derivatives', *Journal of Financial Economics*, 84, pp.110-141.

Adrian, T. and Shin, H. (2008) 'Financial intermediaries, financial stability, and monetary policy', *Federal Reserve Bank of New York Staff Report No. 346.*

Aït-Sahalia, Y., Andritzky, J., Jobst, A., Nowak, S., Tamirisa, N. (2012) 'Market response to policy initiatives during the global financial crisis', *Journal of International Economics,* 87, pp.162–177.

Agarwal, V. and Taffler, R. (2008) 'Comparing the performance of market-based and accounting-based bankruptcy prediction models', *Journal of Banking and Finance*, 32(8), pp.1541-1551.

Ahmed, A., Billings, R., Morton, R. and Stanford-Harris, M. (2002) 'The Role of Accounting Conservatism in Mitigating Bondholder-Shareholder Conflicts over Dividend Policy and in Reducing Debt Costs', *The Accounting Review*, 77, pp.867–890.

Akitoby, B. and Stratmann, T. (2008) 'Fiscal policy and financial markets', *Economic Journal* 118, pp.1971–1985.

Aksu, M. and Onder, T. (2003) 'The size and the book-to-market effects and their role as risk proxies in the Istanbul Stock Exchange', *EFMA 2000 Athens*; Koc University, Graduate School of Business, Working Paper No. 2000-04

Albertus, H., Van Eyden, R. and Gupta, R. (2009) 'Linking global economic dynamics to a South African-specific credit risk correlation model', *Economic Modelling*, 26(5), pp.1000-1011.

Alesina, A. and Ardagna, S. (2010) 'Large changes in fiscal policy: taxes versus spending. In Tax Policy and the Economy', *The University of Chicago Press*, 24, pp.35-68.

Allard, J., Catenaro, M., Vidal, J.P. and Wolswijk, G. (2013) 'Central bank communication on fiscal policy', *European Journal of Political Economy*, 30, pp.1–14.

Altman, E. (1968) 'Financial ratios, Discriminant analysis and the prediction of corporate bankruptcy', *Journal of Finance*, 23, pp.589-610.

Altman, E. and Saunders, A. (2001) 'An analysis and critique of the BIS proposal on capital adequacy and ratings', *Journal of Banking and Finance*, 25(1), pp.25-46.

Altunbas, Y., Gambacorta, L. and Marques-Ibanez, D. (2010) 'Bank risk and monetary policy', *Journal of Financial Stability*, 6(3), pp.121-129.

Alves, P. (2013) 'The Fama French or the Capital asset pricing model: International evidence', *The International Journal of Business and Finance Research*, 7, pp.79-89.

Andrikopoulos, A. and Angelidis, T. (2010) 'Idiosyncratic risk, returns and liquidity in the London Stock Exchange: a spillover approach', *International Review of Financial Analysis*, 19, pp.214–221.

Anderson, R. and Sundaresan, S. (1996) 'Design and valuation of debt contracts', *Review of Financial Studies*, 9(1), pp.37-68.

Andersen, T., Bollerslev, T., Diebold, F. and Vega, C. (2007) 'Real-time price discovery in global stock, bond and foreign exchange markets', *Journal of International Economics*, 73, pp.251-277.

Andreou, E. and Ghysels, E. (2008) 'Quality control for structural credit risk models', *Journal of Econometrics*, 146(2), pp.364-375.

Annaert, J., Ceuster, P., Roy, V. and Vespro, C. (2012) 'What determines Euro area bank CDS spreads?', *Journal of International Money and Finance*, 32, pp.44-461.

Ardagna, S. (2009) 'Financial markets' behaviour around episodes of large changes in the fiscal stance', *European Economic Review* 53, pp.37–55.

Arin, K., Mamun, A. and Purushothman, N. (2009) 'The effects of tax policy on financial markets: G3 evidence', *Review of Financial Economics*, 18(1), pp.33-46.

Arora, N., Bohn, J. and Zhu, F. (2005) 'Reduced Form vs. Structural Models of Credit Risk: A Case Study of Three Models', *Moody's KMV Company: 1-39*

Arora, N., Gandhi, P. and Longstaff, F. (2012) 'Counterparty credit risk and the credit default swap market', *Journal of Financial Economics*, 103(2), pp.280-293.

Asimakopoulos, I. and Athanasoglou, P. (2013) 'Revisiting the merger and acquisition performance of European banks', *International Review of Financial Analysis*, 29, pp.237-249.

Ashcraft, A. and Santos, J. (2009) 'Has the CDS market lowered the cost of corporate debt?', *Journal of Monetary Economics*, 56(4), pp.514-523.

Atkeson, A., Eisfeldt, A. and Weill, P. (2014) 'Entry and exit in OTC derivatives markets', *(No. w20416). National Bureau of Economic Research.*

Aunon-Nerin, D., Cossin, D., Hricko, T. and Huang, Z. (2002) 'Exploring the determinants of credit risk in credit default swap transaction data: Is fixed-income market's information sufficient to evaluate credit risk?', *Working paper (HEC-University of Lausanne and FAME).*

Augustin, P., Subrahmanyam, M., Tang, D. and Wang, S. (2014), 'Credit Default Swaps – A Survey', *SSRN working paper*, 9(1), pp.1-196.

Avellaneda, M. and Cont, R. (2010) 'Transparency in credit default swap markets', *Finance Concepts*, July.

B

Bach, G. and Huizenga, C. (1960) 'Differential effects of tight money', *American Economic Review*, pp.53–80.

Ball, R. and Brown, P. (1980) 'Risk and return from equity investments in the Australian mining industry: January 1958—February 1979', *Australian Journal of Management*, 5(1), pp.45-66.

Bangia, A., Diebold, F., Kronimus, A., Schagen, C. and Schuermann, T. (2002) 'Ratings migration and the business cycle, with application to credit portfolio stress testing', *Journal of Banking and Finance,* 26(2), pp. 445-474.

Banz, R. (1981) 'The Relation between Return and Market Value of Common Stocks', *Journal of Financial Economics*, 9, pp.3-18.

Barro, R. (1974) 'Are government bonds net wealth?', *Journal of Political Economy* 82, pp.1095–1117.

Barro, R., (1979) 'On the determination of public debt', *Journal of Political Economy* 87, pp.940–971.

Barro, R. and King, R. (1984) 'Time-separable preferences and intertemporal-substitution models of business cycles', *Quarterly Journal of Economics*, 99, pp.817–839.

Basu, S. (1977) 'Investment Performance of Common Stocks in Relation to their Price-Earnings: A Test of the Efficient Market Hypothesis', *Journal of Finance*, 32, pp.663-682.

Batta, G. (2011) 'The direct relevance of Accounting information for CDS pricing', *Journal of Business Finance and Accounting*, 38, pp.1096-1122.

Baxter, M. and King, R. (1993) 'Fiscal policy in general equilibrium', *American Economic Review*, 83, pp.315–334.

Becchetti, L., Carpentieri, A. and Hasan, I. (2012) 'Option-Adjusted Delta Credit Spreads: a cross-Country Analysis', *European Financial Management*, 18, pp.183-217.

Berger, A. and Udell, G. (1998) 'The economics of small business finance: The roles of private equity and debt markets in the financial growth cycle', *Journal of Banking and Finance*, 22(6), pp. 613-673.

Berk, J. (1995) 'A critique of size related anomalies', *Review of Financial Studies*, 8, pp.275-86.

Bernanke, B. (2009), Four Questions about the Financial Crisis, *Federal Reserve*, 14th April [online] available at
http://www.federalreserve.gov/newsevents/speech/bernanke20090414a.htm (Accessed: 30 Dec 2015).

Bernanke, B. and Gertler, M. (1995) 'Inside the black box: the credit channel of monetary policy transmission', *National bureau of economic research* (No. w5146).

Bernanke, B. and Kuttner, K. (2005) 'What explains the stock market's reaction to federal reserve policy?', *Journal of Finance*, 6(3), pp.1221–1257.

Bernanke, S., Gertler, M. and Gilchrist, S. (1996) 'The Financial Accelerator and the Flight to Quality', *Review of Economics and Statistics*, 78, pp.1-15.

Berndt, A., Douglas, R., Duffie, D., Ferguson. M., Schranz, D. (2005) 'Measuring de-fault risk premia from default swap rates and EDFs', *BIS Working Papers 173*.

Berndt, A. and Obreja, I. (2010) 'Decomposing European CDS Returns', *Review of Finance*, 14(2), pp.189–233.

Bhandari, L. (1988) 'Debt/Equity Ratio and Expected Common Stock Returns: Empirical Evidence', *Journal of Finance*, 43, pp.507-528.

Bharath, S. and Shumway, T. (2008) 'Forecasting default with the Merton distance to default model', *Review of Financial Studies*, 21, pp.1339-1369.

Black, F. and Scholes, M. (1973) 'The pricing of options and corporate liabilities', *The Journal of Political Economy*, pp.637-654.

Blanchard, O. and Perotti, R. (2002) 'An empirical characterization of the dynamic effect of changes in government spending and taxes on output', *Quarterly Journal of Economics*, 117, pp.1329–1368.

Blanco, R., Brenan, S. and Marsh, I. (2005) 'An empirical analysis of the dynamic relationship between investment grade bonds and Credit default swaps', *Journal of Finance*, 60, pp.2255-2281.

Blume, M., Lim, F., MacKinlay, A. (1998) 'The declining credit quality of US corporate debt: Myth or reality?', *Journal of Finance*, 53, pp. 1389–1413.

Boa, J., Pan, J. and Wang, J. (2011) 'The illiquidity of Corporate bonds', *The Journal of Finance*, 66, pp.911-946.

Boehmer, E., Masumeci, J. and Poulsen, B. (1991) 'Event Study Methodology under Conditions of Event Induced Variance', *Journal of Financial Economics*, 30(2), pp.253–72.

Bondt, W. and Thaler, R. (1987) 'Further evidence on investor overreaction and stock market seasonality', *The Journal of Finance*, 42(3), pp.557-581.

Borio, C. and Zhu, H. (2008) 'Capital regulation, risk-taking and monetary policy: a missing link in the transmission mechanism?', *Working Paper 268: Bank for International Settlement.*

Breitenfellner, B. and Wagner, N. (2012) 'Explaining aggregate credit default spreads', *International Review of Financial Analysis*, 22, pp.18-29.

Brown, S. and Warner, J. (1980) 'Measuring security price performance', *Journal of Financial Economics*, 8(3), pp.205-258.

Brown, S. and Warner, J. (1985) 'Using daily stock returns: The case of event studies', *Journal of Financial Economics*, 14(1), pp.3-31.

Bruner, R., Eades, K., Harris, R. and Higgins, R. (1998) 'Best practices in estimating the cost of capital: Survey and synthesis', *Financial Practice and Education*, 8, pp.13-28.

Bystrom, H. (2006) 'Credit Grades and the iTraxx CDS index market', *Financial Analysts Journal*, 62, pp.65–76.

C

Carhart, M. (1997) 'On persistence in mutual fund performance', *The Journal of Finance*, 52(1), pp.57-82.

Callen, J., Livnat, J. and Segal, D. (2009) 'The impact of earnings on the pricing of credit default swaps', *The Accounting Review*, 84(5), pp.1363-1394.

Calice, G., Chen, J. and Williams, J. (2012) 'Liquidity Spillover in sovereign bond and CDS markets: An analysis of the Eurozone sovereign debt crisis', *Journal of Economic Behaviour and Organization*, 85, pp.122-143.

Campbell, J., Lo, A. and MacKinlay, A. (1997) *The econometrics of financial markets* 5th edn. Princeton, NJ: Princeton University press.

Campbell, C. and Wasley, C. (1996) 'Measuring abnormal daily trading volume for samples of NYSE/ASE and NASDAQ securities using parametric and nonparametric test statistics', *Review of Quantitative Finance and Accounting*, 6(3), pp.309-326.

Campi, L. and Cetin, U. (2007) 'Insider trading in an equilibrium model with default: a passage from reduced-form to structural modelling', *Finance and Stochastic*, 11(4), pp.591-602.

Cantor, R., Hamilton, D. and Tennant, J. (2007) 'Confidence intervals for corporate default rates', *Available at SSRN 995545.*

Cantor, R. and Mann, C. (2003) 'Are Corporate Bond Ratings Procyclical?', *Moody's Investors Service Special Comment (September).*

Cao, Q., Leggio, K. and Schniederjans, M. (2005) 'A comparison between Fama and French's model and artificial neural networks in predicting the Chinese stock market', *Computers and Operations Research*, 32, pp.2499-2512.

Cao, C., Yu, F. and Zhong, Z. (2010) 'The information content of option-implied volatility for credit default swap valuation', *Journal of Financial Markets*, 13(3), pp.321-343.

Carhart, M. (1997) 'On persistence in mutual fund performance', *Journal of Finance,* 52, pp.57-82.

Cassola, N. and Morana, C. (2004) 'Monetary policy and the stock market in the Euro area, *Journal of Policy Modelling*, 26(3), pp.387–399.

Chan, L., Hamao, Y. and Lakonishok, J. (1991) 'Fundamentals and Stock Returns in Japan', *Journal of Finance*, 46, pp.1739-1764.

Chava, S. and Jarrow, R. (2004) 'Bankruptcy prediction with industry effects', *Review of Finance*, 8(4), pp.537-569.

Chan, L., Hamao, Y. and Lakonishok, J. (1991) 'Fundamentals and stock returns in Japan', *The Journal of Finance*, 46(5), pp.1739-1764.

Chen, L., Lesmond, D. and Wei, J. (2007) 'Corporate yield spreads and bond liquidity', *Journal of Finance*, 62, pp.119–149.

Chen, R. and Sopranzetti, B. (2003) 'The valuation of default-triggered credit derivatives', *Journal of financial and quantitative analysis*, 38(02), pp.359-382.

Christiano, L., Eichenbaum, M. and Rebelo, S. (2011) 'When is the Government spending multiplier large?', *Journal of Political Economics*, 119 (1), pp.78–121.

Chung, Y., Johnson, H. and Schill, M. (2006) 'Asset pricing when returns are non-normal: Fama-French factors versus higher-order systematic co-moments', *The Journal of Business*, 79(2), pp.923-940.

Chui, A. and Wei, K. (1998) 'Book-to-market, firm size, and the turn-of-the-year effect: Evidence from Pacific-Basin emerging markets', *Pacific-Basin Finance Journal*, 6, pp.275-293.

Chuliá, H., Martens, M. and van Dijk, D. (2010) 'Asymmetric effects of federal funds target rate changes on S&P100 stock returns, volatilities and correlations', *Journal of Banking and Finance*, 34(4), pp.834-839.

Cohen J. (1988) *Statistical Power Analysis for the Behavioural Sciences*. Hillsdale, NJ: Lawrence Erlbaum Associates, Inc.

Cohen, R., Gompers, P. and Vuolteenaho, T. (2002) 'Who underreacts to cash-flow news? Evidence from trading between individuals and institutions', *Journal of Financial Economics*, 66(2), pp.409-462.

Collin-Dufresne P., Goldstein, R. and Spencer-Martin, J. (2001) 'The determinants of credit spread changes', *Journal of Finance*, 56, pp.2177-2207.

Corrado, C. (1989) 'A nonparametric test for abnormal security-price performance in event studies', *Journal of Financial Economics* 23, pp.385-395.

Corrado, C. (2011) 'Event studies: A methodology review', *Accounting and Finance*, 51(1), pp.207-234.

Corrado, C. and Zivney, T. (1992) 'The Specification and Power of the Sign Test in Event Study Hypothesis Tests Using Daily Stock Returns', *Journal of Financial and Quantitative Analysis*, 27(3), pp.465–78.

Cossin, D. and Hricko, T. (2001) 'Exploring for the Determinants of Credit Risk in Credit Default Swap Transaction Data', *EFMA 2001 Lugano Meetings* (SSRN: 273454, 2001).

Cowan, A. (1992) 'Nonparametric event study tests', *Review of Quantitative Finance and Accounting*, 2(4), pp.343-358.

Cummins, J. and Doherty, N. (2006) 'The economics of insurance intermediaries', *Journal of Risk and Insurance*, 73(3), pp.359-396.

D

Daniel, K. and Titman, S. (1997) 'Evidence on the characteristics of cross sectional variation in stock returns', *Journal of Finance*, 52, pp.1-34.

Danis, A. and Gamba, A. (2015) 'The Real Effects of Credit Default Swaps', *Georgia Tech Scheller College of Business Research Paper No. 2015-09.*

Darrat, A. (1988) 'On fiscal policy and the stock market', *Journal of Money Credit and Banking*, 20, pp.353–363.

Das, R., Hanouna, P. and Sarin, A. (2009) 'Accounting-based versus market-based cross-sectional models of CDS spreads', *Journal of Banking and Finance*, 33, pp.719-730.

Delatte, A., Gex, M. and López-Villavicencio, A. (2012) 'Has the CDS market influenced the borrowing cost of European countries during the sovereign crisis?', *Journal of International Money and Finance*, 31, pp.481–497.

Demirgüç-Kunt, A. and Huizinga, H. (2013) 'Are banks too big to fail or too big to save? International evidence from equity prices and CDS spreads', *Journal of Banking and Finance*, 37, pp.875-894.

Dichev, I. (1998) 'Is the risk of bankruptcy a systematic risk?', *Journal of Finance*, pp.1131-1147.

Dionne, G., Gauthier, G., Hammami, K., Maurice, M. and Simonato, J. (2011) 'A reduced form model of default spreads with Markov-switching macroeconomic factors', *Journal of Banking and Finance*, 35(8), pp.1984-2000.

Dolly, J. (1933) 'Characteristics and procedure of common stock split-ups', *Harvard Business Review*, 11, pp.316-326.

Duffee, G. (1998) 'The relation between treasury yields and corporate bond yield spreads', *Journal of Finance*, 53, pp.2225-2241.

Duffie, D. (2008) 'Innovations in credit risk transfer: Implications for financial stability', *SSRN working paper.*

Duffie, D. and Garleanu, N. (2001) 'Risk and valuation of collateralized debt obligations', *Financial Analysts Journal*, 57(1), pp.41-59.

Duffie, D. and Singleton, K. (1999) 'Modelling term structures of defaultable bonds', *Review of Financial Studies*, 12, pp.197–226.

Duffie, D., Saita, L. and Wang, K. (2007) 'Multi-period corporate default prediction with stochastic covariates', *Journal of Financial Economics*, 83(3), pp.635-665.

Dullman, K. and Sosinska, A. (2007) 'Credit default swap prices as risk indicators of listed German banks', *Financial Markets and Portfolio Management*, 21, pp.269–292.

Dunbar, K. (2008) 'US corporate default swap valuation: the market liquidity hypothesis and autonomous credit risk', *Quantitative Finance Taylor and Francis Journals*, 8(3), pp.321-334.

Dunbar, K. and Amin, A. (2012) 'Credit risk dynamics in response to changes in the federal funds target: The implication for firm short-term debt', *Review of Financial Economics*, 21(3), pp.141–152.

Dunkelberg, W. and Cooper, A. (1983) 'Financing the start of small enterprise', in J.A Hornaday et al. (editors), *Frontiers of Entrepreneurship Research*, 1983 (Wellesley MA: Babson College, 1983), pp. 369-381.

E

Edward, A., Harris, L. and Piwowar, M. (2007) 'Corporate bond market transaction costs and transparency', *The Journal of Finance*, 62, pp.1421-1451.

Eggertsson, G. and Krugman, P. (2012) 'Debt, deleveraging, and the liquidity trap: a Fisher–Minsky–Koo approach', *Quarterly Journal of Economics*, 127 (3), pp.1469–1513.

Eickmeier, S. and Hofmann, B. (2013) 'Monetary policy, housing booms, and financial (im) balances', *Macroeconomic dynamics*, 17(04), pp.830-860.

Elton, E., Gruber, M., Agarwal, D. and Mann, C. (2001) 'Explaining the rate spread on corporate bonds', *Journal of Finance*, 56, pp.247-277.

Elton, E., Gruber, M., Agrawal, D. and Mann, C. (2004) 'Factors affecting the valuation of corporate bonds', *Journal of Banking and Finance*, 28(11), pp.2747–2767.

Ericsson, J., Jacobs, K. and Oviedo, R.(2009) 'Determinants of credit default swap premia', *Journal of Financial and Quantitative Analysis*, 44, pp.109-132.

Ericsson, J. and Renault, O. (2006) 'Liquidity and credit risk', *Journal of Finance*, 61, pp.2219-2250.

ESMA (2014) 'Credit Rating Agencies' 2014 market share calculations for the purposes of Article 8d of the CRA Regulation', ESMA/2014/1583[Online]. Available at http://www.esma.europa.eu/system/files/2014-1583_credit_rating_agencies_market_share_calculation_2014.pdf (Accessed on 20 May 2015)

F

Faff, R. (2004) 'A simple test of the Fama and French model using daily data: Australian evidence', *Applied Financial Economics*, 14, pp.83-92.

Fairfield, P., Whisenant, S. and Yohn, T. (2003) 'The differential persistence of accruals and cash flows for future operating income versus future profitability', *Review of Accounting Studies*, 8(2-3), pp.221-243.

Falkenstein, E., Boral, A. and Carty, L. (2000) 'RiskCalc for private companies: Moody's default model', *As published in Global Credit Research, May.*

Fama, E. (1976) *Foundations of Finance*. New York: Basic Books Inc.

Fama, E., Fisher, L., Jensen, M. and Roll, R. (1969) 'The Adjustment of Stock Prices to New Information', *International Economic Review*, 10, pp.1-21.

Fama, E. and French, K. (1989) 'Business conditions and expected returns on stocks and bonds', *Journal of Financial Economics*, 25(1), pp.23-49.

Fama, E. and French, K. (1992) 'The Cross Section of Expected Stock Returns', *Journal of Finance,* 47, pp.427-465.

Fama, E. and French, K. (1993) 'Common Risk Factors in the Returns on Stocks and Bonds', *Journal of Financial Economics*, 33, pp.3-56.

Fama, E. and French, K. (1995) 'Size and book-to-market factors in earnings and returns', *The Journal of Finance*, 50(1), pp.131-155.

Fama, E. and French, K. (1996) 'The CAPM is wanted, dead or alive', *The Journal of Finance*, 51(5), pp.1947-1958.

Fama E. and French, K. (1998) 'Value versus Growth: The International Evidence', *Journal of Finance*, 53, pp.1975–1999.

Fama, E. and French, K. (2006) 'Profitability, investment and average returns', *Journal of Financial Economics*, 82(3), pp.491-518.

Fama, E. and French, K. (2008) 'Dissecting anomalies', *The Journal of Finance*, 63(4), pp.1653-1678.

Fama, E. and French, K. (2015) 'A five-factor asset pricing model', *Journal of Financial Economics*, 116(1), pp.1-22.

Fama, E. and MacBeth, J. (1973) 'Risk, return, and equilibrium: Empirical tests', *The Journal of Political Economy*, pp.607-636.

Ferson, W., Sarkissian, S. and Simin. T. (1999) 'The alpha factor asset pricing model: A parable', *Journal of Financial Markets*, 2, pp.49–68.

Ferguson, M. and Shockley, R. (2003) 'Equilibrium anomalies', *Journal of Finance*, 58, pp.2549–80.

Figlewski, S., Frydman, H. and Liang, W. (2012) 'Modelling the effect of macroeconomic factors on corporate default and credit rating transitions', *International Review of Economics and Finance*, 21(1), pp.87-105.

Fiordelisi, F., Galloppo, G. and Ricci, O. (2014) 'The effect of monetary policy interventions on interbank markets, equity indices and G-SIFIs during financial crisis', *Journal of Financial Stability*, 11, pp.49–61.

Fratianni, M. and Marchionne, F. (2009) 'Rescuing banks from the effects of the financial crisis', *Available at SSRN 1476786.*

Friewald, N., Jankowitsch, R. and Subrahmanyam, M. (2012) 'Illiquidity or credit deterioration: A study of liquidity in the US corporate bond market during financial crisis', *Journal of Financial Economics*, 105, pp.18-36.

Freedman, C., Kumhof, M., Laxton, D., Muir, D. and Mursula, S. (2010) 'Fiscal multipliers galore', *IMF Working Papers, forthcoming.*

Frost, C. (2007) 'Credit rating agencies in capital markets: A review of research evidence on selected criticisms of the agencies', *Journal of Accounting, Auditing and Finance*, 22(3), pp.469-492.

G

Galbraith, J. (1957) 'Market structure and stabilization policy', *Review of Economics and Statistics*, 39, pp.124–133.

Gaunt, C. (2004) 'Size and book to market effects and the Fama and French three factor asset pricing model: evidence from the Australian stock market', *Accounting and Finance*, 44, pp.27–44.

Gerding, E. (2011) 'Credit Derivatives, Leverage, and Financial Regulation's Missing Macroeconomic Dimension', *Berkeley Business Law Journal*, 8(2) pp. 29-73.

Gharghori, P., Chan, H. and Faff, R. (2007) 'Are the Fama-French factors proxying default risk?', *Australian Journal of Management*, 32(2), pp.223-249.

Goldsmith-Pinkham, P. and Yorulmazer, T. (2010) 'Liquidity, bank runs, and bailouts: spillover effects during the northern rock episode', *Journal of Financial Services Research*, 37, pp.85–98.

Gramlich, E. (1999) 'Remarks by Governor Edward M. Gramlich before the Wharton Public Policy Forum Series', Philadelphia, Pennsylvania.

Graham, J. and Harvey, C. (2001) 'The theory and practice of corporate finance: Evidence from the field', *Journal of Financial Economics*, 60(1), pp.187-243.

Greatrex, C. and Rengifo, E. (2010) 'Government Intervention and the CDS Market: A Look at the Market's Response to Policy Announcements During the 2007–2009 Financial Crisis', *Fordham University Department of Economics Discussion Paper Series 2010–12.*

Griffin, J. (2002) 'Are the Fama and French Factors Global or Country Specific?', *Review of Financial Studies*, 15, pp.783–803.

Griffin, J. and Lemmon, M. (2002) 'Book-to-market equity, distress risk, and stock returns', *Journal of Finance*, pp.2317-2336.

Gómez-Biscarri, J. and López-Espinosa, G. (2008) 'Accounting Measures and International Pricing Models: Justifying Accounting Homogeneity', *Journal of Accounting and Public Policy*, 27, pp.339–354.

Gorton, G. and Metrick, N. (2010) 'Securitized Banking and the Run on Repo', *Journal of Financial Economics*, 104, pp.425-451.

Gündüz, Y., Lüdecke, T. and Uhrig-Homburg, M. (2007) 'Trading credit default swaps via interdealer brokers', *Journal of Financial Services Research*, 32(3), pp.141-159.

Gurkaynak, R., Sack, B. and Swanson, E. (2005) 'Do actions speak louder than words? The response of asset prices to monetary policy actions and statements', *International Journal of Central Banking*, 1, pp.55–93.

Guo, H. (2004) 'Stock prices, firm size, and changes in the federal funds rate target', *The Quarterly Review of Economics and Finance*, 44, pp.487–550.

Guo, X., Jarrow, R. and Zeng, Y. (2009) 'Modelling the recovery rate in a reduced form model', *Mathematical Finance*, 19(1), pp.73-97.

H

Hart, O. and Zingales, L. (2011) 'A new capital regulation for large financial institutions', *American Law and Economics Review*, 13(2), pp. 453-490.

Han, S. and Zhou, H. (2007) 'Nondefault bond spread and market trading liquidity', *Working paper, Federal Reserve Board.*

Hanson, S., Pesaran, M. and Schuermann, T. (2008) 'Firm heterogeneity and credit risk diversification', *Journal of Empirical Finance*, 15(4), pp.583-612.

Haugen, R. (1995) *The new finance: the case against efficient markets*. Englewood Cliffs, NJ: Prentice Hall.

Haugen, R. and Baker, N. (1996) 'Commonality in the determinants of expected stock returns', *Journal of Financial Economics*, 41(3), pp.401-439.

Heise, S. and Kühn, R. (2012) 'Derivatives and credit contagion in interconnected networks', *The European Physical Journal B*, 85(4), pp.1-19.

Hettenhouse, G. and Sartoris, W. (1976) 'An analysis of the informational value of bond rating changes', *Quarterly Review of Economics and Business*, 16(2), pp.65-78.

Hillegeist, S., Keating, E., Cram, D. and Lundstedt, K. (2004) 'Assessing the probability of bankruptcy', *Review of Accounting Studies*, 9, pp.5–34.

Hilscher, J., Jarrow, R. and Van Deventer, D. (2008) 'Measuring the risk of default: A modern approach', *RMA Journal*, 90(10), pp.70.

Houweling, P. and Vorst, T. (2005) 'Pricing default swaps: Empirical evidence', *Journal of International Money and Finance*, 24(8), pp.1200–1225.

Hu, H. and Black, H. (2008) 'Debt, Equity, and Hybrid Decoupling: Governance and Systemic Risk Implications', *European Financial Management*, 14, pp. 663-709.

Hu, G., Pan, J. and Wang, J. (2014) 'Tri-Party Repo Pricing', *Available at SSRN.*

Huang, J. and Huang, M. (2003) 'How much of the corporate-Treasury yield spread is due to credit risk', *Review of Asset Pricing Studies*, 2, pp.153-202.

Huang, X., Zhou, H. and Zhu, H. (2009) 'A framework for assessing the systemic risk of major financial institutions', *Journal of Banking and Finance*, 33(11), pp.2036-2049.

Hull, J., Predescu, M. and White, A. (2004) 'The relationship between credit default swap spreads, bond yields, and credit rating announcements', *Journal of Banking and Finance*, 28, pp.2789-2811.

I

Ioannidou, V., Ongena, S. and Peydro, J. (2009) 'Monetary Policy, Risk-Taking and Pricing: Evidence from a Quasi-Natural Experiment', *Working Paper Tilburg University IMF,* Global Financial Stability Report.

Ismailescu, I. and Phillips, B. (2015) 'Credit default swaps and the market for sovereign debt', *Journal of Banking and Finance*, 52, pp, 43-61.

Iqbal, J. and Brooks, R. (2007) 'Alternative beta risk estimators and asset pricing tests in emerging markets: The case of Pakistan', *Journal of Multinational Financial Management*, 17(1), pp.75-93.

Iqbal, J. and Robert, B. (2007) 'Alternative beta risk estimators and asset pricing tests in emerging markets: The case of Pakistan', *Journal of Multinational Financial Management*, 17, pp.75–93.

IOSCO (2012) *The Credit Default Swap Market report. The Board of the International Organisation of Securities Commission.* [Online] Available at: https://www.iosco.org/library/pubdocs/pdf/IOSCOPD385.pdf (Accessed: 2 June 2015)

J

Jarrow, R. (2011) 'Credit market equilibrium theory and evidence: Revisiting the structural versus reduced form credit risk model debate', *Finance Research Letters*, 8(1), pp.2-7.

Jarrow, R. and Protter, P. (2006) *Structural versus Reduced-Form Models: A New Information-Based Perspective. The Credit Market Handbook: Advanced Modelling Issues*, Hoboken: NJ [ua], pp.118-131.

Jarrow, R., Lando, D. and Turnbull, S. (1997) 'A Markov model for the term structure of credit risk spreads', *Review of Financial Studies*, 10(2), pp.481-523.

Jarrow, R. and Turnbull, S. (1992) 'Credit risk: Drawing the analogy', *Risk Magazine*, 5(9), pp.63-70.

Jarrow, R. and Turnbull, S. (1995) 'Pricing Derivatives on Financial Securities Subject to Credit Risk', *Journal of Finance*, 50, pp.53-85.

Jarrow, R. and Yu, F. (2001) 'Counterparty risk and the pricing of defaultable securities', *The Journal of Finance*, 56(5), pp.1765-1799.

Jegadeesh, N. and Titman, S. (1993) 'Returns to buying winners and selling losers: Implications for stock market efficiency', *Journal of Finance*, 48, pp.65-92.

Jegadeesh, N. and Titman, S. (2001) 'Profitability of momentum strategies: An evaluation of alternative explanations', *Journal of Finance*, 56, pp.699–720.

Jensen, M., Black, F. and Scholes, M. (1972) 'The capital asset pricing model: Some empirical tests', *Available at SSRN*

Jonsson, J. and Fridson, M. (1996) 'Forecasting default rates on high-yield bonds', *The Journal of Fixed Income*, 6(1), pp.69-77.

Jorion, P. and Zhang, G. (2007) 'Good and bad credit contagion: evidence from credit default swaps', *Journal of Financial Economics*, 84(3), pp.860-83.

Jorion, P. and Zhang, G. (2009) 'Credit contagion from counterparty risk', *Journal of Finance*, 64(5), pp.2053-2087.

K

Kahle, K. and Stulz, R. (2013) 'Access to capital, investment, and the financial crisis', *Journal of Financial Economics*, 110(2), pp.280-299.

Kandrac, J. (2012) 'Monetary policy and bank lending to small firms', *Journal of Macroeconomics*, 34(3), pp.741-748.

Karadi, P. and Gertler, M. (2015) 'Monetary Policy Surprises, Credit Costs, and Economic Activity', *Society for Economic Dynamics* Meeting Papers (2015-No. 447).

Katz, S. (1974) 'The price and adjustment process of bonds to rating reclassifications: A test of bond market efficiency', *Journal of Finance*, 29, pp.551–559.

King, M. (2009) 'Time to Buy or Just Buying Time? The Market Reaction to Bank Rescue Packages', *BIS Working Paper 288*.

Klomp, J. (2013) 'Government interventions and default risk: Does one size fit all?', *Journal of Financial Stability*, 9(4), pp.641–653.

Kolari, J. and Pynnönen, S. (2010) 'Event study testing with cross-sectional correlation of abnormal returns', *Review of Financial Studies*, 23 (11), pp.3996-4025.

Kolari, J. and Pynnonen, S. (2011) 'Nonparametric rank tests for event studies', *Journal of Empirical Finance*, 18(5), pp.953-971.

Kothari, S., Shanken, J. and Sloan, R. (1995) 'Another look at the cross-section of expected Returns', *Journal of Finance*, 50, pp.185–224.

Kunt, A. and Huizinga, H. (2013) 'Are banks too big to fail or too big to save? International evidence from equity prices and CDS spreads', *Journal of Banking and Finance*, 37, pp.875-894.

L

Laeven, L. and Tong, H. (2012) 'US monetary shocks and global stock prices', *Journal of Financial Intermediation*, 21(3), pp.530-547.

Lakonishok, J., Shleifer, A. and Vishny, R. (1994) 'Contrarian investment, extrapolation, and risk', *The Journal of Finance*, 49(5), pp.1541-1578.

LaPorta, R. (1996) 'Expectations and the cross-section of stock returns', *Journal of Finance*, 51, pp.1715–1739.

LaPorta, R., Lakonishok, J., Shleifer, A. and Vishny, R. (1997) 'Good news for value stocks: further evidence on market efficiency', *Journal of Finance*, 52, pp.859–874.

Lakonishok, J., Shleifer, A. and Vishny, R. (1994) 'Contrarian investment, extrapolation, and risk', *Journal of Finance*, 49, pp.1541–78.

Leland, H. (1994) 'Corporate debt value, bond covenants, and optimal capital structure', *Journal of Finance*, pp.1213-1252.

Leland, H. and Toft, K. (1996) 'Optimal capital structure, endogenous bankruptcy, and the term structure of credit spreads', *Journal of Finance*, pp.987-1019.

Lesplingart, C., Majois, C. and Petitjean, M. (2012) 'Liquidity and CDS premium on European companies around the Subprime crisis', *Review of Derivatives Research*, 15, pp.257-281.

Leung, K. and Kwok, Y. (2009) 'Counterparty risk for credit default swaps: Markov chain interacting intensities model with stochastic intensity', *Asia-Pacific Financial Markets*, 16(3), pp.169-181.

Liew, J. and Vassalou, M. (2000) 'Can book-to-market, size and momentum be risk factors that predict economic growth?', *Journal of Financial Economics*, 57(2), pp.221-245.

Linkings, J. (2010) 'Exxon Valdez: How That Disaster Destroyed the Economy 20 Years Later', *Huffington post*, 6 August [Online]. Available at: http://www.huffingtonpost.com/2010/06/08/exxon-valdez-how-that-dis_n_605080.html (Accessed: 25 Jan 2013).

Lintner, J. (1965) 'The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets', *The Review of Economics and Statistics*, pp.13-37.

Longstaff, F., Mithal, S. and Neis, E. (2005) 'Corporate yield spreads: default risk or liquidity? New evidence from the credit-default swap market', *Journal of Finance*, 60, pp.2213-2253.

Loon, Y. and Zhong, Z. (2014) 'The impact of central clearing on counterparty risk, liquidity, and trading: Evidence from the credit default swap market', *Journal OF Financial Economics*, 112, pp.91-115.

Luoma, T. (2011) 'Nonparametric Event Study Tests for Testing Cumulative Abnormal Returns', *Unpublished manuscript*

M

MacKinlay, A. (1995) 'Multifactor models do not explain deviations from the CAPM', *Journal of Financial Economics*, 38, pp.3–28.

Maclennan, D., More, A. and More, A. (1999) 'Evidence, what evidence? The foundations for housing policy', *Public Money and Management*, 19(1), pp.17-23.

Madura, J. and Schnusenberg, O. (2000) 'Effect of Federal Reserve policies on bank equity returns', *Journal of Financial Research*, 23(4), pp.421-447.

Markose, S., Giansante, S., Gatkowski, M., and Shaghaghi, A. R. (2009) 'Too Interconnected To Fail: Financial Contagion and Systemic Risk In Network Model of CDS and Other Credit Enhancement Obligations of US Banks', *COMISEF Working paper Series*.

Mason, R. and Harris, F. (1979) 'Technical note. Predicting company failure in the Construction Industry', *ICE Proceedings Thomas Telford*, 66(2), pp.301-307.

Maddaloni, A. and Peydró, J. (2011) 'Bank risk-taking, securitization, supervision, and low interest rates: evidence from the Euro area and U.S. lending standards', *Review of Financial Studies* 24 (6), pp.2121–2165.

Mayordomo, S., Peña, J. and Schwartz, E. (2014) 'Are all credit default swap databases equal?', *European Financial Management*, 20(4), pp.677-713.

Mckenzie, A., Thomsen, M. and Dixon, B. (2004) 'The performance of event study approaches using daily commodity futures returns', *Journal of Futures Markets*, 24(6), pp.533-555.

Merton, R. (1974) 'On the pricing of corporate debt: The risk structure of interest rates', *Journal of Finance*, 29, pp.449-470.

Micu, M., Remolona, E. and Wooldridge, P. (2004) 'The pricing impact of rating announcements: evidence from the credit default swap market', *BIS Quarterly Review*, 34, pp.45-62.

Milonas, N. (1987) 'The effects of USDA crop announcements on commodity prices', *Journal of Futures Markets*, 7(5), pp.571-589.

Mishkin, F. (2009) 'Is monetary policy effective during financial crises?', *NBER Working Paper No. w14678.*

Moerman, G. (2005) 'How domestic is the Fama-French three factor model? An application to the Euro Area', *ERIM Report Series,* Reference no. ERS-2005-035-FandA.

Mountford, A. and Uhlig, H. (2009) 'What are the effects of fiscal policy shocks?', *Journal of Applied Economics*, 24, pp.960–992.

Mun, J., Vasconcellos, G. and Kish, R., (2000) 'The contrarian/overreaction hypothesis. An analysis of the US and Canadian stock markets', *Global Finance Journal,* 11, pp.53–72.

N

Nartea G., Gan C. and Wu, J. (2008) 'Persistence of size and value premia and the robustness of the Fama-French Three Factor Model in the Hong Kong Stock Market', *Investment Management and Financial Innovations*, 5, pp.9–49.

Norden, L. (2011) 'Why do CDS spreads change before rating announcements?', *SSRN Working Paper Series.*

Norden, L. and Weber, M. (2010) 'When Senior meets Junior: Information in Credit Default Swap Spreads of Large Banks', *Social Science Research Network (SSRN) Paper*
Novy-Marx, R. (2013) 'The other side of value: The gross profitability premium', *Journal of Financial Economics*, 108(1), pp.1-28.

O

Ohlson, J. (1980) 'Financial ratios and the probabilistic prediction of bankruptcy', *Journal of Accounting Research*, 18, pp.109-131.

OICU-IOSCO (2012) 'The Credit Default Swap Market report, International Organization of Securities Commissions 2012', [Online]. Available at https://www.iosco.org/publications/?subsection=public_reports. (Accessed: 16 Dec 2014)

P

Pan, J. and Singleton, K. (2008) 'Default and recovery implicit in the term structure of sovereign CDS spreads', *Journal of Finance*, 63, pp.2345-2384.

Panetta, F., Faeh, T., Grande, G., Ho, C., King, M., Levy, A., Signoretti, F., Tabago, M. and Zaghini, A. (2009) 'An Assessment of Financial Sector Rescue Programmes', *Occasional Paper Banca D'Italia 47.*

Park, N. (2004) 'A guide to using event study methods in multi-country settings', *Strategic Management Journal*, 25(7), pp.655-668.

Pástor, L. and Stambaugh, R. (2003) 'Liquidity risk and expected stock returns', *Journal of Political Economics*, 111, pp.642–685.

Patell, J. (1976) 'Corporate Forecasts of Earnings per Share and Stock Price Behaviour: Empirical Tests', *Journal of Accounting Research*, 14(2), pp.246–76.

Patel, K. and Pereira, R. (2007) 'Expected default probabilities in structural models: empirical evidence', *The Journal of Real Estate Finance and Economics*, 34(1), pp.107-133.

Peltonen, T., Scheicher, M. and Vuillemey. G. (2014), 'The network structure of the CDS market and its determinants', *Journal of Financial Stability*, 13, pp.118–133.

Penman, S. (1991) 'An evaluation of accounting rate of return', *Journal of Accounting, Auditing, and Finance*, 6, pp.233-255.

Perotti, R. (2004) 'Estimating the Effects of Fiscal Policy in OECD Countries', *Università Bocconi Discussion Paper No. 276.*

Pesaran, M., Schuermann, T., Treutler, B. and Weiner, J. (2006) 'Macroeconomic Dynamics and Credit Risk: A Global Perspective', *Journal of Money, Credit and Banking*, 38, pp.1211-1262.

Pinches, G. and Singleton, J. (1978) 'The adjustment of stock prices to bond rating changes', *Journal of Finance* 33, pp.29–44.

R

Rath, S. and Durand, R. (2015) 'Decomposing the size, value and momentum premia of the fama-french-carhart four-factor model', *Economics Letters, 132*, pp.139-141.

Raunig, B. and Scheicher, M. (2009) 'Are banks different?: evidence from the CDS market', *BIS working paper: Oesterreichische Nationalbank.*

Ravn, M., Stephanie, S. and Martin, U. (2007) 'Explaining the effects of government spending shocks on consumption and the real exchange rate', *NBER Working Paper No. 13328.*

Ricci, O. (2014) 'The impact of monetary policy announcements on the stock price of large European banks during the financial crisis', *Journal of Banking and Finance,*52, pp.245-255.

Richardson, S. and Sloan, R. (2003) 'External financing and future stock returns. *Rodney L. White Center for Financial Research Working Paper, (03-03).*

Rigobon, R., and Sack, B. (2004) 'The impact of monetary policy on asset prices', *Journal of Monetary Economics*, 51(8), pp.1553-1575.

Rolph, D. (2003) 'Co-skewness, firm-level equity returns and financial leverage', *Working paper, Seattle University.*

S

Sarno, L., Eichengreen, B., Mody, A. and Nedeljkovic, M. (2009) 'How the Subprime Crisis Went Global: Evidence from Bank Credit Default Swap Spreads', *National Bureau of Economic Research.*

Sarig, O. and Warga, A. (1989) 'Some empirical estimates of the risk structure of interest rates', *Journal of Finance*, 44, pp. 1351–1360.

Schroeder, T., Blair, J. and Mintert, J. (1990) 'Abnormal returns in livestock futures prices around USDA inventory report releases', *North Central Journal of Agricultural Economics*, 12(2), pp.293-304.

Schultz, P. (1998) 'Corporate bond trading costs and practices: A peek behind the curtain', *Unpublished manuscript, University of Notre Dame.*

Sengupta, P. (2004) 'Disclosure timing: Determinants of quarterly earnings release dates', *Journal of Accounting and Public Policy*, 23, pp.457-482.

Sharpe, W. (1964) 'Capital asset prices: A theory of market equilibrium under conditions of risk', *The Journal of finance*, 19(3), pp.425-442.

Silvia, J. and Iqbal, A. (2011) 'Monetary policy, fiscal policy, and confidence', *International Journal of Economics and Finance*, 3(4), pp.22-35.

Simpson, M. and Ramchander, S. (2008) 'An inquiry into the economic fundamentals of the Fama and French equity factors', *Journal of Empirical Finance*, 15, pp.801-805.

Skeel, D. and Partnoy, F. (2007) 'The Promise and Perils of Credit Derivatives', *University of Penn, Institute for Law & Econ Research Paper No. 06-22.*

Sobehart, J., Keenan, S. and Stein, R. (2000) 'Benchmarking quantitative default risk models: a validation methodology', *Moody's Investors Service.*

Subrahmanyam, M., Tang, D. and Wang, S. (2014) 'Does the Tail Wag the Dog?: The Effect of Credit Default Swaps on Credit Risk', *Review of Financial Studies*, 27(10), pp.2927-2960.

Sutherland, A. (1997) 'Fiscal crises and aggregate demand: Can high public debt reverse the effects of fiscal policy', *Journal of Public Economics,* 65, pp.147-162.

Svec, J. and Maurice, P. (2010) 'Systematic Risk, CDS spread and Market integration- An empirical Investigation', *Working paper JASSA*, 3, pp.06-11.

Swanson, E., Reichlin, L. and Wright, J. (2011) 'Let's Twist Again: A High-Frequency Event-Study Analysis of Operation Twist and Its Implications for QE2/Comments and Discussion', *Brookings Papers on Economic Activity,* pp. 151-207.

Switzer, L. and Wang, J. (2013) 'Default risk estimation, Bank Credit risk and Corporate Governance', *Financial Markets Institutions and Instruments*, 22, pp.91-112.

T

Tagkalakis, A. (2008) 'The effects of fiscal policy on consumption in recessions and expansions', *Journal of Public economics*, 92(5), pp.1486-1508.

Tan, D. and Yan, H. (2006) 'Liquidity, Liquidity Spillover, and Credit Default Swap spreads', *Working paper Federal Reserve Board.*

Tan, D. and Yan, H. (2010) 'Market conditions, default risk and credit spreads', *Journal of Banking and Finance*, 34, pp.743-753.

Taylor, J. (2000) 'Reassessing discretionary fiscal policy', *Journal of Economic Perspectives* 14 (3), pp.21-36.

Taylor, J. (2009) 'The financial crisis and policy responses: An empirical analysis of what went wrong', *NBER Working Paper No. w14631.*

Taylor, J. and Williams, J. (2009) 'A black swan in the money market', *National Bureau of Economic Research No: w13943.*

Titman, S., Wei, K. and Xie, F. (2004) 'Capital investments and stock returns', *Journal of Financial and Quantitative Analysis,* 39, pp.677–700.

Thorbecke, W. (1997) 'On stock market returns and monetary policy', *Journal of Finance,* 52, pp.635-654.

Titman, S., Wei, K. and Xie, F (2004) 'Capital investments and stock returns', *Journal of Financial and Quantitative Analysis*, 39(04), pp.677-700.

Tong, H. and Wei, S. (2011) 'The composition matters: capital inflows and liquidity crunch during a global economic crisis', *Review of Financial Studies,* 24, pp.2023-2052.

V

Vassalou, M. (2003) 'News related to future GDP growth as a risk factor in equity returns', *Journal of Financial Economics*, 68(1), pp.47-73.

Vassalou, M. and Xing, Y. (2004) 'Default risk in equity returns', *Journal of Finance*, 59, pp.831-868.

W

Wall Street Journal (2009) *One way to stop bear raids: Credit default swaps need much stricter regulation: The Wall Street Journal* [Online]. Available at http://www.wsj.com/articles/SB123785310594719693 (Accessed: 12 Sept 2012)

Weinstein, M. (1977) 'The effect of a rating change announcement on bond price', *Journal of Financial Economics*, 5, pp.329–350.

Wilson, T. (1997) 'Portfolio credit risk (I)', *Risk,* 10(9), pp. 111–117.

Wongswan, J. (2009) 'The response of global equity indexes to US monetary policy announcements', *Journal of International Money and Finance*, 28, pp.344–365.

X

Xiao, Y. (2009) 'French Banks amid the Global Financial Crisis', *IMF Working Paper 201 Washington.*

Y

Yang, C. (2013) 'The Impact of the Interest Rate on Insurance/Financials Industries: The Analysis of the Stock Market's Reactions to Federal Funds Rate Changes', *North American Actuarial Journal*, 17(1), pp. 29-40.

Yin, H. and Yang, J. (2013) 'Bank characteristics and stock reactions to federal funds rate target changes', *Applied Financial Economics*, 23(23), pp.1755-1764.

Yu, F. (2005) 'Accounting Transparency and the Term Structure of Credit Spreads', *Journal of Financial Economics*, 75, pp.53-84.

Yu, F. (2007) 'Correlated Defaults in intensity based models', *Mathematical Finance*, 17(2), pp.155-173.

Z

Zhang, B., Zhou, H. and Zhu, H. (2009) 'Explaining credit default swap spreads with the equity volatility and jump risk of individual firms', Review of Financial Studies, 22(12), pp.5099-5131.

Zhu, H. (2006) 'An empirical comparison of credit spreads between the bond market and the credit default swap market', *Journal of Financial Services Research*, 29, pp.211–235.

Websites

http://www.standardandpoors.com
http://www2.isda.org/
https://www.iosco.org
http://www.bis.org/
http://www.tradingeconomics.com/
www.sba.gov
http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html