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Doctoral Thesis

Intrinsic cyclicality and spatial coupling in U.S. housing market instability, 1975-2020

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Declaration of Authorship

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Abstract

Where did the national U.S. house price boom-bust that triggered the Global Financial Crisis come from? In this thesis I show that approaching U.S. housing as a network of sub-national markets with their own non-trivial intrinsic dynamics helps us to understand the character and timing of housing market instability, both at the sub-national and national levels.

A detailed empirical analysis of U.S. house prices across historical time (Jan 1975 - Jun 2020) and geographical space reveals striking spatio-temporal patterns in the data. I argue these empirical results are hard to account for within existing theoretical frameworks (idiosyncratic shocks or bubbles), but are consistent with the intrinsic cyclicality of local markets combined with local spatial dependence between cycles in neighbouring markets. I show that a simple model based implementation of this hypothesis is able to easily replicate my key empirical results.

My first thesis paper shows, using wavelet spectra of state level price series, that state level markets exhibit evidence of a permanent c.10 year cycle component over the entire historical sample period. My next two papers introduce instantaneous phase based methods as a spectrally focussed dynamic framework within which to study the relative timing of these cycles. I show that permanent cycles at the state level, whilst asynchronous during earlier periods, synchronised dramatically from the mid 1990s (coinciding with important shifts in housing finance in the U.S.), and that this synchronisation of cycles contributed significantly to the historically unprecedented national house price boom-bust of the 2000s. Moreover my analysis shows a clear and stable "*traveling-wave*" pattern in the relative timing of local cycles across markets over the entire historical sample period. My fourth paper investigates the relationship between the timing of "bubbles" and of cycles: combining bubble date-stamping strategies employed in the empirical bubble literature with instantaneous phase information obtained via complex wavelet analysis, I show a systematic relationship between the phase of the permanent cycle component and the timing of explosive bubble and collapse episodes. This result suggests that the underlying price cycles influence the likelihood a bubble may emerge or burst. In my fifth paper I show that both the synchronisation of cycles over time and the specific spatial patterns documented by my empirical analysis are easily reproduced in a simple model of endogenous local speculative house price cycle dynamics extended to a spatial network setting – in which price expectations are partly influenced by neighbouring markets. I argue, nevertheless, that my empirical results suggest shifts in housing finance may have played an important role in the synchronisation of U.S. housing cycles that I document.

Taken together these different empirical and theoretical contributions suggest a possible significant paradigm level re-interpretation of U.S. housing market instability, with distinctive implications for theory, methods, policy and finance.

JEL Classification: C33, E32, R30
Keywords: *housing cycles*; *synchronisation*; *ripple effect/spatial diffusion*; *housing bubbles.*

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Any errors in this thesis are of course, my own and mine alone.

Dedication

To my parents,
who nurtured my natural curiosity
about the world around me.

Contents

1 Introduction

1.1 Overview

This thesis presents a series of empirical and theoretical contributions on the dynamic character of U.S. housing market instability.

The U.S. experienced a dramatic national housing boom-bust during the 2000s (widely believed to have triggered the Global Financial Crisis) and has a long history of housing boom-bust at the sub-national level. The type of forces and mechanisms driving this has been and remains the subject of intense debate. A key question has been whether fluctuations are principally driven by *shocks* or exhibit temporary *bubble* dynamics. In either case, this leads to a view of housing market fluctuations as irregular and episodic. This view has implications for how we interpret and analyse housing cyclicality at different spatial scales of aggregation, as well as spatial dynamics in housing market data. In particular, under this view of housing fluctuations as irregular and episodic, what does not average out is assumed to reflect some common national *shock* or *bubble* component[1] - thus the national boom-bust of the 2000s has motivated huge interest in *aggregate* factors that could potentially explain house prices over this period.

In this thesis, I make a detailed empirical analysis of U.S. house prices across historical time (Jan 1975 - Jun 2020) and geographical space, revealing: a periodic component to state level house price dynamics; the synchronisation of cycles over time; and striking spatio-temporal patterns in the relative timing of cycles in different markets. I argue these empirical results are hard to account for with standard irregular shock or bubble hypotheses, but are consistent with the intrinsic cyclicality of local markets combined with local spatial dependence between cycles in neighbouring markets. I show that the key empirical results I obtain are easily reproduced in a simple model of endogenous local speculative house price cycle dynamics extended to a spatial network setting.

Together, these contributions re-conceptualise the local vs. national character of housing market dynamics such that national housing fluctuations *emerge* (endogenously or under common or local shocks) out of the intrinsic local dynamics of individual markets. This offers a novel conceptual framework within which to interpret, analyse and model housing market fluctuations, with distinctive implications for theory, methods, policy and finance.

1.2 Motivation and context

Fluctuations in national house prices and housing aggregates have come to be widely considered as a source of macroeconomic fluctuations (see for example Leamer (2007), Cesa-Bianchi (2013), Iacoviello (2005), Liu et al. (2013)). In particular, the central role the historically unprecedented national U.S. housing market boom-bust of the 2000s seemed to play in the Global Financial Crisis and

[1] Since *idiosyncratic local* shock or bubble driven fluctuations should be expected to average out at the national level.

Great Recession, has motivated huge and on-going research and policy interest in the dynamics of house prices and the sources and propagation of housing market instability (Ben S Bernanke, 2010).

While the *national* boom-bust of the 2000s is unprecedented since the Great Depression era, at the *sub-national* level the U.S. has a long history of housing boom-bust (Glaeser, 2013). Evidence of sub-national house price cycles goes back at least to Homer Hoyt's classic study of Chicago land prices (Hoyt, 1933) in which he documented real estate cycles between 1830-1933 with a 17-20 year periodicity. Moreover regional boom-bust episodes were not uncommon in the decades immediately preceding the national boom of the 2000s and had been widely documented in the literature (Karl E Case, 1992; Karl E Case & Shiller, 1993; Riddel, 1999; Shiller, 1990; Wheelock, 2006).

A key debate in the real estate literature even before the Global Financial Crisis therefore, has been whether house prices are stable but subject to shocks; or can exhibit temporary bubble episodes, uncoupling from fundamentals over extended periods (Abraham & Hendershott, 1996; Clark & Coggin, 2011; Mikhed & Zem, 2009; Shiller, 1990). In the more recent literature, evidence of temporarily explosive dynamics (Greenaway-mcgrevy & Phillips, 2015; Hu & Oxley, 2018a; Efthymios Pavlidis, Martínez-García, & Grossman, 2018; Shi, 2017) - the time series signature of an unstable bubble process[2] - provides empirical support for the bubble hypothesis.

In either case however, both the shock and bubble hypotheses lead to a view of housing boom-bust as idiosyncratic.

Consistent with this view, historically the boom-bust that characterised sub-national markets, largely averaged out at the national level, supporting the natural conclusion that the volatility of local markets reflected idiosyncratic local shocks or bubbles.

This view had important implications for housing finance (leading to a perceived risk diversification opportunity from the pooling of mortgages from different parts of the country – helping first to motivate interstate banking reforms (Amel, 2000; Rice & Johnson, 2007) then providing the logic for the development and pricing of structured products such as *mortgage backed securities* (BIS Committee on the Global Financial System, 2005; Cotter, Gabriel, & Roll, 2015; Coval, Jurek, & Stafford, 2009)); and for monetary policy (since the effects of a policy shock depend on the initial distribution of regional housing market conditions; moreover heterogeneous regional shocks are outside of the scope of monetary policy making (Del Negro & Otrok, 2007; Fratantoni & Schuh, 2003)).

Meanwhile the national boom-bust of the 2000s is generally assumed to reflect the emergence of significant common national factors, or perhaps some national "mania" resulting in a national housing bubble. A wide range of possible explanations have been put forward including interest rates; subprime lending; speculation and irrationality; and international capital flows.[3] While the causes

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[2] See Phillips (2015a) for an overview.

[3] Interest rates (Campbell et al., 2009; Glaeser et al., 2013; Himmelberg et al., 2005); mortgage credit and subprime lending (Dell'Ariccia, Igan, Laeven, et al., 2012; Favilukis et al., 2016; Levitin & Wachter, 2012; Mian & Sufi, 2009; Pavlov & Wachter, 2009; C. W. Wheaton & Nechayev, 2008); speculation and irrationality (Barlevy & Fisher, 2011; Bayer, Geissler, Mangum, & Roberts, 2011; Bayer, Mangum, & Roberts, 2016; Burnside, Eichenbaum, & Rebelo, 2016; K E Case, Quigley, & Shiller, 2005; Karl E Case &

of the national boom-bust of the 2000s continue to be debated, a view widely shared among academics and policymakers is that this period saw U.S. house prices temporarily depart from their fundamental values, ending in the price correction that eventually precipitated the crisis (Ben S Bernanke, 2010).

Spatial patterns, such as the so called "ripple effects" observed or hypothesised in some markets (Meen, 1999) are also interpreted and analysed within the same frameworks - either in terms of the *spatial diffusion* of random local shocks (Barros, Gil-Alana, & Payne, 2012; Holmes, Otero, & Panagiotidis, 2011)); or (less often) *contagion* of bubbles between spatially adjacent markets (DeFusco, Ding, & Ferreira, 2013; Nneji, Brooks, & Ward, 2015; Riddel, 2011).

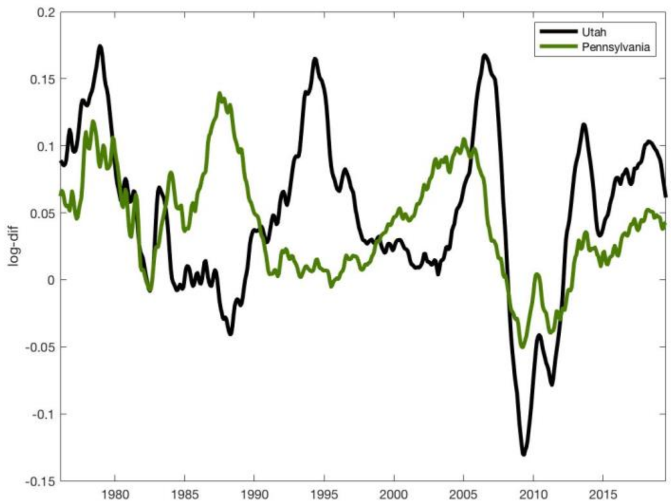

Figure 1: This chart plots log-differences of monthly house price index for the states of Utah (black) and Pennsylvania (Green) since January 1975.

It is interesting to notice however, that not only had many regional markets experienced similarly dramatic boom-bust episode *prior* to the 2000s, but also that the succession of boom-bust in some markets seems to much more resemble an *on-going cycle* than isolated events (Figure 1 shows two example price series illustrating the sort of repeated cycles experienced in *many* states).

This apparent continuity in house price dynamics when observed at a sub-national level, seems to raise the question whether local cycles are best understood - as has been widely assumed - as an irregular episodic process (mainly a response to persistent exogenous shocks, or else temporary bubble dynamics), or could they instead reflect an endogenous mechanism, which produces recurrent boom-bust phenomena?

Intrinsic cyclicality in local markets would have potentially wide ranging consequences for our understanding and interpretation of housing instability not just at the local level, but at wider spatial scales including national house price developments. For one thing, in the presence of permanent cycles a temporary global shock can potentially have a permanent impact on the degree of co-movement among cycles (thus aggregate volatility) meaning the impact of

Shiller, 2003; J. M. Lee & Choi, 2011; Shiller, 2005); and international capital flows (Favilukis, Kohn, Ludvigson, & Nieuwerburgh, 2013; Favilukis et al., 2016).

a succession of common shocks could plausibly accumulate over time resulting in a national cycle. What is more even weak local interactions between cyclical markets could give rise to local synchronisation of clusters of markets, or traveling-wave patterns across markets (similar to the ripple-effects that have been widely studied in the real estate literature where they are interpreted in terms of the spatial diffusion of local shocks); or even the emergence of a national cycle via the local endogenous synchronisation of locally interacting cycles.

While not widely considered, the possibility of endogenous house price cyclicality has been shown to arise in a number of theoretical housing market model settings, especially a recent but growing 'behavioural' housing market literature (Baptista et al., 2016; Defusco, Nathanson, & Zwick, 2017; Dieci & Westerhoff, 2012a, 2016; He, Wright, & Zhu, 2015; Ryoo, 2015; Sommervoll, Borgersen, & Wennemo, 2010; Uluc & Bank of England, 2015; W. C. Wheaton, 1990)). The empirical relevance of models of endogenous house price cyclicality however, hardly seems to have been empirically motivated or validated at all in the previous literature. Meanwhile the possibility and implications from the interaction among multiple intrinsically cyclical markets seems not to have been previously considered, either as a theoretical possibility, or empirically.

1.3 Research

In this thesis I make both an empirical (Phase 1) and a theoretical (Phase 2) exploration and development of these issues and questions.

Phase 1: Empirical analysis

In the empirical phase of the thesis I first take a data driven approach to the following series of interlinked questions:

- What is the dynamic character of local housing cycles in U.S. markets? Are they best understood as an irregular episodic process, or do they instead reflect an endogenous mechanism, which produces recurrent boom-bust phenomena?
- What is the dynamic character of national house price cycles? To what extent can the national boom-bust of the 2000s be understood as arising from the intrinsic cyclicality of local markets vs. (as is generally assumed) directly reflecting some temporary aggregate shock or temporary national bubble?
- What is the role of spatial links between markets in local and national housing cycle comovement? Can the spatio-temporal patterns in house price cyclicality help provide evidence on my first two research questions (the dynamic character of housing instability at the local and national level)?

Regarding the dynamic character of local house price cycles: a series of random shocks could generate a 'cycle' in the sense of successive periods of expansion and contraction (analogous to modern business cycle theory) (Bracke, 2013);

alternatively if markets are '*bubbly*' enough (i.e. if bubbles easily emerge but eventually burst) this explosiveness could be the engine behind a cycle formed by a sequence of bursting bubbles (Evans, 1991; Shi, 2007, 2017).

Whether driven by successive shocks or bubbles, under this episodic view, housing cycles might recur, but would in *either* case be fundamentally *irregular* and *unpredictable*. However (as recently argued in a business cycle context by Beaudry et al. (2020)) irregular fluctuations may also emerge as the interplay between exogenous shocks and endogenous cycles (wherein the system is buffeted by exogenous shocks, but where the deterministic part of the system admits a limit cycle). Distinguishing between these alternative dynamic possibilities is thus not necessarily straightforward.

One common approach (suitable for stationary time series) to distinguishing between these alternative interpretations is to inspect the *spectral density*. This of course depicts the importance of cycles of different frequencies in explaining the data over some given sample period (which should be sufficiently long) and can reveal the periodic component of a noisy cycle process (B. P. Beaudry et al., 2020).[4] In a noisy limit-cycle setting, fluctuations whilst irregular, would nevertheless exhibit some preferred period (something the other hypothesised processes do not have).[5]

However cycle episodes may be transient (if their amplitude quickly decays); or the onset of cyclicality may occur at a particular time (in response to a structural change); or cycle characteristics (duration, magnitude) may change over time. Indeed the possible emergence of a national cycle from the intrinsic cyclicality of local markets that I set out to investigate, would imply a dynamic process in which the phase and perhaps frequencies of local cycles adjust towards each other over time (Pimenova, Goldobin, Rosenblum, & Pikovsky, 2016). If spatial dependencies play a role in this convergence process, then spatial clusters of synchronised markets may also develop and merge over time; or traveling-wave patterns may form and evolve over time.

To investigate whether there is any empirical evidence of these sorts of phenomena, thus calls for methods able to capture not only the *spectral*, but also *time-evolving* character of house price dynamics individually and as a system. In this thesis I introduce and deploy methods based on the *complex continuous wavelet transform*, which performs the estimation of the spectral characteristics of a signal as a function of time, revealing how the different periodic components of a time series (if any) change over time (Aguiar-Conraria & Soares, 2014) with the ability to identify trends or abrupt shifts in cyclic dynamics. The complex wavelet transform also provides the phase-amplitude decomposition of a signal.

As I will show, this combined *time-frequency* and *phase-amplitude* decomposition provides a basis for methods that are uniquely suited to my research problem and provide a number of significant advantages over other available methodological strategies.

I exploit the combined *time-frequency* and *phase-amplitude* decomposition applied to spatially granular (state level) monthly house price data since January

[4] It is well known that if the spectral density of a time series displays a significant peak at a given frequency, this is an indication of recurrent cyclical phenomena at that frequency.

[5] This approach has been used recently by Gray (2013, 2015) although the periodic tendency implied by a non-zero frequency spectral peak in the spectral density is not explicitly developed.

1975 (c.50 years of data) in order to study U.S. housing cycle dynamics over *time* and *space*: I assess the existence, historical timing and dynamic character of cyclical episodes; compare the characteristics of cycles in different markets over time; quantify the time-evolving overall synchronisation among cycles across the U.S.; and finally study - within the same spectrally focussed dynamic framework - spatial patterns in the relative timing of state level cycles.

Key results include:

(i) Evidence of persistent cycle components with a similar preferred period of c.10 years in markets across the U.S. over the entire historical sample period.
(ii) The contribution from these state level cycles to mean house price variation at the national level was significantly moderated prior to the 2000s by the phase shifts between markets, but a dramatic increase in synchronisation after 1995 contributed to the subsequent national boom-bust.
(iii) The phase-shifts between markets for this common cycle component describe a clear spatial pattern (over the entire sample period and multiple cycles) resembling a *traveling-wave.*

Having obtained these results, indicating the presence of permanent cycle components and spatial dependencies between these cycles, I make a follow up investigation of the relationship between the *permanent cycles* I document, and the temporary bubble episodes studied in the existing empirical housing bubble literature in order to understand whether these are connected or independent phenomena.

I find a systematic relationship between the timing of the onset of explosive bubbles (as dated in the empirical bubble identification literature based on econometric tests for time-localised explosive dynamics) and the timing of the permanent cycle components (as measured by the instantaneous-phase of these cycles) documented in the first phase of my analysis.

Phase 2: Dynamical model

Taken together the empirical phenomena I document seem to suggest a novel hypothesis that the interaction among intrinsically cyclical markets may help us to explain and interpret U.S. housing market instability. What is more they suggest some rather strong restrictions on any model of house price cycles, and are not easily accounted for within standard stochastic shock or bubble frameworks in the existing literature.

Motivated by these empirical results obtained in Phase 1, in the second phase of the thesis, I develop a simple theoretical model of *spatially coupled* endogenous house price cycles.

Simulation of this model based on the spatial adjacency pattern (based on spatial contiguity) for U.S. states, shows that this simple framework of locally coupled housing cycles is able to simultaneously explain: repeating local boom-busts; their synchronisation over time; and (perhaps most interestingly) neatly reproduces the east-west traveling spatial waves I empirically documented in the first empirical phase of the thesis.

1.4 Significance

This systematic spatio-temporal pattern, and the continuity between the historical period of "local" and "national" housing market instability that I document in the empirical phase of this thesis, at once challenge both the view that housing market instability was idiosyncratic prior to the national boom-bust; and the subsequent emphasis (following the national boom-bust of the 2000s) on the search for an aggregate explanation for the simultaneous run up and collapse of prices in markets across the country.

Taken together evidence of a cycle component with a preferred period, and of persistent traveling-wave spatial pattern in the timing of cycles across different markets suggest U.S. housing market dynamics might be understood in terms of a system of spatial coupled intrinsically cyclical markets.

Moreover the systematic relationship I identify between the phase of permanent cycle components and the timing of temporary explosive bubble episodes further suggests low frequency housing fluctuations may play an important role in the occurrence and timing of housing bubbles shedding new light on a problem we have so far made little progress on: how can we explain where and when bubbles occur? At the same time it also suggests slow fluctuations may have significance for housing market dynamics beyond their own amplitude contribution since the slow cycle seems to modulate shorter-run housing market volatility.

Finally the ability of the simple model of coupled speculative house price cycles that I introduce, to provide a unified explanation and reproduce not only the key stylised empirical facts, but also the specific spatial pattern observed in the data, supports and reinforces the idea that this may provide a useful new paradigm for understanding and interpreting U.S. housing market data. This is to the best of my knowledge the first model of its kind and provides both further support for this interpretation of the data, and a first contribution towards the theoretical work my empirical results suggest may be needed.

Taken together these results thus suggest a possible significant re-interpretation of U.S. housing market instability, leading to a novel alternative conceptual framework – offering nothing short of a new paradigm - within which to interpret, analyse and model U.S. housing market cyclicality. This framework generates a range of distinctive implications, more readily accounting for a rich set of empirical features of the historical data than existing frameworks can.

The work I present clears the path for a number of new research programs in housing economics, the housing-macro-finance nexus and beyond. Indeed, while my focus and contribution here is entirely on understanding U.S. housing market dynamics, both the conceptual frameworks and the empirical methods I develop here seem likely to have wider relevance for a range of other problems and applications in economics, such as perhaps sectoral or international business cycle comovement.

1.5 Detailed overall outline

This thesis is organised as five independent but closely linked substantive chapters (each could be a stand-alone paper, but each successive chapter builds on the results of, and addresses questions raised or motivated by the preceding ones) followed by an overall discussion of the significance of results over all five chapters for economic theory and policy (thus the overall contribution of the thesis). In this section (Section 1.5) I provide a brief summary of each section.

1.5.1 Essay 1

In Essay 1 (Section 2) I study the character of house price dynamics at the local level. I introduce the *continuous complex wavelet transform.* The *time-frequency* and *phase-amplitude* decomposition provided by this transform is the fundamental methodological basis not only for my analysis in this chapter, but for the range of different *time-frequency* methods derived from this transform that I will introduce and employ in subsequent empirical chapters. I then introduce the *wavelet power spectrum* (widely employed in the analysis of noisy dynamical systems, but still little known in economics) and use this to analyse monthly state level house price data since Jan 1975. This allows me to study the spectral characteristics/frequency components of state level housing cycles in different markets *over time*, allowing me to observe and distinguish between transient and/or permanent cycles in these markets and assess time variation in cycle frequency and amplitude. This analysis thus provides a first and direct test of one of my central research questions: are local cycles best understood as an irregular episodic process, or do they instead reflect an endogenous mechanism, which produces recurrent boom-bust phenomena? I find surprisingly striking evidence of *persistent* or *permanent* cycles (with fairly stable frequency) over the entire historical sample period (1975:01-2020:06) for the majority of U.S. states, consistent with significant intrinsic cyclic dynamics in these markets. These recurrent cycles have not been previously documented. They are not consistent with the widely accepted view that local housing boom-bust was idiosyncratic prior to the national episode of the 2000s. Meanwhile, evidence of permanent cycles spanning both local and national housing instability eras suggests a surprising continuity of dynamics between these periods begging the question whether the intrinsic cyclicality of local markets played a central role in the national boom-bust episode. This challenges the widely accepted view that the national boom-bust reflected some sort of temporary national bubble.

1.5.2 Essay 2

In Essay 2 (Section 3) I study the co-cyclicality of U.S. state level housing cycles over time. I introduce the *average wavelet power spectrum* in order to assess the phase-adjusted similarity of cycles across markets. This reveals a common cycle frequency of 10-12 years over the entire sample period as well as an important higher frequency common shock in the early 1980s that average out in the time domain due to phase differences. I introduce *instantaneous phase* (obtained via continuous complex wavelet transform), and a multivariate measure of synchronisation based on instantaneous phase information that allows me to study how the synchronisation among cycles in different markets has evolved over time with good temporal resolution. These methods are widely used in the study of dynamic synchronisation phenomena, but apparently unknown in the economics literature, where the business cycle literature relies on "concordance index" approaches – a time-averaged measure of phase-synchronisation quantified as the fraction of time both series are simultaneously in the same binary (expansion or contraction) 'phase' state, using turning points identified in the time-domain. Using my multivariate instantaneous phase based approach I show that a marked de-synchronisation between 1984 and 1995 significantly moderates aggregate house price volatility over this period; but that after 1995 a dramatic synchronisation of existing cycles contributed to the national housing boom-bust over the subsequent period. I discuss the possible connections between these important shifts in synchronisation of local markets and historical context and events. These results suggest the possible need for a significant re-interpretation of the national "bubble period" and the local vs. national distinction common in the literature.

1.5.3 Essay 3

In Essay 3 (Section 3) I study local synchronisation of state level housing cycles and spatial patterns in the lead-lag relationships between cycles across the U.S. (focussing on the cycle components identified in Section 2 (Essay 1)). I introduce pairwise instantaneous phase-difference (obtained via continuous wavelet transform) and an instantaneous measure of *local* synchronisation based on pairwise differences. This multivariate measure of local phase-synchronisation is new for economics. I use it to quantify the time varying average level of synchronisation among cycles in spatially adjacent markets. I find adjacent markets are well synchronised over the entire sample period (but increases after 1995). While spatial correlation among house prices is well documented, the question of what frequency components matter has not been addressed and I specifically study the 9-12 year periodicity band associated with the common c.10 year cycle component. I then introduce *relative phase analysis* (also new for economics) and employ the spatial projection both of the phase series (introduced in Essay 2), and of relative phase relationships (also a novel methodological approach), in order to assess (possibly time varying) spatial patterns in the relative timing of cycles across U.S. states. While the empirical literature is inconclusive on the evidence for a spatial "ripple-effect" in U.S. markets (Barros et al., 2012; Clark & Coggin, 2009; Gil-Alana, Barros, & Peypoch, 2014; Gupta & Miller, 2012; S Holly, Pesaran, & Yamagata, 2010; Pollakowski & Ray, 1997; Zohrabyan, Leatham, & Bessler, 2008), I document a striking ripple pattern in the development of state level cycles, resembling a traveling wave. This spatial pattern has not been previously documented – indeed a number of recent studies find no particular spatial pattern in the timing of boom-bust, moreover a number of studies have argued that other forms of economic links/distance are (more) important than spatial links (Hernández-Murillo, Owyang, & Rubio, 2017; Malone, 2017; Zhu, Füss, & Rottke, 2013). The particular pattern I document, and its stability over time, are more consistent with the local interaction of intrinsically cyclical markets, than with either the spatial diffusion of random local shocks, or contagious bubbles hypothesised within the existing literatures. This suggests a new paradigm within which to interpret empirical ripple-effect phenomena. It also further reinforces evidence of permanent cycle dynamics presented in Section 2 (Essay 1). One implication is the plausible possibility that a national cycle could have emerged as the result of the endogenous synchronisation of cycles via weak local interdependencies.

1.5.4 Essay 4

In Essay 4 (Section 5) I investigate the relationship between two important empirical features of U.S. state level house price fluctuations: (i) occasional extreme explosive "bubble" episodes (documented in the existing literature); and (ii) the permanent cycle components (documented in section 3). I review the econometric bubble identification literature for dating the onset and termination of "bubble episodes" and introduce the PSY test by Phillips, Shi and Yu (2015a, 2015b) now popular in the literature. I then develop a novel methodological strategy for assessing the relationship between the timing of bubble episodes - dated using the PSY test - and the timing of underlying cycles - captured by the instantaneous phase-angle (introduced in Section 3). I find a systematic relationship between the timing of the onset of explosive bubbles and the instantaneous phase of the underlying permanent cycles suggesting this low frequency cycle may play an important role in the occurrence and timing of housing bubbles. This result sheds new light on a problem we have so far made little progress on: how can we explain where and when bubbles occur? Various studies have failed to find any particular spatial pattern in the timing of bubbles, others interpret spatial patterns in the timing of cycles as contagion dynamics. Given the traveling-wave phenomena documented in Section 4, the systematic relationship between cycle phase and bubble timing suggests that there is an underlying spatial process to housing bubbles, but that this spatial pattern in bubbles should not be interpreted as contagion. It also suggests slow fluctuations may have significance for housing market dynamics beyond their own amplitude contribution since the slow cycle seems to modulate shorter-run housing market volatility. It also suggests there is an underlying spatial process to housing bubbles, though this is less easily observed in studying spatial distribution of the timing of bubbles.

1.5.5 Essay 5

In Essay 5 (Section 6) I develop a simple model of spatially coupled endogenous housing cycles. I argue that the existing theoretical frameworks within which housing market instability is interpreted in the literature are unable to provide a satisfactory account of the spatio-temporal patterns that I document in the empirical phase of this thesis (Essay 1-4/Sections 2-5). What is more that collectively, these key features of the spatio-temporal dynamics of these markets can provide some rather strong restrictions on any theory of U.S. housing market cyclicality. I then take a model and simulation based approach to exploring a novel hypothesis: that wide scale spatial patterns, and national housing fluctuations of the sort I document in the data, may *emerge* out of the interaction of interconnected cyclical local markets. Concretely I extend the workhorse housing cycle framework of Dieci and Westerhoff (2012b) to model a network of 49 identical housing cycles locally bi-directionally coupled according to the spatial adjacency matrix for the 49 spatially contiguous U.S. states. I show that this simple framework of locally coupled housing cycles is able to simultaneously explain: repeating local boom busts; their synchronisation over time; and not only generates travelling-wave patterns, but - most strikingly - neatly reproduces the specific spatial pattern that I document in the historical data (Essay 3 (Section 5)). That this simple framework is sufficient to provide a unified explanation for these key spatio-temporal features of empirical house price dynamics suggests that the local coupling of intrinsically cyclical markets may offer a useful new framework within which to interpret and analyse U.S. housing market instability, and provide a departure point for further empirical and theoretical work.

1.5.6 Discussion and concluding sections

In Section 7, reflecting jointly on the results presented over the preceding five substantive chapters, I first discuss their significance and relation to key relevant existing literatures (Section 7.1) with an emphasis on: our understanding of housing instability (Section 7.1.1 - 7.1.2); and how my work relates to previous work using wavelet based methods in the study of housing and other applications in economics (Section 7.1.3). I then discuss the policy implications from my work (Section 7.2). Section 8 provides a summary of the overall contribution made by this thesis and concludes.

2 Essay 1: The dynamic character of local housing market instability: evidence of permanent cycles in most sub-national markets

Summary: In this essay I use time-frequency methods to re-examine the cyclical properties of US house prices over time and across different markets based on monthly state level data covering the entire available historical sample period 1975:01-2020:06. While the national U.S. housing boom-bust of the 2000s is unprecedented since the Great Depression era, at the sub-national level the U.S. has a long history of housing market instability. Indeed the succession of boom and bust in some markets more resembles a repeating cycle than independent isolated episodes. One possible explanation for these recurrent fluctuations is that they represent the equilibrium adjusting responses to a *series* of random shocks; another that they represent a *succession* of temporary bubbles - in either case *transient* dynamics implying an irregular and unpredictable cycle. Another possibility (that has been shown to arise in various theoretical housing market settings but not studied empirically) is simple *limit-cycle* or *near limit-cycle* dynamics. In this Essay I use *wavelet power spectrum* analysis (which can determine not only all the frequencies present in a signal, but also when they are present) of state level house price data since Jan 1975, to study the spectral characteristics of state level housing cycles over time. I find surprisingly striking evidence of *persistent* or *permanent* cycles over the entire c.50 year historical sample period for the majority of US states. Moreover an analysis of the distribution of instantaneous frequencies of cycles in different states suggests that most states share cycles with similar periodicity with both a cycle in the 8-10 year band and a cycle in the 12-15 year band. Moreover these have been fairly stable over time. The existence of these clear cyclical components with fairly stable preferred periodicity provides evidence consistent with a significant intrinsic component to housing instability, motivating further work to distinguishing between e.g. limit-cycle and noise driven oscillations, as well as to discriminate between competing hypotheses regarding the underlying cycle mechanisms.

2.1 Introduction

The central role the U.S. housing market price run-up and collapse seem to have played in the global financial crisis and recession, have generated huge renewed interest in the dynamics of house prices. A view widely shared among academics and policymakers is that the 2000s boom period saw US house prices depart from their fundamental values, ending in the price correction that eventually precipitated the crisis (Ben S Bernanke, 2010).

While the national scale of this episode may have been unprecedented since the Great Depression era and brought housing market dynamics to a new prominence, the US has a long history of house price instability (Glaeser, 2013). Evidence of sub-national house price cycles goes back at least to Homer Hoyt's classic study of Chicago land prices (Hoyt, 1933) in which Hoyt documented city level real estate cycles within a 17-20 year periodicity band between 1830-1933. *Regional* boom-bust episodes were not uncommon in the decades preceding the national boom of the 2000s and had been widely documented (Karl E Case, 1992; Karl E Case & Shiller, 1988, 1993; Riddel, 1999; Shiller, 1990; Wheelock, 2006).

Indeed not only had many regional markets experienced similarly dramatic boom-bust episode prior to the 2000s, but the succession of boom-bust episodes in some markets more resemble a repeating cycle than isolated episodes (Figure 2 plots historical price series for house an example).

In this essay I study the dynamic character and historical and geographical prevalence of U.S. house price cyclicality.

The character and causes of house price cyclicality have been and remain hotly debated. A key question has been whether house prices are locally stable but subject to *shocks;*[6] or can exhibit temporary *bubble* episodes, uncoupling from fundamentals over extended periods (Abraham & Hendershoti, 1994; Clark & Coggin, 2011; Mikhed & Zem, 2009; Shiller, 1990).

While few now would argue that house price movements are orderly and driven entirely by obvious changes in fundamentals,[7] nevertheless economic theory suggests a variety of market imperfections and/or 'alternative'[8] behavioural assumptions that may amplify fundamental shocks – key examples are credit-constraints (Ortalo-magné, 2006; Stein, 1995),[9] search market externalities (Diaz & Jerez, 2013; W. C. Wheaton, 1990), (policy) constraints on the elasticity of supply (Glaeser & Gyourko, 2007), and e.g. backward-looking expectations schemes (Capozza, Hendershott, & Mayer, 2002; Karl E Case & Shiller, 1988).[10]

While economic theory suggests many reasons housing markets may generate larger swings in house prices than seem justified by fundamentals, the enormous increases and subsequent crashes in house prices during the 2000s boom-bust, as well as the range of evidence on the role of speculation during this time,[11] have led many to argue that housing cycles are driven not by fundamental shocks, but by psychological factors – an argument that has

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[6] Can housing market fluctuations be explained as the adjustment process of house prices and stocks towards a new stable equilibrium following an exogenous shock to fundamentals (real and/or financial such as e.g. population, real income, interest rates and credit markets etc.)?

[7] It has long been widely documented in the literature that models based on equilibrium adjustment of prices in response to fundamental shocks in perfect foresight rational expectations setting do a poor job empirically of explaining housing market boom-bust in terms of observed fundamentals (see e.g. surveys of the literature going back at least to the 1980s by Gatzlaff and Tirtiroglu (1995), and Maier and Herath (2009) as well as more recent studies such as Schindler (2013)).

[8] I.e. 'deviations' from perfect foresight rational expectations setting.

[9] Also macroeconomic models which e.g. following Iacoviello (2005) introduce a housing based collateral constraint into New Keynesian financial-accelerator models (B S Bernanke, Gertler, & Gilchrist, 1999) generating pro-cyclicality among house prices, and household borrowing and spending.

[10] Where households are credit constrained, the capital gains resulting from price increases may relax borrowing constraints generating momentum on the way up, and visa versa on the way down; if increasing house prices bring more homes onto the market this increases available choice, reduces search time and improves match quality (potentially increasing prices) in a search and matching markets; planning and zoning policies restrict the elasticity of supply leading to larger price adjustments to positive and negative shocks.

[11] Just some examples of analyses that have emphasized and presented evidence of the important role of speculation in observed house price boom-bust (Albanesi, DeGiorgi, & Nosal, 2017; Barlevy & Fisher, 2011; Bayer et al., 2011; Bayer, Geissler, Mangum, & Roberts, 2015; Karl E Case, Shiller, & Thompson, 2014, 2012; Chinco & Mayer, 2012, 2016; Defusco et al., 2017; Gao, Sockin, & Xiong, 2017; Haughwout, 2011; Riddel, 1999).

featured prominently in popular financial and academic debate. Robert Shiller for example has long argued that irrational exuberance and unrealistic expectations of future price appreciation have played a defining role in housing market dynamics both at a metropolitan area level and in the national US boom-bust of the 2000s (see e.g. Shiller (2005); Ackerloff and Shiller (2009)).

Both equilibrium adjustment in response to a one-time fundamental (or non-fundamental) shock; and explosive bubble dynamics as a result of e.g. an episode of irrational exuberance, describe *temporary* phenomena.

Nevertheless either process could provide an episodic explanation for the sort of repeating boom-bust cycles that many local housing market price series seem to exhibit: a series of random shocks could generate a 'cycle' in the sense of successive periods of expansion and contraction (closely analogous to modern business cycle theory) (Bracke, 2013); alternatively if markets are "bubbly" enough (i.e. if bubbles easily emerge but inevitably burst) this explosiveness could be the engine behind a cycle formed by a sequence of bursting bubbles (Evans, 1991; Shi, 2007).[12]

Under this episodic view of housing cycles - with each cycle being driven by different shocks or bubbles and limited dependence between one episode and the next - housing cycles might recur, but would be fundamentally *irregular* and *unpredictable* (although they may have distinct time series signatures, with temporarily explosive dynamics the hallmark of a bubble process (Greenaway-mcgrevy & Phillips, 2015; Hu & Oxley, 2018a; Efthymios Pavlidis et al., 2018; Shi, 2017)).

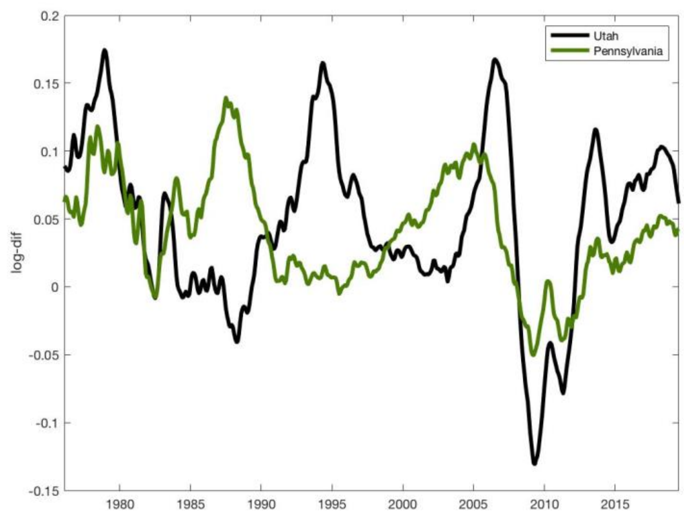

Figure 2: This chart plots log-differences of monthly house price indices for the states of Pennsylvania and Utah since Jan 1975, illustrating the sort of repeated boom-bust historically experienced in many markets.

A further dynamic possibility, that has been shown theoretically to arise in various (especially heterogeneous agent) settings (e.g. Baptista et al. (2016), Defusco et al. (2017), Dieci and Westerhoff (2012a, 2016), He et al. (2015),

[12] In extreme the price formation process does no temporarily destabilise, but always explosive, however bubbles cannot grow forever so eventually collapse.

Sommervoll et al. (2010), Ryoo (2015), Ulc (2015) are some examples),[13] is that repeating boom-bust house price cycles could be the result of limit-cycle (i.e. on-going fluctuations around a locally unstable equilibrium meaning cycles occur even in the absence of shocks) or near limit-cycle dynamics (i.e. shocks may give rise to repeating cycles with a stable frequency but decaying amplitude thus the amplitude of cycles depends on perturbations).

In either case cycles would not only *recur*, but recur with some *predictability* (although if such intrinsic cyclic dynamics existed they would of course also be altered by external perturbations and irregular cycles can emerge from the regular forces of a limit cycle setting when combined with shocks that move the system away from an attracting orbit (P. Beaudry, Galizia, & Portier, 2016b)).

In the empirical literature on housing market instability, some strands focus specifically on extreme or "pathological" episodes consistent with the idea of occasional discrete sub-periods of instability, while others have been more interested in housing "cycles".

In particular the empirical "bubble" literature seeks to identify discrete bubble episodes based on their time series signature (generally tests for explosive behaviour) (see e.g. (Freese, 2015; Hu & Oxley, 2018a; Kivedal, 2013; Efthymios Pavlidis et al., 2018; Phillips & Yu, 2011; W. Zhou & Sornette, 2005)); while a more macro-financial literature studies the occurrence, causes and economic impact of occasional "boom" and "bust" episodes (which tend to be identified in terms of prices considerably and persistently out of line with an estimated historical reference level (Bordo & Jeanne, 2002) or trend (Agnello & Schuknecht, 2011; Borio & Lowe, 2002)).

Meanwhile a large, macro motivated literature relying mostly (though not exclusively)[14] on aggregate national level time series, studies housing cycles in the traditional business cycle sense of alternate phases of expansions and contractions (generally identified through turning points analysis) and their relationship to other variables (such as credit and GDP) ((Bracke, 2013; Claessens, Kose, & Terrones, 2011; Girouard, Kennedy, van den Noord, & André, 2006; Leamer, 2007) are just some examples).

While the interesting theoretical possibility of endogenous housing market cycles seems to have become increasingly considered in recent years (Baptista et al., 2016; Dieci & Westerhoff, 2012a, 2016; He et al., 2015; Ryoo, 2015; Sommervoll et al., 2010), to the best of my knowledge the empirical motivation and validation for these models is often rather cursory and hand-waving. I am unaware of any serious empirical work testing for permanent house price cycles and good methods for studying this problem may not have been readily available to the literature.

Econometric methods employed in empirical housing cycle research may either fail to identify or even miss-characterise permanent cycles in the data:

Beaudry, Galizia and Portier (2016a) show that standard unit root-tests systematically fail to identify local instability in data generated by a limit-cycle

[13] Wheaton (1999) is an unusual early example of consideration and modeling of endogenous cycles as a relevant possibility and characterizing some markets.

[14] Some exceptions are Ghent et al. (2010) who studies whether the results of Leamer (2007) on housing as a leading business cycle indicator hold a the sub-national level; of Akimov et al. (2015) apply turning point and concordance index based methods to the study of metropolitan Australian house price series.

process, mistaking non-explosive (globally stable) dynamics for equilibrium reverting (locally stable) behaviour.

Similarly Evans (1991) shows standard unit root tests mistake periodically collapsing bubbles (a non-equilibrium process) for a mean reverting time series.[15]

Moving window (Chong & Hurn, 2017; Shi, 2007) and recursive (Phillips, Shi, & Yu, 2015b, 2015a; Phillips, Wu, & Yu, 2006) unit-root tests subsequently introduced in response to Evans (1991) and now widely applied in the econometric bubble identification literature, are designed to identify *time localised* explosive autoregressive behaviour in a non-stationary signal (test for explosive real root) and do not provide a test for or characterisation of sinusoidal components in a time-series. They may thus miss linear cycles and potentially miss-characterise explosive phases in a nonlinear limit-cycle process as a series of temporary bubbles.

Meanwhile turning-point based methods widely applied in business cycle literature may struggle to parse noisy data (e.g. in the sort of stochastic limit cycle setting considered by Beaudry et al. (2016b)) or make sense of complex spectral structure (where more than one sinusoidal component is present in a signal).[16]

Methods that are designed for testing for the presence of sinusoidal components to time series dynamics sometimes employed in the business cycle/economics literature include Fourier based methods (it is well known that an oscillation contributes a non-zero frequency spectral peak to the Fourier spectrum)[17] and explicit time series tests for complex unit roots (it is well known that each pair of complex roots in an autoregressive process contribute and oscillation). Unfortunately both suffer from important limitations.

Fourier based methods employed in the business cycle literature (and employed by Beaudry et al. (2016b) in specifically this context), whilst model and assumption free and providing spectral detail, since the transform aggregates across time, are unsuitable for non-stationary signals and shed no light on time varying aspects of dynamics (e.g. transient dynamics may generate a spectral peak, meanwhile time-evolving frequency of a well defined cycle can result in a broad spectrum).

Meanwhile a drawback of methods used to test for complex unit roots (Bierens, 2001; Gil-Alana, 2007; Gil-Alana & Gupta, 2014) is that the parameter estimates are sensitive to the class of models considered and may be misleading because of misspecification. While methods have been introduced to identify multiple cycle components (Gil-Alana, 2007), similarly to Fourier transform these are obtained over the entire sample window, and model estimation may be hampered by nonstationarities.

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[15] Note Evans periodically bursting bubbles come very close to a limit cycle process, except that the bubble is not contained by deterministic dynamics, but rather bursts randomly (with probability in every period).

[16] Some of these issues for turning-point methods may be mitigated by filtering. However filtering introduces its own problems such as the need for *a priori* choice of bands, and potential distortions (E.g. Cogley & Nason (1995) have shown that the HP filter can induce cycles into filtered data). By contrast the wavelet based analysis which I employ provides a time-frequency expansion of the signal, and is a reversible transformation – no information is thrown away. The time-frequency decomposition means no filtering is required in order to makes scale specific analysis.

[17] Gray (2013, 2015) are rare examples of Fourier methods applied in housing market analysis.

In this paper, I use wavelet power spectrum analysis – which has been shown to be useful in distinguishing periodic signals in data generated by noisy dynamical systems, and analysing time varying oscillatory data - as a simple method by which to study whether regional house price dynamics exhibit any evidence of persistent or permanent cyclicality; in which markets; and over what historical period.

This is based on the projection of house price series into the *time-frequency* plane where its spectral content can be followed over time.

Where the bubble identification literature employs time-localised tests for zero-frequency unit roots to date the onset of bubble episodes; I use the time-frequency localised wavelet power spectrum to assess whether there is any evidence of non-zero frequency spectral ridges - the time series signature of a cyclical process - and date the onset of any such cycles. [18]

Concretely I study the wavelet power spectra of monthly state level house price series from when data becomes available in Jan 1975 to the present time. Stochastic shocks and measurement error undoubtedly play a role in house price series. The question is whether some regularities are also empirically observable in the data. The answer is yes: I find surprisingly striking evidence of persistent or permanent cycle components with stable cycle frequency (estimated based on the local peak of spectral ridge in time-frequency plane) over the entire historical sample period for the majority of US states.

What is more an analysis of the distribution of instantaneous frequencies of state level cycles, suggests that most states share cycles with similar periodicities of c.10 years.

The existence of these clear longstanding cyclical components with fairly stable periodicity provides evidence consistent with a significant deterministic/intrinsic component to housing cycle dynamics, motivating further work to distinguishing between e.g. limit-cycle and noise driven oscillations; as well as to discriminate between competing hypotheses regarding the likely underlying cycle mechanism.

The geographically widespread incidence of permanent cycles spanning both the *local* and *national* housing instability eras, suggests a surprising continuity of dynamics between these periods as observed at the state level and raises the important question why the long history of cycles observable at the state level, does not show up at the national level – especially given the similarity of cycle periods - and contribution (if any) these existing persistent cycle components played in the national boom-bust of the 2000s.

Indeed, besides changing our understanding of house price dynamics at the individual market level, evidence of some periodic tendency to house price dynamics in state level data may also have wide ranging implications for our understanding of housing market dynamics at the national level.

In what follows I first introduce the wavelet methods employed in this study (Section 2.2) and briefly discuss their advantages over traditional and other available techniques, also providing some simulation based demonstration of these capabilities (Section 2.2.4). Section 2.3 presents my analysis and results, of which I make some discussion in Section 2.4. Section 3.6 concludes.

[18] Distinct from the flat spectrum of pure noise, or increasing power with decreasing frequency that characterises auto-correlated noise.

2.2 Methods

Methods describing the cyclical properties of economic data widely employed in business cycle analysis, and likewise housing cycle studies, include the analysis of turning points (e.g. Claessens et al. (2012)), frequency-based filter methods (e.g. Drehmann et al. (2012)), and also traditional Fourier analysis (e.g. Strohsal et al. (2015)).

The frequency domain representation of a time-series allows observation of several characteristics that may be difficult to see, or not visible at all in the time-domain or based on other available methods. The spectrum quantifies the importance of cycles of different frequencies in explaining the data. As is well known, if the spectrum of a time series displays a substantial peak at a given frequency, this is an indication of recurrent cyclical phenomena at that frequency (P. Beaudry et al., 2016b).

Wavelets transform based time-frequency methods provide another less well-known (anyway in economics) approach with a number of distinct advantages over traditional Fourier methods: where the Fourier transform decomposes a time series into a sum of sine and cosine functions (thus not time-localised), wavelet analysis uses a set of functions locally defined in both time and frequency domains. As a result wavelet based methods are suitable for studying time varying or transient dynamics and for analysing non-stationary time series, leading them to be widely used in many fields of research,[19] and increasingly adopted within economics since Crowley (2007), Soares & Aguiar-Conraria (2011), and Aguiar-Conraria & Soares (2014) especially in studying cyclical properties of economic and financial time series, and their cyclical comovements.

With the wavelet transform no information is thrown away and all scales[20] are considered, but the separation of scales by the time-frequency decomposition provided allows scale specific features in the data to be identified and studied. One key advantage of wavelets transform based methods is thus that they allow scale-specific analysis without requiring any prior assumptions on cycle frequencies or prior filtering of the data, avoiding the risk of missing relevant features or introducing distortions/artificial features.[21]

2.2.1 Continuous wavelet transform

The continuous wavelet transform, decomposes a time series into "stretched" and "translated" versions of an analysing function – "mother wavelet" ψ - that is well-localized in both time and in frequency domains, in order to obtain an expanded *time-frequency* space representation of the original signal.

Given a time series $x(t)$, its continuous wavelet transform (CWT), with respect to the analysing wavelet ψ (Eq.1), is a function of two variables (a and τ) defined as

[19] Wavelets analysis is widely employed in a range of applied sciences (it is extensively used in physics, neuroscience, epidemiology, ecology, climate science, seismology, signal processing, etc.).

[20] All scales meaningful given the length and sampling rate of the time series.

[21] E.g. Cogley & Nason (1995) have shown that the HP filter can induce cycles into filtered data.

$$W_{x;\psi}(a,\tau) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} x(t)\bar{\psi}\left(\frac{t-\tau}{a}\right) dt \qquad (1)$$

where the over-bar denotes complex conjugation; a is a "scaling" factor that controls the width of the mother wavelet; and τ is a "translation" parameter controlling its temporal location. 'Scaling' a wavelet means to stretch or compress it, and 'translating' means to shift its position in time.

Obtaining the CWT can be thought of as a "template-matching" procedure, in which each time point in the signal is compared against a template (the stretched/dilated wavelet). By considering each time point and continuously varying[22] the scaling factor a (which can be easily translated into frequency – see 10.1.1), the result is a matrix of wavelet coefficients ("similarities" between the time-series and the wavelet), with elements each corresponding to a scale a and time location τ. By mapping the original time series into a function of a and τ the CWT simultaneously gives us information on both the time and frequency distribution of variation in the time series.

When the wavelet ψ is complex-valued (see also Section 2.2.3 below), the corresponding wavelet transform $W_{x;\psi}(a,\tau)$ is also a complex-valued function of *scale* and *position* and may be separated into its real part $\Re\{W_{x;\psi}(a,\tau)\}$ and imaginary part, $\Im\{W_{x;\psi}(a,\tau)\}$, thus yields time-frequency localised information about both the *amplitude* and *phase* of a time series.

2.2.2 (Scale normalised) wavelet power spectrum

The local *wavelet power spectrum* (WPS) is computed by

$$(WPS)_x(a,\tau) = \left|W_{x;\psi}(a,\tau)\right|^2 \qquad (2)$$

This gives us a measure of the variance distribution of the time-series in the *time-scale* plane (where *scale* relates to *frequency* see 10.1.1).

This usual power spectrum (Eq.2) is biased toward low frequencies. In order to allow for a comparison of the spectral peaks across different scales, in the following analysis each energy value of the power spectrum is divided by the scale to which it corresponds, following Liu et al. (2007) who demonstrate that

[22] Of course in practice for the purpose of data analysis we must make a discretization of the scale parameter a, and need to choose how finely to discretize/sample it (how smoothly to vary a between minimum and maximum scales – lower and upper periods - of analysis) i.e. choose a frequency *resolution* of the decomposition. The cost to higher resolution is only computational. A key choice of course is the lower and upper period of the decomposition. The lower period has a minimum feasible at $2dt$ where dt is the sampling rate (studying oscillations with a higher frequency than this would require a more granular sampling rate). Because my data is monthly this would correspond to fluctuations with a 2-month period. Because I am only interested in explaining variation of periodicities beyond seasonal variation, I choose 1-*year* as my lower period (but still benefit from the improved resolution provided by monthly sampling rate of the house price data). The upper period of the decomposition has a maximum feasible upper limit of $length(x)dt$ (which corresponds to a cycle period equal to the length of the entire time-series). However edge effects make it pointless to analyze periods that approach this limit. I present analysis for an upper period of 20 years and clearly mark areas where edge effects may be distorting results.

this normalization provides a simple and effective solution to the bias problem in the estimate of wavelet power spectra.

The global wavelet power spectrum is defined as the average energy (average variance) contained in all wavelet coefficients of the same scale, a, over all time (thus may be compared to the Fourier spectrum of a signal).

$$(GWPS)_x(a) = \int_{-\infty}^{\infty} \left|W_{x;\psi}(a,\tau)\right|^2 d\tau \qquad (3)$$

2.2.3 Choice of wavelet function

There are several wavelet functions available with differing characteristics and the appropriate choice of analysing function depends on the application. For this application (and throughout the thesis) I employ the widely used *Morlet* wavelet (Goupillaud, Grossmann, & Morlet, 1984).[23] This wavelet is a complex exponential modulated by a Gaussian (see Figure 3 for a visualisation)

$$\psi_{\omega_0}(t) = Ke^{i\omega_0 t}e^{-\frac{t^2}{2}}, \;\; K = \pi^{-\frac{1}{4}} \qquad (4)$$

My interest not only in the *frequency* and historic timing of important shocks or cyclical episodes in house price dynamics, but also to analyse the *temporal relationship* between house price fluctuations in different regions (later sections 3-0), requires the application of a complex-valued wavelet - in order to obtain an estimate of local[24] instantaneous *phase* as well as *amplitude* (see Section 2.2.1 above)[25]. Among complex-valued wavelets, the *Morlet* provides optimal joint time–frequency resolution;[26] and under certain parameterisation[27] allows easy interpretation of scales a in terms of Fourier *frequencies*[28] f (thus also *periodicity* $\left(\frac{1}{f}\right)$, which may be far more intuitive in economic applications) simplify interpretation of results (see 10.1.1 for a more detailed explanation of this relation).

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[23] First introduced by Goupillaud, Grossman, and Morlet (1984) this wavelet is a complex exponential modulated by a Gaussian and its simplified version can be represented as: $\psi(t) = \pi^{-1/4}e^{-i\omega_0 t}e^{-t^2/2}$.

[24] In the vicinity of each time/scale location (τ, a).

[25] Phase is undefined for real-valued wavelets. The useful features of analytic wavelets are sited by Olhede & Walden (2002) and covered in depth by Lilly & Olhee (2009), Aguiar-Conraria et al. (2008, p. 2868) and Hudgins et al. (1993).

[26] In the sense that the Heisenberg uncertainty attains the minimum possible value.

[27] If the dimensionless frequency ω_0 is set to 6.

[28] See Torrence & Compo (1998).

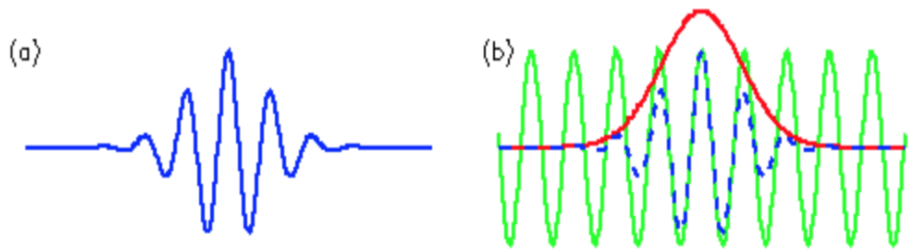

Figure 3: (a) Morlet wavelet of arbitrary width and amplitude, with time along the x-axis. (b) Construction of the Morlet wavelet (blue dashed) as a Sine curve (green) modulated by a Gaussian (red).

2.2.4 Demonstration of wavelet power spectrum

The continuous wavelets transform, only recently introduced to economics but increasingly widely employed (Aguiar-Conraria & Soares, 2011; Aloui & Hkiri, 2014; Crowley & Mayes, 2008; ECB, 2018; Flor & Klarl, 2017; Klarl, 2016; Li, Chang, Miller, Balcilar, & Gupta, 2015; Reboredo, Rivera-castro, & Ugolini, 2017), offers a number of key advantages well known in other literatures that make it useful in this application.

These include (i) their ability to reveal cyclical components even in noisy dynamical systems;[29] (ii) parse complex spectral content (e.g. multiple cycle components); and crucially (iii) optimisation of the uncertainty principal trade-off between temporal and spectral resolution - thus usefulness for studying time varying or transient dynamics and suitability for analysing non-stationary time series (useful for long historical analyses where the probability of finding marked non-stationarities/interesting shifts and structural breaks increases with the length of the time series).

As recently argued by Beaudry et al. (2016b) irregular fluctuations may emerge as the interplay between exogenous shocks and endogenous cycles. In this sort of setting wavelets analysis should have some power to distinguish the signature of the cycle dynamics in the signal from the spectrum of the stochastic environment in which it is embedded (which will depend on the specific process but will not have a preferred period).

[29] See e.g. Mallat (1998) .

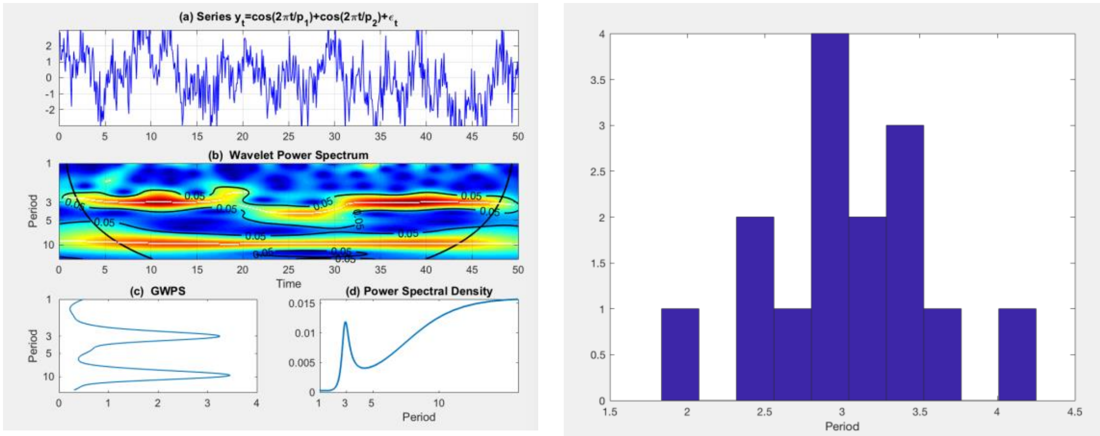

Figure 4: This chart plots (b) the wavelet power spectrum, (c) the global wavelet power spectrum, (d) the Fourier spectrum, and (e) a histogram of the cycle durations (peak-to-peak) as calculated based on turning points (obtained using the widely employed Bry-Boshan (1971) method), for the same time series which was simulated as two periodic cycle components, one with some transient dynamics (a temporary shift from periodicity of 3 to 4), and some auto-correlated noise.

Wavelets have a number of distinct advantages over the better known Fourier spectrum – in practice even transient dynamic may generate a spectral peak in the Fourier spectrum; meanwhile an abrupt shift in the frequency of well defined cycle may generate a broad spectrum. The wavelet based time-frequency projection by contrast allows the stability of a spectral peak to be assessed over time, where stability provides evidence of a preferred period (something an auto-correlated noise process does not have).

Some of these (relative) capabilities/properties of the wavelet power spectrum are briefly demonstrated/illustrated based on the following two applications to simulated data: **Figure 4** (a) presents the scale normalised wavelet power spectrum for a time series simulated as two periodic cycle components with the same amplitude but different periodicity, one with some transient dynamics (a temporary shift from periodicity of 3 to 4), and some auto-correlated noise.

We see that the power spectrum does a good job of distinguishing the two periodic components, and the temporary frequency shift against the background noise spectrum. (b) Shows the effectiveness of the normalisation procedure in facilitating the comparison between spectral peaks at different frequencies, with GWPS showing two peaks of similar magnitude centred at relevant periodicities. (d) The Fourier spectrum picks up the first peak but the second is obscured by spectrum of the auto-correlated noise, meanwhile transient dynamics and other temporal information are entirely lost. (e) Presents a histogram of cycle durations based on turning points obtained via commonly used Bry-Boshan (1971) algorithm.

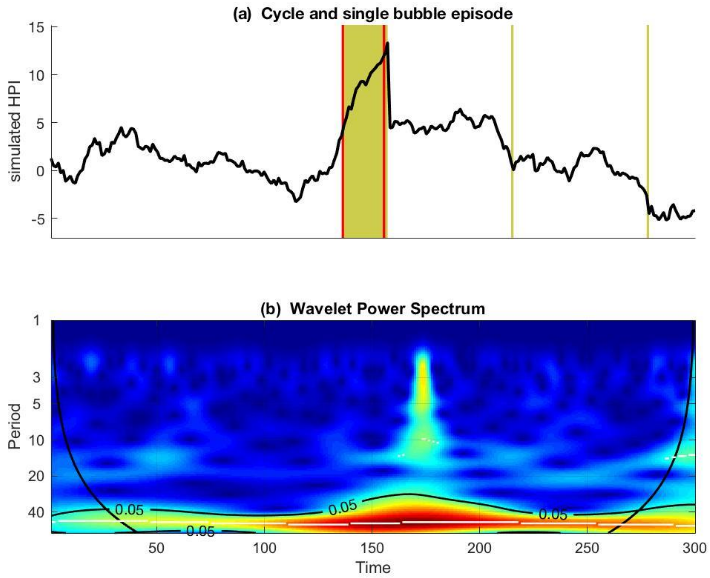

Figure 5: This figure presents (a) a time series simulated as a combination of a periodic cycle process (of 50 quarters so c.12 years) and a random walk process, with a single 'explosive episode'/'collapsing bubble', the true *onset* and *termination* dates for which are marked by vertical red lines. Meanwhile the green shading indicates the "explosive episodes" as identified by applying the PSY procedure (Phillips et al., 2015b) (95% level) to the simulated data – we see the procedure dates the single explosive episode almost exactly (as well as suggests two extremely short false positives). Meanwhile (b) presents the wavelet power spectrum for the same simulated series. This change of perspective via transformation very clearly highlights the 12-year cycle - this shows up clearly in time-frequency representation as a spectral ridge, the peak of which - white line in the centre of the area of high power - identifies the true cycle periodicity almost exactly (something obscured in visual inspection of the time series plot by the martingale and explosive dynamics).

Figure 5 presents (a) a time series simulated as a combination of a periodic cycle process (of 50 quarters so c.12 years) and a random walk process, with a single 'explosive episode'/'collapsing bubble' of the sort studied by the a number of studies of US and other housing markets which report evidence of temporary bubble periods (Hu & Oxley, 2018a; Efthymios Pavlidis et al., 2018; Shi, 2017) (the data generating process is set out in detail in Section 5.3.3.1.1). The true onset and termination dates for the bubble episode are marked by vertical red lines, meanwhile the green shading indicates the "explosive episodes" as identified by applying the procedure introduced by Phillips, Shi and Yu (2015a, 2015b) (95% level) which is employed by these empirical studies (I introduce this literature in more detail in Section 5.3.1).

This simulated example illustrates: (i) the usefulness of the PSY procedure for identifying temporary explosive dynamics; (ii) the usefulness of time-frequency methods for identifying cyclical components that may be obscured by other processes. While the bubble is clearly visible on inspection of the time-series plot, the PSY test provides an objective, consistent and accurate dating strategy.[30] Meanwhile the change of perspective provided by the wavelet

[30] Note one might e.g. easily (and incorrectly) have dated bubble onset earlier based on visual inspection.

transform of the series reveals the stable underlying periodic component (the 50 quarter or 12.5 year cycle) very clearly – something otherwise obscure in the combined signal and in fact making only a limited contribution to the overall variation in the series given its amplitude.

2.2.5 *Statistical significance*

The wavelet transform (from which the power spectrum is derived) is merely a transformation (projecting the signal onto the time–frequency plane). It is a useful transform because it can help to clarify certain structures in a signal - including periodic components - that may be obscured by noise, or the existence of multiple periodic or other dynamic components at different frequencies, and nonstationarities. As a mere transform no statistical test on the power spectrum is necessary as such - a spectral ridge in the time-scale plane is a spectral ridge in the time-scale plane. It is interesting nevertheless to ask whether the observed power spectra at a particular position on the time-scale plane are not due to a random process. The significance of a wavelet power spectrum is assessed by comparison with simulated or theoretical spectra representing a null hypothesis.[31]

In this study I use Monte Carlo methods (i.e. simulated spectra). Under this approach one starts with the observed time series, which are to be tested against the hypothesis of surrogate data generated in order to share some statistical properties with the original series, but which are generated by different random processes.

The choice of the null model is of course central and can affect the potential conclusions. While many studies assess against the null of a white noise process, this is inappropriate for house price (or other economic) time series given commonly observed persistence. In this study, I am interested in particular, in the question whether or not the cyclical fluctuations U.S. house price series exhibit are consistent with a random process – house prices may be susceptible to appearing to vary over long time periods solely owing to their stability over short time periods.

I test cycles in the wavelet spectrum against a null hypothesis that takes account of the highly auto-correlated character of house price series. Statistical significance is assessed with Monte Carlo simulations - the distribution of the wavelet power spectrum under the null hypothesis is constructed based on the wavelet power spectrum of N_{sur} surrogates, and the 95th percentile of this distribution extracted. Surrogates are obtained by fitting an ARMA(p,q) model to the series and constructing new samples by drawing errors from a Gaussian distribution.

The null hypothesis tested thus states that the *significant periodic characteristics of house price series studied are identical to those of an ARMA(p,q) process*. The synthetic series generated have the same mean, the same variance,

[31] In existing wavelets studies in the economics literature e.g. Crowley et al. (2010) assess the power spectrum against theoretical spectrum of an AR(1), and white noise background; Verona et al. (2016) do not explain significance test used.

a Gaussian distribution of their values and similar ARMA structure to the original series – obtained by fitting ARMA(p,q) model (which provides a flexible model structure) to each time series.[32]

2.3 Analysis and results

2.3.1 Assessing cyclicality of state level markets over sample period

In order to assess the time-frequency characteristics of state level house price dynamics, I obtain the local wavelet power spectrum (Eq.2) of seasonally log-differenced monthly house price indices for each of 50 U.S. states and the District of Columbia, 1975:01-2020:06.[33] **Figure 6** presents the results of this analysis for a selection of states and the interested reader is invited to inspect Appendix section 12.1 where (in the interests of space) the local power spectra for all 51 series are exhaustively presented.

In these charts, hot colours represent areas of high power (and cool colours areas of low power). Periodic components thus show up as 'spectral ridges' (narrow bands of high power over time). The white lines show the local maxima of the wavelet power spectrum undulations, providing an estimate of the cycle period. Black contour lines mark areas of statistical significance (95% level). Statistical significance has been assessed here with Monte Carlo simulations: in each case 2,000 surrogates are obtained by fitting an ARMA(1,1) model to the price series and constructing new samples by drawing errors from a Gaussian distribution. The surrogate series generated have the same mean and variance as the original series.

The null hypothesis tested thus states that the *significant periodic characteristics of the house price series studied are identical to those of an ARMA(1,1) process,* taking into account the highly auto-correlated nature of house price series - which could cause them to appear to vary over long time periods owing to their stability over short time periods (see methods 2.2.5). The black parabola marks the cone of influence (outside of which edge effects may distort results – see methods appendix 10.1.2).

Strikingly, while a small minority of states show no significant evidence of a periodic component to house price dynamics (Alaska, Mississippi, West Virginia);[34] most exhibit evidence of well-defined permanent cycles - these show

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[32] Since I want to test for cycles, in order to rule out complex roots in the null, I use ARMA(1,1) process.

[33] I use seasonally adjusted monthly Freddie Mac House Price Index data. The availability of monthly data (unlike widely used FHFA data which is available on a quarterly basis) improves temporal but also spectral resolution. I take seasonal log-differences of the data before obtaining wavelet transform and power spectrum. However using other standard price indices yields very much the same results. See appendix section 11.1 on house price data. The Freddie Mac House Price Index data employed in analysis presented here can be found at the following link:
http://www.freddiemac.com/research/indices/house-price-index.page

[34] It is interesting to ask why these specific states do not exhibit evidence of periodic components to house price fluctuations. Notably, from the 1970s through to the present decade West Virginia and Mississippi have the *smallest shares* of *urban dwelling population* (U.S. decennial census data the 1970-2010). Alaska is of course also a rather rural state with a lot of pace. This may suggest an explanation: metropolitan housing markets behave differently than rural housing markets, among other things being subject to greater supply constraints (in cities that lack construction land, urbanisation leads to price increases (Hilber & Vermeulen, 2012; Saiz, 2010)), and higher levels of housing transactions and churn. Glaeser et al. (2008) for example

up as clear spectral ridges over the entire sample period. In many cases these periodic components are statistically significant under the testing procedure employed (e.g. California, DC, Oregon, Washington), in others a spectral ridge, whilst not statistically significant, is nevertheless clearly visible in the power spectrum (e.g. Nebraska, Ohio, Texas).

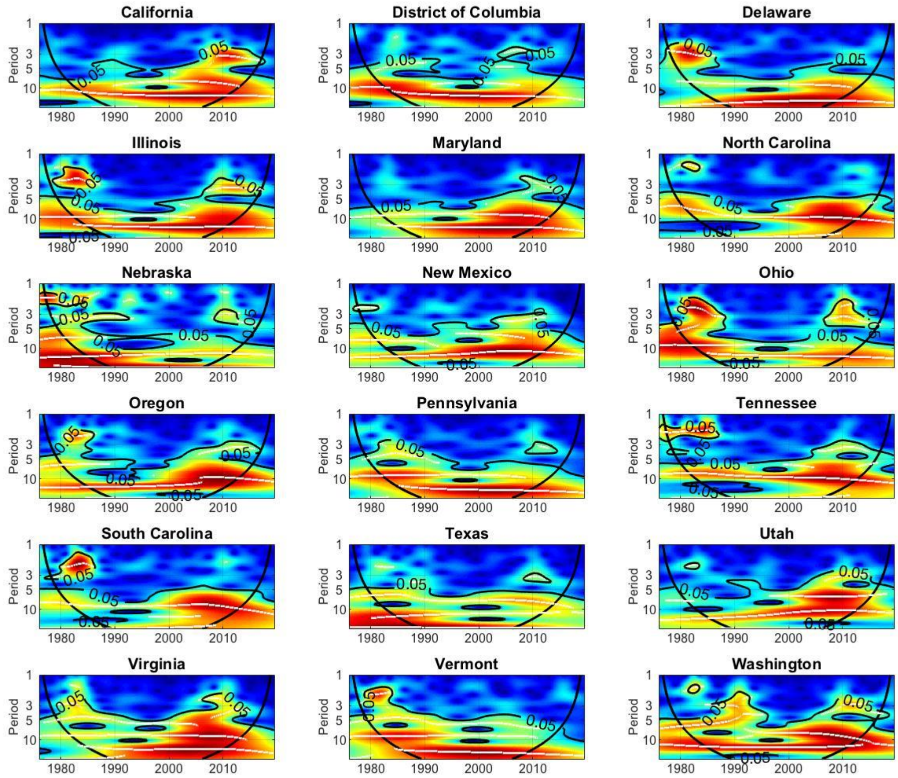

Figure 6: This figure presents example wavelet power spectra obtained for state level US house price series (transform obtained for seasonal log differences of monthly data – see footnote 33). Hot colours indicate areas of high power thus cycles show up as 'spectral ridges' (narrow bands of high power over time). The local maxima of spectral ridges are marked by white lines, providing instantaneous estimates of cycle periods. Black contour lines mark areas of statistical significance in the local power spectrum, assessed using Monte Carlo methods (based on 2,000 surrogate series) against null of ARMA(1,1) process. The parabola marks the 'cone of influence' outside of which edge effects may influence the spectrum.

Most states exhibit some evidence of two cycle components – in particular ridges are observed in the power spectra roughly around 9-10-year periodicity

illustrate that house prices in the U.S. grow much more strongly in metro areas with inelastic supply during boom phases and Huang & Tang (2012) found that supply constraints amplified the fall in house prices in U.S. cities from 2006 to 2009. Moreover supply elasticity has been widely argued to play a crucial role in both the onset and amplitude of speculative house price cycles (see e.g. from Malpezzi & Wachter (2005) to Dieci & Westerhoff (2016)). Future work might look at the empirical variation in cycle characteristics (such as cycle amplitudes) vs. market characteristics including supply constraints.

(implying c.5 cycles over the sample period spanned by the data) and roughly around 12-14-year periodicity (implying c.3.5 cycles over the sample period spanned by the data). This detail can be observed thanks to the effective separation of scales achieved by the wavelet transform of the data.

2.3.2 Comparing state level cycle periodicity across states and over time

In order to obtain a more precise assessment of relevant frequency bands and assess variation in cycle frequencies across different markets, I look at the *distribution* across all 51 series, of estimated instantaneous cycle periodicity (given by the local maxima of the wavelet power spectrum (Ramirez & Montejo, 2015). For an individual state these are the white lines visible in **Figure 6**).

The results of this analysis are presented in Figure 7 where I aggregate (a) across all U.S. states (but retain time-frequency dimensions) and (b) across both states and time.

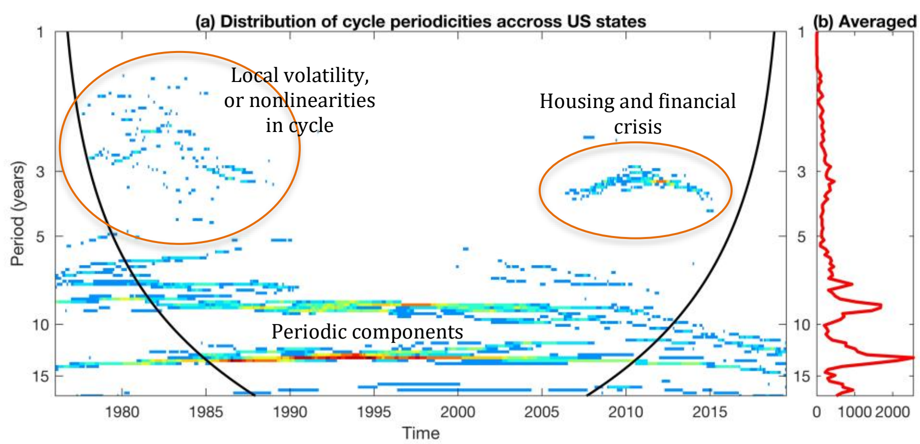

Figure 7: This figure presents the *distribution* of estimates of instantaneous cycle periodicity (given for individual states by the white lines in **Figure** 6), aggregated (a) across all U.S. states (colour represents the density, with hotter colours indicating higher density) and (b) across both states and time, from 1975 to 2020. This analysis reveals that the cycles exhibited by different states have remarkably similar periodicities with cycle components of between 8 and 10, and between 12 and 15 years. This is clearly indicated by the two sharp peaks in the density in figure (b) and the time-frequency information provided by chart (a) (where the cycles show up as narrow and clearly separated bands) makes clear that these common cycles are not only a feature of the national bubble episode, but have existed across the entire sample period. The crisis shows up clearly however as a well-defined area of density around the 3 year periodicity band between 2006 and 2014.

In Figure 7 (a) hotter colours indicate regions of higher density (i.e. multiple different markets with spectral peaks at the same frequency) - white areas are not associated with local spectral peaks.

This analysis reveals that the cycles exhibited by different states have remarkably similar (narrow distribution in frequency domain at each time step) and stable (limited temporal variation in the estimated instantaneous frequencies over time) preferred periodicities with cycle components of between 8 and 10 (c.5 cycles over sample period), and between 12 and 15 years (c.3 cycles over the sample period). This is clearly indicated by the two sharp peaks in the density in figure (b) meanwhile the time-frequency information provided by chart (a) (where the cycles show up as narrow and clearly separated bands) makes clear that these common cycles are not only a feature e.g. of the national bubble episode, but have been a national phenomena across the entire sample period – a particularly interesting result in the case of the 8-10 year periodic component given the longer time series dimension relative to cycle period.

Note that – as can be seen from inspection of individual power spectra in **Figure 6** – it is not the case that some markets have an 8-10 year cycle and some a 12-15 year cycle, but rather most states tend to exhibit evidence of both.

Transient dynamics associated with the crisis do clearly show up in the form of a well-defined area of time-frequency localised density around the 3-year periodicity band between 2006 and 2014. Meanwhile the scattered local peaks over a similar frequency band during the 1980s suggest more local volatility operating at higher frequencies, or local nonlinearities in the cycle over this period. The "whitespace" between 1990 and 2005 at periodicities less than 8 years is consistent with reduced contribution to house price variation from these higher frequency bands over this period.

2.3.3 How geographically widespread has cyclicality been over sample period?

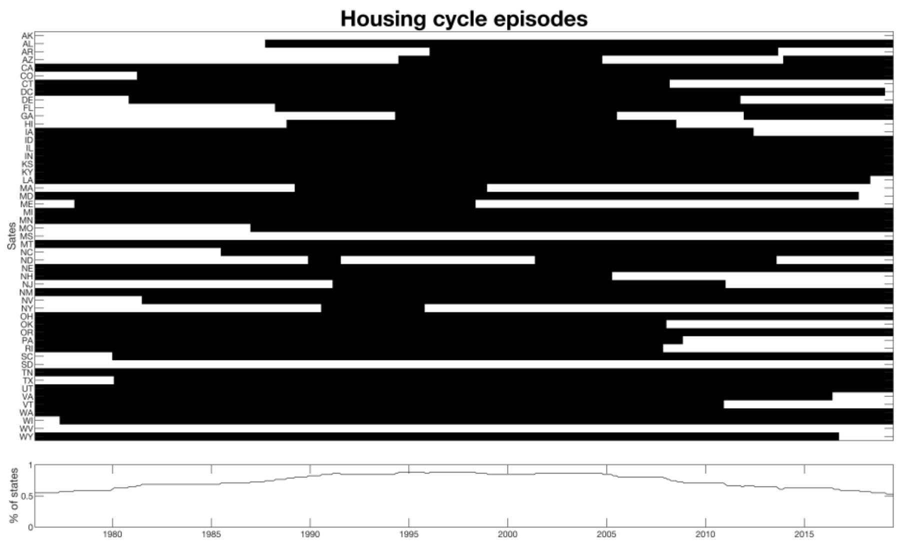

Figure 8: This presents a summary of which states exhibit cyclicality in 8-15 year periodicity band over the 1975:01-2020:06 sample period. In (a) each row represents a state over time: black represents a cycle episode, while white indicates the absence of a statistically significant peak in the power spectrum over the periodicity band. (b) plots the percentage of US states classified as exhibiting a cycle episode at each time step.

Given that many states exhibit evidence of permanent cycles (**Figure 6**) with very similar periodicities (Figure 7) it is interesting to assess in a systematic and quantitative way, the geographical prevalence of cyclical episodes across US states over time. To do this I define a binary state variable at each time step for each market, equal to one if that market has a spectral ridge within the relevant 9-14 year periodicity band and zero otherwise (choice of periodicity band is based on analysis presented in **Figure 6** and in particular Figure 7 above in order to both capture the variation in cycle frequencies between markets and be robust to some drift in dominant frequency within this band over time). Figure 8 visualises this analysis: here each row represents a single state (see y-axis labels) and each column a month. Strikingly the majority of states exhibit periodic components in this frequency band over the entire sample period – permanent cycles. Note the percentage of states exhibiting cycle episodes at each time step is summarized at the bottom of Figure 8.

2.4 Relevant literature

The literature on house price instability is vast, and I have provided in the introduction a general review in order to contextualise this study. The question of endogenous cyclicality does not appear to have been empirically studied in the literature, although a small handful of studies attempt to estimate the behavioural parameters of agent-based housing market models based on national house price data (Bolt, Demertzis, Diks, Hommes, & van der Leij, 2014; Chia, Li, & Zheng, 2017; Kouwenberg & Zwinkels, 2015).

Wavelets analysis is widely employed in a range of applied sciences (physics, neuroscience, epidemiology, ecology, climate science, seismology, signal processing, etc.), and has become increasingly employed in economics since Soares & Aguiar-Conraria (2011) and Aguiar-Conraria & Soares (2014), especially in studying cyclical properties of economic and financial time series, and their cyclical comovements.

This work adds to a growing number of studies that have employed the wavelet power spectrum in order to assess the cyclical properties of economic and financial time-series (Aguiar-Conraria & Soares, 2011; Poměnková, Klejmová, & Kučerová, 2019; Verona, 2016).

Only a handful study house price cyclicality: Li et al. (2015) look at the wavelet power spectrum of the national annual transaction-based Shiller housing returns data for the U.S. from 1890 to 2012.[35] Verona (2016) looks at the wavelet power spectrum of national U.S. house price series since 1975 (data taken fro OECD.stat). Mandler & Scharnagl (2019) present the wavelet power spectra of national house price series for G7 economies. Zhou (2010) uses wavelet coherence to study the comovement between publicly traded real estate securities in different countries.

Only Flor & Karol (2017) use wavelet analysis to study sub-national house price cycles. They study MSA level data between 2001 and 2013 - c.10 years of data compared to the c.50 years of data I study here). A sample of this length of course makes it impossible for them to study lower frequency dynamics, and is only really suitable for analysis of variance in a 2-3 year periodicity band. As a result the c.10 year cycles I identify and study here is out side the scope of their analysis. It is not clear why they do not use the full historical time-series

[35] This data is available at: http://www.econ.yale.edu/~shiller/data.htm

dimension that was available to them given on the one hand the problem of edge effects (see methods appendix 10.1.2), and on the other hand the good temporal resolution provided by the transform.[36]

2.5 Discussion

Many sub-national housing markets in the U.S. exhibit a long history of repeated boom-bust. The dynamic character of these cycles represents an important question. A key debate in the literature has been whether house prices are stable but subject to shocks; or exhibit bubble episodes. A series of random shocks could generate a 'cycle' in the sense of successive periods of expansion and contraction (closely analogous to modern business cycle theory) (Bracke, 2013); alternatively if markets are 'bubbly' enough (i.e. if bubbles easily emerge but inevitably burst) this explosiveness could be the engine behind a cycle formed by a sequence of bursting bubbles (Evans, 1991; Shi, 2007, 2017). Indeed the multiple bubbles hypothesis is empirically supported by evidence of temporarily explosive dynamics (Hu & Oxley, 2018a; Efthymios Pavlidis et al., 2018; Shi, 2017) - the time series signature of an unstable bubble process (see Phillips (2015a) for an overview).

Whether cycles are being driven by successive shocks or bubbles, under this episodic view housing cycles might recur, but would be fundamentally *irregular* and *unpredictable*.

On the contrary the stable spectral ridges exhibited by the majority of sub-national markets suggest that housing cycles - while they may be subject to shocks thus exhibit some *noisy* behaviour and/or exhibit 'bubbly' behaviour - also have a cycle component with a preferred period, consistent with significant intrinsic cycle dynamics (i.e. persistent fluctuations around an either unstable or only weakly stable equilibrium).

This feature has not been previously documented and suggests a potential empirical relevance for models of endogenous house price cycles, which have up to now, received only limited theoretical attention and even less serious empirical motivation. This calls for further empirical work to further qualify and diagnose the cyclic dynamics in the data – e.g. to try and distinguish between limit-cycle and noise driven oscillations. It also calls for effort to develop theoretical models able to explain observed cyclicality, and strategies by which to test and empirically discriminate between alternative hypotheses regarding the underlying cycle mechanism.

These results thus suggest a possible need for a significant shift in our understanding of U.S. housing market instability at the local level. Perhaps even more importantly however, evidence of persistent cyclicality in sub-national markets also has a range of significant consequences for the sorts of dynamics that may potentially arise at a wider spatial scale with implications for the

[36] There are other important differences in their procedure (they employ MSA level data, first perform a clustering routine, then look at the power spectrum of the average price series for each cluster). However the simplest and most important reason why they failed to identify the cyclic behaviour I document, is that they only study data between 2001-2013 (c.10 years of data compared to the c.50 years of data I study here). They also study synchronisation of regional markets, something I will study in subsequent chapters obtaining, again, to very different results.

relevant theoretical framework within which to think about national house price (in)stability, and also e.g. spatial "ripple effects" widely studied in the real estate literature.

For one thing, in the presence of permanent cycles a temporary global shock can potentially have a permanent impact on the degree of co-movement among cycles - thus aggregate volatility – meaning the impact of a succession of common shocks could plausibly accumulate over time. What is more, local links between cyclical markets could give rise to local synchronisation and e.g. spatial-pattern formations across markets; or even the emergence of a national cycle via the endogenous synchronisation of cycles across different markets.

These interesting dynamic phenomena/possibilities have not, to the best of my knowledge, been considered in the real estate (or indeed wider economics) literature, not least because house price fluctuations have been assumed to reflect either idiosyncratic shocks or non-stationary bubble processes. They become relevant however, in the context of the evidence I present of widespread cyclical dynamics in markets across the U.S.

The presence of a permanent cycle component in sub-national markets thus implies nothing less than a need potentially to radically re-think our view of U.S. housing market instability and the conceptual and theoretical frameworks through which we approach it.

2.6 Conclusion

In this essay I used time-frequency methods to re-examine the cyclical properties of US house prices over time and across different markets based on monthly state level data covering the period 1975:01-2020:06.

While methods widely employed to characterise cyclicality in economic variables are not able to distinguish stochastic from regular, or episodic from permanent cycle dynamics, wavelets have been shown to be useful in this respect.

The time-frequency decomposition of house price variation provided by the wavelet power spectrum allows me to study the evolution of the spectral structure of house price cyclicality over time, thus assess whether and over what historical periods state level markets exhibit evidence of transient/episodic or permanent/persistent cycles.

I find surprisingly striking evidence of persistent or permanent cycles spanning the entire historical sample period 1975:01-2020:06 for the majority of U.Ss states. An analysis of the distribution of instantaneous frequencies for state level cycles suggests that most states share cycles with a similar periodicity (both 8-10 and 12-14 year fluctuations).

The existence of these clear cyclical components with fairly stable preferred periodicity provides evidence consistent with a significant deterministic/intrinsic component to housing instability, motivating further work to distinguishing between e.g. limit-cycle and noise driven oscillations, as well as to discriminate between competing hypotheses regarding underlying cycle mechanism.

The geographically widespread incidence of permanent cycles spanning both the local and national housing instability eras, also suggests a surprising continuity of dynamics between these periods as observed at the state level, and raises the important question why cyclical instability has not featured more prominently at the national level.

3 Essay 2: Co-movement of permanent cycle components: evidence of dramatic phase synchronisation across sub-national markets

Summary: In this chapter I study developments in the *co-cyclicality* of U.S. state level housing cycles over time. House price comovement across markets is an important issue for portfolio risk and for macro-financial stability. In Essay 1 (Section 2) I show using monthly state level data from 1975:01-2020:06, that the majority of subnational markets across the U.S. exhibit evidence of permanent cycle components of similar periodicities (in the 8-10 and 12-15 year periodicity range). In this chapter I study the *extent* and *evolution* of overall *comovements* among these cycles. For this purpose I introduce multivariate statistics based on an instantaneous *phase* and *amplitude* decomposition of the data (obtained here via complex continuous wavelet transform). These methods allow me to assess the contribution to average U.S. house price fluctuations from time-varying *phase-synchronisation* (ignoring magnitudes) vs. time varying similarities in the *amplitude-envelopes* of cycles across local markets. A comparison of (i) the mean of the power spectra of state level price series and (ii) the power spectrum of the mean of state level price series (providing a time-frequency decomposition of mean variance vs. variance of the mean), shows states across the US shared a common cycle component over the entire sample period, however this cycle only shows up as a significant feature of the national price index (based on simple mean) after 1995. My analysis of overall phase synchronisation across markets shows a dramatic transition from low to high *phase*-synchronisation of cycles occurred in the mid 1990s. I thus show that prior to the mid 1990s anti-phase relationships moderated the impact of common cycle components on aggregate house price volatility, but that after 1995 (coinciding with changes in mortgage finance) a dramatic phase synchronisation of existing cycles made a significant contribution to the national housing boom-bust over the subsequent period. There is also evidence of a marked *de*-synchronisation after the early 1980s, following a significant common shock in the early 1980s (that entirely averages out in national price index but is clearly revealed by the mean power spectrum analysis). The de-synchronisation between 1984 and 1995 coincides with on-going Savings and Loans company failures over this period, and the period over which de-synchronisation significantly moderates aggregate house price volatility (1984-2000), coincides closely with the "Great Moderation" period. These results provide rich new insight into the dramatic housing market gyrations of the 2000s, and the debate over the localness vs. national character of house price instability.

3.1 Introduction

Motivation

In this essay I study the *extent* and *evolution* of overall co-cyclicality of state level house price cycles across the U.S., over the available sample period 1975:01-2020:06. The covariation of regional housing markets is of course an issue of great importance: it is central to diversification opportunities, rating and pricing in mortgage lending and derivatives and housing investment portfolios (BIS Committee on the Global Financial System, 2005; Cotter et al., 2015; Cotter, Gabriel, & Roll, 2018; Coval et al., 2009; Sanders, 2008; Zimmer, 2012); and assumes particular significance given that aggregate house price fluctuations have come to be widely considered as a source of macroeconomic fluctuations (the empirical literature on housing spillovers and housing in the business cycle is very extensive. Some relevant examples are e.g. Leamer (2007), Cesa-Bianchi (2013), Iacoviello (2005), Liu et al. (2013)).

The widespread run-up and subsequent near simultaneous collapse of house prices in markets across the U.S. during the 2000s is well known. While the synchronicity of housing market gyrations during this period was unprecedented perhaps since the Great Depression era, periods of dramatic housing boom-bust have been far from uncommon at the sub-national level (Karl E Case, 1992; Karl E Case & Shiller, 1993; Riddel, 1999; Shiller, 1990).

It has been previously documented in the literature (see e.g. Del Negro and Otrok (2007) for an early study), that prior to the "national bubble" period of the 2000s, house price variation was dominated by idiosyncratic movements (consistent with local shocks or local bubbles), but that a common component dominated house price movements from the mid-2000s (consistent with the significant influence of a global/national shock or bubble during this period).

Similarly systematic studies by a recent empirical literature that employs time-localised tests for explosive dynamics (argued to be the hallmark of an unstable bubble - rather than equilibrium adjustment - process) find evidence of a history of bubbles in most markets prior to the national boom-bust, but finds bubbles arose simultaneously across the US during the 2000s, and burst even more synchronously in 2006-7 (Hu & Oxley, 2018a)[37].

The apparently idiosyncratic character of housing market instability before the 2000s and a traditional acceptance in the literature that idiosyncratic factors are the primary sources of shocks is in line with the apparently *local* character of housing supply and demand/as a non-tradable asset.

Meanwhile the national boom-bust of the 2000s is widely believed to reflect the emergence of significant common *national* drivers in house price formation during this period – a wide range of factors have been put forward including interest rates; mortgage credit and subprime lending; speculation and irrationality; and international capital flows.[38]

However in Essay 1 I have presented evidence that house price series for most states across the US exhibit striking evidence of a highly persistent or permanent cycle component of 8-10 year periodicity over the entire available sample period 1975:01-2020:06 (see analysis and results presented in Section 2).

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[37] Hu and Oxley (2018a) are surprisingly one of the few existing studies to make a formal comparison between the regional housing boom-busts of the 1980s - as studied in e.g. (Karl E Case & Shiller, 1993; Shiller, 1990)) - with regional bubbles during the 2000s (as has been widely documented there was significant regional heterogeneity in the magnitude and timing of regional house price movements over the national bubble period. See e.g. Sinai (2012)). Hu and Oxley (2018a) apply the univariate right-tailed unit root test procedure of Phillips et al. (2015b, 2015a) to state level data. This test was explicitly designed to capture forming and bursting bubbles and to "date-stamp" the beginning and end of the bubble to state level time series data for all US states and the District of Columbia.

[38] Interest rates (Campbell et al., 2009; Glaeser et al., 2013; Himmelberg et al., 2005); mortgage credit/market "innovations" and subprime lending (Dell'Ariccia, Igan, & Laeven, 2012; Favilukis et al., 2016; Levitin & Wachter, 2012; Mian & Sufi, 2009; Pavlov & Wachter, 2009; C. W. Wheaton & Nechayev, 2008); speculation and irrational bubbles (Barlevy & Fisher, 2011; Bayer et al., 2011, 2016; K E Case et al., 2005; Karl E Case & Shiller, 2003; J. M. Lee & Choi, 2011; Shiller, 2005; C. W. Wheaton & Nechayev, 2008); contagion and "fads" (Bayer et al., 2016; Burnside et al., 2016); and international capital flows (Favilukis et al., 2013, 2016).

This evidence of permanent cycles in state level data suggests a surprising continuity in house price dynamics as observed at the state level across the "local" and "national" instability eras. This sinusoidal component (non-zero frequency spectral ridge) to price movements is at odds with the irregular fluctuations implied by random shocks or the irregular boom-bust implied by occasional temporary bubble episodes; and distinct from the time localised (temporary) zero-frequency explosive root that is the time series signature of an explosive bubble process (Hu & Oxley, 2018a; Efthymios Pavlidis et al., 2018; Shi, 2017).

Moreover - and seemingly at odds with the common view that the shift from local to national instability in the 2000s reflected a shift from the dominance of idiosyncratic local, to common national factors in driving house price variation - there is strong evidence that the permanent cycle in state level data has been a *national* phenomenon (in the sense of a common feature: cycle periodicities are remarkably similar across different states (See Figure 7 in section 2.3)) not just during the national boom-bust episode of the 2000s but over the entire sample period.

Taken together the combined continuity of cycle dynamics as observed at the state level; and the similarity of cycle periodicities across different geographical markets, raises interesting questions regarding the relationship between state level cycles and their contribution to national house price movements: if states across the U.S. shared a similar cycle since the early 1970s, why was this not a source of national boom-bust over this entire period?

One obvious possibility is that while states share cycles of similar *periodicity*, there may be significant *phase shifts* between these cycles (after all, in a stylized example, two identical signals with a phase-shift of $\pm\frac{\pi}{2}$ will be contemporaneously uncorrelated with each other, or given a phase shift of π (anti-phase relationship) will not generate a mean cycle).

Moreover, what (if any) contribution did these cycles make to the national boom-bust of the 2000s?

Research questions and methods

In this essay I do not attempt to answer the question what factors can explain the similar periodicity permanent cycles observed in the data, but rather I study their co-cyclicality and how this may have varied or changed over time.

To address this problem I introduce multivariate statistics based on an instantaneous phase and amplitude decomposition of the data, obtained here via the continuous wavelet transform recently introduced to the economics literature (Aguiar-Conraria & Soares, 2014).

Wavelets analysis has the ability to identify not only time variation, but also abrupt shifts in the cyclic dynamics of population.

These allow me to identify common cycle components across state level markets and disentangle and quantify the contribution to aggregate house price variance from the time-varying *amplitude* envelope and time varying *phase-synchronisation* of these cycles as observed at the state level.

Existing literature

The question of how the co-movement of US markets has changed over time has been previously addressed in the literature, based on a variety of different methods, datasets, and sample periods. Methodologically these studies rely variously on: simple correlation analysis (Kallberg, Liu, & Pasquariello, 2014; Landier, Sraer, & Thesmar, 2017)[39] quantifying the tendency of prices across different markets to co-move from one time-step to the next; cointegration and error correction methods (Yunus & Swanson, 2013)[40] to test whether price differences between markets are mean reverting - thus whether regional housing cycles move around/share a common stochastic trend in the 'long-run'; latent factor models (Del Negro & Otrok, 2007)[41] or simple multivariate regression frameworks (Cotter, Gabriel, & Roll, 2011)[42] as a way to try and estimate the relative importance of common (respectively latent or observed) national (vs. idiosyncratic local) factors in house price movements; and spatial econometric models (Abate & Anselin, 2016)[43] in order to assess the co-movement of contiguous markets. In all cases these methods are made dynamic through the use of rolling-windows or recursive estimation.

All these studies seem to report a trend to increasing co-movement across subnational markets starting well before the housing and sub-prime crisis of 2006-8.[44] However

(1) The time-domain methods on which these studies rely are uninformative with regard to the character of common price dynamics driving these results - co-movement may vary across frequencies as well as over time thus it is important, in general, to question whether the trend to increased comovement is driven by long-run trend, cycles, or short-run volatility components of the data - here I am specifically interested to study the comovement of the 8-9 year cycles identified in Essay 1 (see Section 2);
(2) Correlation based methods are sensitive to both *phase* and *amplitude* variation, moreover rolling window based methods employed to make correlations dynamic are subject to a number of problems or biases in the

[39] Kallberg et al. (2014) using monthly data from Case-Shiller Home Price Indices for 14 MSAs between 1992 and 2008, find mean pairwise correlations (based on 30 month rolling window) experienced a sharp increase over this period; Landier et al. (2017) using state level data find the mean of pairwise correlations have increased between 1976–1996 (based on five-year-forward rolling window correlations with quarterly data).

[40] Yunus and Swanson (2013)

[41] Del Negro et al. (2007) estimate a dynamic factor model for state-level data 1986-2005 in order to disentangle the relative importance of the "common component" in house price movements from "local shocks" and report increased importance of the common component in the 2001-2005 period.

[42] Cotter et al. (2011) evaluate the average level of regional housing market integration over time by the R-squares from a multi-factor model fitted for a moving window and find an upward trend over the 2000s in the proportion of variance in house prices explained by "national factors".

[43] Abate and Anselin (2016) use the recursive estimation of a house price spatial econometric model for 373 MSAs during 1987:Q1 to 2014:Q3, find their spatial correlation coefficient has increased over time, indicating an increasing synchronization of house prices.

[44] Although I focus here on more dynamic methods, further evidence of increased co-movement also comes from other studies using a non-overlapping window/sub-sampling approach.

presence of cyclical dynamics [ref], and/or time varying volatility [refs] or phase-differences [refs] (as will often be the case) (see Section 3.2.2).

By contrast the phase-amplitude decomposition and time-frequency localisation made possible by the complex wavelet transform (Eq.1), provides the basis for a scale-specific analysis of time-varying co-movement that distinguishes *phase* and *amplitude* contributions and is robust to non-stationarity.

This also both provides the basis for a much more continuous measure, and is more robust to noise, than methods for quantifying phase-synchronisation based on the joint distribution of binary state variables (such as expansion/contraction (Harding & Pagan, 2003, 2006); or sign based deviations from trend (Bordon & Reade, 2013; Gogas & Kothroulas, 2009; Mink, Jacobs, & Haan, 2012))[45] widely employed in the existing business cycle literature (indeed I would go as far as to suggest they come close to the 'ideal' measure of cycle synchronisation the literature has sought (Bordon & Reade, 2013; W. Miles, 2015a; Mink et al., 2012) but not yet found).

Results

A comparison of (i) the mean of the power spectra of state level price series and (ii) the power spectrum of the mean of state level price series (providing a time-frequency decomposition of mean variance vs. variance of the mean), shows states across the U.S. shared a common cycle component over the entire sample period (1975:01-2020:06) however this cycle only shows up as a significant feature of the mean price index after 1995. These results are clarified by an instantaneous phase-based analysis, which reveals a dramatic phase synchronisation - starting in 1995 - of the common cycle component across state level markets. I also find evidence of a marked *de*-synchronisation starting in the early 1980s, coinciding with a significant common shock at this time that entirely averages out when price movements across different markets are aggregated, but is clearly revealed by the mean power spectrum of state level data.

Contribution and significance

With this analysis I am thus able to show that:

State level markets shared a common cycle component over the entire sample period, although prior to the mid 1990s the contribution from this common cycle component to aggregate house price variation was strongly moderated by anti-phase relationships among cycles in different markets.

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[45] Mink et al. (2012) introduce a statistic to quantify synchronisation among trend-deviation cycles (when cycles are defined as difference from trend) based on their *sign concordance* – the fraction of time movements in both series have the same *signs* (negative or positive output gaps). This sort of approach has in fact been used in other applications and was previously introduced in business cycle analysis by other authors e.g. Gogas and Kothroulas (2009)). They also introduce a statistic to quantify the similarity in the size of the output gap between one series and a reference series. These methods are applied for example in a recent paper from ECB working group on econometric modelling (ECB, 2018); and in a housing study by Miles (2015a).

After 1995 however, a dramatic phase synchronisation of this common cycle component across markets made a significant contribution to the aggregate housing boom-bust over the subsequent period.

These results provide rich new insight into the dramatic housing market gyrations of the 2000s and the trend to increased comovement across U.S. markets documented in the existing literature.

The existence of a significant common cycle component over the entire sample period is in contrast to the widely established result that a significant common component only emerged during the period associated with the national housing boom-bust and the idea that housing market instability was essentially a local phenomenon prior to the 2000s.

Meanwhile the synchronisation of the *existing* common cycle component raises interesting questions for analyses that look to explain the national boom-bust episode entirely in terms of the emergence of some important national factor as a common driver of house prices across markets over this period.

These results beg interesting questions regarding (i) the source of the cyclicality of sate level data; (ii) the cause of the de-synchronisation from the mid 1980s and (iii) the cause of the dramatic re-synchronisation starting in 1995.

While I do not draw any conclusions, it is interesting to note that the significant common shock indicated by the mean power spectrum in the early 1980s coincides with the introduction at this time of a whole raft of regulatory changes aimed at boosting savings and loans (S&L) companies resulting in a dramatic S&L expansion over this period (Chaudhuri, 2014; Federal Reserve Hisotry, 2013)) Meanwhile the entire de-synchronisation period from the mid 1980s-1995, coincides with the period of S&L failures not wrapped up until 1995 (Green & Wachter, 2005; Snowden, 1997).

Meanwhile the beginning of dramatic phase synchronisation from 1995 coincides not only with end of S&L failures but also with the Interstate Banking act of 1995 (e.g. Landier (2017) has linked housing market comovement to interstate banking) and a fundamental restructuring following the Savings and Loan crisis with mortgage finance shifting from being dominated by local 'balance sheet lending' by depositories, to a national market based system of securitized mortgage finance (Schnure, 2005).

It is also notable that the period 1985-2000 over which de-synchronisation of local markets significantly moderates aggregate house price volatility, coincides closely with the "Great Moderation" period. Whether or not there may be any causal links behind these associations, and the direction of influence, begs further study.

My results also seem to raise the question whether we should expect on-going cyclicality of U.S. house prices at the aggregate level given that phase synchronisation across state level markets remains as high today as it was during the last national boom-bust, meanwhile house prices and housing market liquidity have largely recovered or exceeded their pre-crisis levels, with some areas "running hotter" now than during the 2002-06 boom (Famiglietti, Garriga, & Hedlund, 2019).

The mean phase-angle as at June 2020 implies the current growth cycle in U.S. markets has peaked. However the power spectrum analysis in Section 2 suggests a moderation of cycle amplitude since the Global Financial Crisis, as well as a possible convergence of 9-12 year cycle components towards the 12-15 year cycles in the data. The presence of edge effects also mean we should be cautious in our interpretation of recent data at these frequencies.

Organisation of chapter

The chapter is structured as follows. In Section 3.2 I review existing empirical literatures relating to housing cycle synchronisation with an emphasis on the U.S.; then in Section 3.3 I separately review methods for studying synchronisation available in the wider economics literature (section 3.2.2) before introducing in detail, the novel methods and definitions I introduce for use in my analysis for this study (Section 3.3). Section 3.4 presents my analysis and results, which I discuss in section 3.5. Section 3.6 concludes.

3.2 Relevant literature

3.2.1 U.S. housing market co-cyclicality with an emphasis on methods

A common and natural hypothesis is that housing market fluctuations may reflect both national and local factors. Spatial dependence and spillovers, or other local links between markets may also be a source of co-movement across markets and are well-established themes in real estate economics.

Some studies attempt to estimate unobserved common factors using a latent factor decomposition approach (Del Negro & Otrok, 2007; Vansteenkiste, 2007) - a panel of price growth rates is decomposed into loadings on a low-dimensional vector of latent factors, and a vector of market-specific variation (satisfying weak cross-sectional dependence).[46]

This latent factor model approach typically does not allow for phase-shifts between common components (that may e.g. naturally arise as a result of local propagation), and by assuming local components are independent from each other, preclude the meaningful study of bilateral linkages between markets as a source of co-movement across all markets.

While such a variance decomposition is always possible, care must thus be taken in its interpretation as common shocks, rather than the result of endogenous co-movement generated by the interactions between different markets (a concern raised for example by Carvalho (2019) in the analogous context of production networks).

Investigating the role of local links in co-movement presents some methodological challenges. Local dependencies between markets - especially spatial dependence - are well-established themes in real estate economics. However standard spatial econometric models may fail in the presence of strong cross-sectional dependence (generally requiring weak forms of cross-sectional dependence, in the sense that dependence decreases sufficiently quickly along the spatial dimension (Chudik, Pesaran, & Tosetti, 2011; Pesaran & Tosetti, 2011)).

[46] This approach is also widely employed in the study of international house price cycles. E.g. Hirata (2013), Cesa-Bianchi (2013), Igan et al. (2009) are just some examples.

What is more, the spatial coefficients yielded by these models provide only a measure of contemporaneous local correlation averaged across links (adjacent pairs based on the introduction of a spatial adjacency matrix) and across the sample period or window.

Even where dynamic spatial effects are considered through the inclusion of a time-lagged spatial correlation (Baltagi & Li, 2014; DeFusco et al., 2013), the resulting spatial coefficients in either case provide only a measure of average spatial dependence, and do not provide any information on spatial patterns.

Some studies employ methods designed to accommodate both common factors and local links between markets as a sources of correlation (Pesaran, 2006; Pesaran & Tosetti, 2011): first using variation that can be captured by a common component to control for strong cross-sectional dependence, then studying residual spatial dependence across the idiosyncratic components using a standard spatial econometric model (e.g. spatial autoregressive model) (applications in U.S. housing market context include (Baltagi & Li, 2014; S Holly et al., 2010)).

Although studies employing this approach still find significant spatial dependence (Baltagi & Li, 2014; S Holly et al., 2010), this methodology also starts from the assumption that covariance that can be captured by common components is driven by common factors. What is more, the standard spatial model estimated based on residual covariance, again only provides a test of spatial dependence based on average correlations.

The considerable existing empirical "ripple-effect" literature - which researches spatial propagation of house prices - has mostly relied on cointegration tests for convergence (Meen, 1999), asking whether markets move around/share a common stochastic trend in the 'long-run' (whether they move together over time exhibiting mean-revering "spreads") and rely on restrictive assumptions on the order of integration of time series.

The existence of a "ripple-effect" (in the simple sense of spatial propagation of disturbances) might occur however even in the absence of long-run convergence; what is more even where convergence occurs cointegration tests do not measure the synchronisation or reveal the spatio-temporal pattern of short run adjustments or provide a dynamic view of the data.

Indeed studies for the U.S. in fact report mixed but limited evidence of convergence for U.S. markets and this has been argued to cast doubt on the existence of a ripple-effect (Clark & Coggin, 2009; Gil-Alana et al., 2014; S Holly et al., 2010; Pollakowski & Ray, 1997).[47]

While these methods all provide time-averaged estimates of co-movement, some studies have employed rolling-windows or recursive estimations in order to address the question of how the co-movement of U.S. markets has changed over time.[48]

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[47] By far the largest literature on the "ripple-effect" is for the U.K. (Meen, 1996, 1999), but ripple-effects have been tested for in many countries.

[48] Simple correlation analysis (Kallberg et al., 2014; Landier et al., 2017); cointegration and error correction methods (Yunus & Swanson, 2013); latent factor models (Del Negro & Otrok, 2007) or simple multivariate regression frameworks (Cotter et al., 2011) as a way to try and estimate the relative importance of common (respectively latent or observed) national (vs. idiosyncratic local) factors in house price movements; and spatial econometric models (Abate & Anselin, 2016) in order to assess the co-movement of contiguous markets.

However, not only are there a number of potential issues with employing rolling-windows with many of these approaches,[49] but also none of these time domain methods provide the spectral information or phase-amplitude decomposition possible with wavelet analysis.

By contrast with a latent factor model approach, I study the phase-adjusted similarity between cycles in different markets (given by the wavelet power spectra in Essay 1/Section 2 and the mean wavelet power spectra presented in Section 3.4.1 above); then study the phase synchronisation (this Essay) and pattern of phase-differences between markets (Essay 3/Section 4) for an empirically identified cycle component[50] associated with a common frequency band across markets. I am thus able to study the role of amplitude vs. phase in changing correlation among markets over time.

Given my focus on the pattern of phase-lead lags, strong cross-sectional dependence does not pose a problem (as it does for spatial econometric models) and the simple spatial projection of the instantaneous phase of the common cycle component that I introduce allows a rich elucidation of the exact pattern of relationships.[51]

Unlike the existing ripple-effect literature that has focused on convergence of house price levels, I thus directly study the temporal pattern in house price fluctuations.

What is more, the instantaneous phase based approach that I introduce allows me to study the development of overall synchrony and of spatial patterns with good temporal resolution (thanks to the optimal time-frequency resolution provided by the adaptive windowing of the continuous wavelet transform (see methods Section 2.2)).

3.2.2 Methods for measuring cycle synchronisation in economics literature

Co-cyclicality has been widely studied in the business cycle and other related literatures in economics where a range of different methods for quantifying synchronisation are in use. Here I will focus on methods for quantifying variation in co-cyclicality over time, and across different frequencies.

Correlations have been widely relied upon as a measure of 'synchronisation' in the existing literature (not just in the study of housing market synchronisation but by the business cycle synchronisation literature)[52] and made dynamic through the use of rolling-window approach. However rolling correlations based methods may generate nonsense results in the presence of

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49 Rolling correlations based methods may generate nonsense results in the presence of persistent cycle components (oscillate even for stationary data and vary as a function of choice of window length relative to cycle period - see e.g. Yule (1926) on problems with rolling window correlations of oscillatory signals.

50 Note no assumptions are required as for turning point based methods widely used in the business cycle literature, and to some extent housing cycle analysis.

51 Although I also consider the phase-coherence of adjacent markets which provides an amplitude independent measure of spatial correlation.

52 "The business cycle synchronisation literature has widely relied on the pairwise correlation (of e.g. GDP growth or de-trended GDP) between countries as a measure of "synchronization" and employed in cross-section analysis to assess its main determinants." (Ductor & Leiva-leon, 2016)

persistent cycle components (oscillate even for stationary data and vary as a function of choice of window length relative to cycle period - see e.g. Yule (1926) on problems with rolling window correlations of oscillatory signals and Figure 9 for a simple illustration).

Moreover there is a problem that contemporaneous correlation based methods are sensitive to both *amplitude* and *phase* relationships, thus *heteroskedasticity* can generate varying correlations even for variables with a stable phase relationship (in the contagion literature Forbes and Rigobon (2002) identifies that this analysis is subject to heteroskedasticity/volatility bias); and shifts in the phase-relationship between variables can generate varying correlations even for a stable amplitude envelope.

Finally co-movement may vary not only over time, but also across different frequencies, however standard correlation methods are not able to provide any information on this.

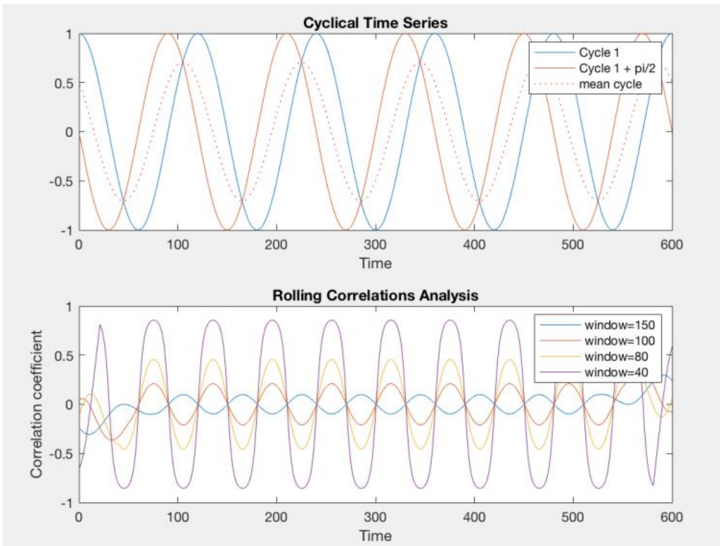

Figure 9: Nonsense correlations from *rolling correlation* analysis of two identical cycles with constant phase-difference.

These different issues have motivated the use and introduction of methods that attempt to separate *phase* and *amplitude* information or adjust correlation coefficient values for possible phase shifts, as well as to provide spectral information.

Croux et al. (2001) introduce a 'coherence' measure obtained as the averaged all-to-all pairwise 'dynamic correlations' - where 'dynamic correlations' are equivalent to ordinary correlations for band-pass filtered time series. This provides spectral information, but throws away temporal information and suffers from the drawback of assuming constant phase-differences within the entire sample period studied.

Azevedo & Koopman (2008) decompose contemporaneous correlation into a part due to differences in the timing of two cycles (their "phase shift") and a "phase adjusted correlation". They allow for time variation in the phase differences and phase-adjusted correlation between series, but also make the overly restrictive assumption that they are a monotonic function of time (correlation can either go up or down over the sample period).

Another widely employed method is simply the *maximum correlation coefficient* (i.e. using the lag time/length that maximises correlation between two cycles/signals to identify time-lag and time-lag adjusted correlation - Kovacic and Vilotic (2017) are some recent examples). Though widely employed in the business cycle literature, these methods are not, as far as I am aware, used in studying the synchronisation or integration of regional housing market cycles.

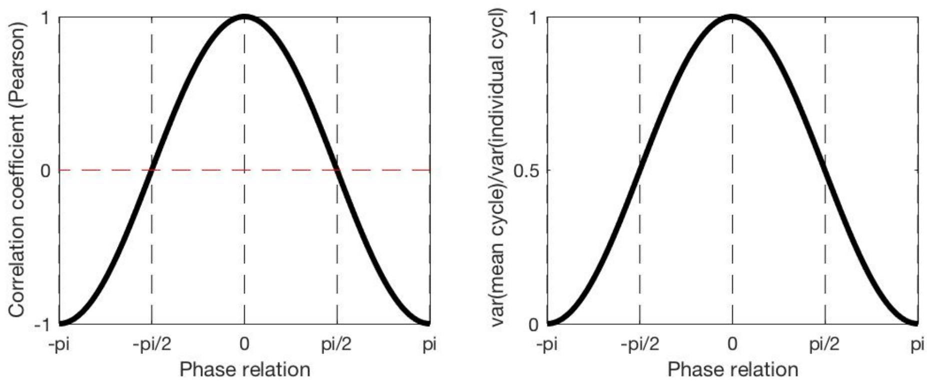

Figure 10: Phase-difference vs. correlation and suppression of variance of mean relative to mean variance.

While effort has been expended on methods for obtaining phase-adjusted correlations, synchronisation in the *timing* of cycles, or phase-synchronisation, has also received much interest.

Here the business cycle literature has relied on measures based on the joint distribution of binary state variables encoding information on some definition of the phase of a cycle, such as *expansion/contraction* (Harding & Pagan, 2003, 2006); or *sign* based deviations from trend (Bordon & Reade, 2013; Gogas & Kothroulas, 2009; Mink et al., 2012).[53]

Particularly well known and widely employed, is the method introduced by Harding and Pagan who define the synchronisation of cycles (when these are defined through their turning points) based on the fraction of time that two series spend in the same binary (expansionary or contractionary) phase (Harding & Pagan, 2003). They also proposed statistical tests of the hypotheses that cycles are either unsynchronized or perfectly synchronized (Harding & Pagan, 2006).

These methods have also been widely borrowed to study housing cycle synchronisation (Akimov, Stevenson, & Young, 2015; L J Álvarez, Bulligan, Cabrero, Ferrara, & Stahl, 2009; Luis J Álvarez & Cabrero, 2010; Hirata, Kose,

[53] Mink et al. (2012) introduce a statistic to quantify synchronisation among trend-deviation cycles (when cycles are defined as difference from trend) based on their *sign concordance* – the fraction of time movements in both series have the same *signs* (negative or positive output gaps). This sort of approach has in fact been used in other applications and was previously introduced in business cycle analysis by other authors e.g. Gogas and Kothroulas (2009)). They also introduce a statistic to quantify the similarity in the size of the output gap between one series and a reference series. These methods are applied for example in a recent paper from ECB working group on econometric modelling (ECB, 2018); and in a housing study by Miles (2015a).

Otrok, & Terrones, 2013; Jackson, Stevenson, & Watkins, 2008; Stevenson, Akimov, Hutson, & Krystalogianni, 2014).[54]

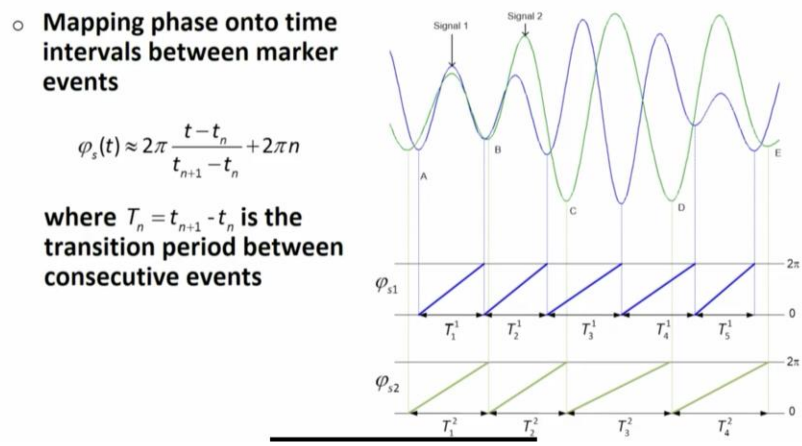

Figure 11: Discrete distance approximation of phase.

Since these "concordance index" type methods only employ information on the timing (and not magnitude) of cycles, they are not impacted by heteroskedasticity and provide a measure of phase-synchrony. While the Harding-Pagan index can in principal be computed recursively in order to study whether the degree of synchronization has changed over time (Harding & Pagan, 2003),[55] by only using discrete distances between turning points (or in the case of sign based indexes zero-crossings) to approximate the underlying phase and phase-differences (see **Figure 11** for visual explanation of this), these methods throw away valuable information on phase dynamics making these indices rather crude from a dynamic perspective – this may explain why in practice the method tends to be employed based on an average over an entire sample period (Stevenson et al., 2014) or based on large non-overlapping sub-samples in order to study whether synchronisation has changed over time (Hirata et al., 2013).

What is more, they suffer from all the limitations of turning point analysis (including sensitivity to noise, difficulty in parsing complex spectral structures, requirements for prior assumptions on relevant frequency bands etc. - see Section 2.2.4).[56]

[54] The Harding-Pagan index is used to study housing market synchronisation in for example: Jackson et al. (2008) for London-New York office markets; Álvarez et al. (2009) for national Euro area housing cycles; Hirata et al. (2013) for international housing market synchronisation; Stevenson et al. (2014) for international office market, and Akimov et al. (2015) for Australian cities.[54] Other studies have looked at concordance between aggregate housing and cycle and other macro-variables - Álvarez and Carero (2010) for Spain. Ferrara & Vigna (2009) for France. Although curiously the Harding-Pagan method has not yet, to the best of my knowledge, been used to study sub-national markets for the US, Miles (2015a) uses the Mink index (Mink et al., 2012) to study house price convergence in US markets. In an earlier study Klyuev (2008) report a sign-based "diffusion index" for regional house price data (where the index equals the percentage of divisions in which house price growth is positive minus the percentage in which it is negative (thus 100% if all rising, and -100% if all falling)) and reports increased synchronisation after 1990.

[55] In practice recursive implementation seems to be little used. Bovi (2003) is a rare exception.

[56] Although any method for detecting/defining/identifying turning points can be employed in order to calculate concordance, methods for detecting turning points may all share certain limitations.

3.3 Methods

3.3.1 Instantaneous phase and multivariate phase-coherence

Two cycles, whilst sharing exactly the same frequency, need not exactly overlap and may be shifted along the time axis. This shift in the time axis can be quantified by the *phase-difference* between the two cycles (this is illustrated by **Figure 12** (a)). However the phase relationship between cycles need not be fixed (indeed a constant phase-difference between two series is strong evidence of interdependence), but may vary or change over time, either randomly or as a result of endogenous dynamics (this is illustrated by a stylized example in **Figure 12** (b) which shows two otherwise identical cycles - here also sharing a common trend - that desynchronise over time).

The business and credit cycle literature has taken much interest in phase synchronisation, but relied methodologically on the intuitive but crude measures provided by turning point based *concordance indexes* such as that introduced by (Harding & Pagan, 2003, 2006). These throw away valuable information on phase dynamics by only using discrete distances between turning points to approximate the underlying phase (thus equivalence with discrete distance approximation based phase estimates (Brouwer, Poel, & Hofmijster, 2013)). Multivariate measures are then based on average pairwise relationships.

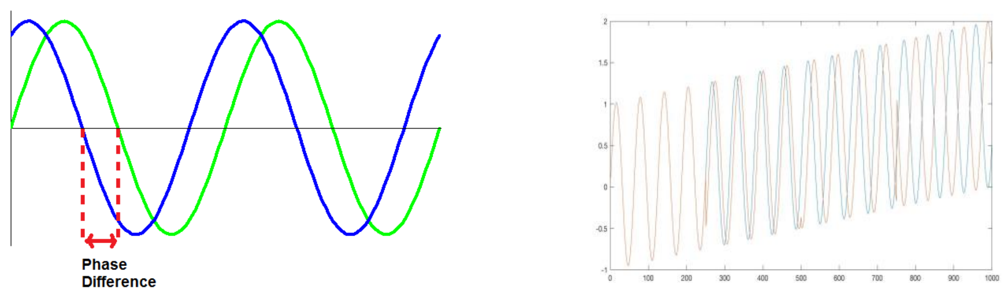

Figure 12: This figure illustrates (a) two cycles with a constant phase-difference between them (but otherwise identical) (b) Two cycles that start out identical (same frequency, amplitude, phase and sharing a common trend) but that desynchronise over time (here via a series of phase jumps by one of the cycles).

3.3.1.1 Instantaneous phase

Outside of economics, instantaneous phase based methods have been widely used.[57] Instantaneous phase information may be obtained (frequency by frequency and time step by time step) using the Wavelet transform (Torrence & Compo, 1998) or from the Hilbert-Huang transforms (N. E. Huang et al., 1998,

[57] Instantaneous phase based methods have been widely used (Arenas & Albert, 2008; A S Pikovsky et al., 2001; Rodrigues et al., 2015; Schroder et al., 2017).

2003, 2009) of available time series. Here I employ the continuous wavelet transform (Eq.1).[58] As already noted (see Sections 2.2 and 2.2.3 above) for a complex-valued wavelet ψ, the corresponding wavelet transform $W_{x;\psi}(a,\tau)$ (Eq.1) is also complex-valued (yields a complex scalar field), where the modulus and argument of $W_{x;\psi}(a,\tau)$ represent, respectively, the instantaneous *amplitude* (Eq.5) and *phase* (Eq.6) of the signal

$$a_x(a,\tau) = \left|W_{x;\psi}(a,\tau)\right| \tag{5}$$

$$\theta_x(a,\tau) = \mathrm{Arg}\,(W_{x;\psi}(a,\tau)\,) \tag{6}$$

Phase for a particular frequency band are calculated as mean phase over that band using the circular mean of (Mardia & Jupp, 2000) phase angles.

3.3.1.2 *Multivariate phase coherence*

An intuitive and useful approach to quantifying the overall level of phase synchrony in a multivariate system is the so-called Kuramoto synchronization index or "order parameter" (Kuramoto, 1984). Given a collection of N phase series $(\theta_{x_i}, i = 1, \dots, N)$ describing the evolution of phase over time, the phase positions on the unit circle at each time step are represented by the complex exponentials $e^{i\theta_{x_i}(t)}$. The complex order parameter R is obtained simply as the average of these positions

$$R(t) = \frac{1}{N}\sum_{j=1}^{N} e^{i\theta_{x_i}(t)} \tag{7}$$

which may also be written as

$$R(t) = r(t)e^{i\phi(t)} = \frac{1}{N}\sum_{j=1}^{N} e^{i\theta_{x_i}(t)} \tag{8}$$

Here the statistics r and ϕ provide a quantification of the collective dynamics and current state of the whole population, where the modulus $r = |R|$, $0 \leq r \leq 1$ measures the *phase coherence* of the population (achieving its maximum $r = 1$ when all phases are identical and its minimum $r = 0$ when phases are balanced around the circle[59]), thus provides a measure of the overall phase-synchrony in the system (without the need to define a reference cycle), and ϕ is the average phase (i.e. the vector R points in the average direction of all the $e^{i\theta_{x_i}}$ vectors). Since the instantaneous phase is obtained scale-by-scale, these statistics can be

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[58] The standard approach is the Hilbert transform for narrowband data, or the Morlet wavelet transform for broadband signals (Allefeld, Müller, & Kurths, 2007; Arkady S. Pikovsky, Rosenblum, Osipov, & Kurths, 1997; M. G. Rosenblum, Pikovsky, & Kurths, 1996). See also Quyen et al. (2001) for a comparison of these methods in empirical phase synchronisation study applications.

[59] Such as evenly spread or in clusters that balance each other out. For a detailed discussion of the structure/local order that may be missed by Kuramoto order parameter see e.g. (Frank & Richardson, 2010; Richardson et al., 2012).

calculated for every scale at every time step, or, by averaging over a specific scale band, it is possible to characterise overall phase relationships for differed frequency ranges and track the evolution of this over time.

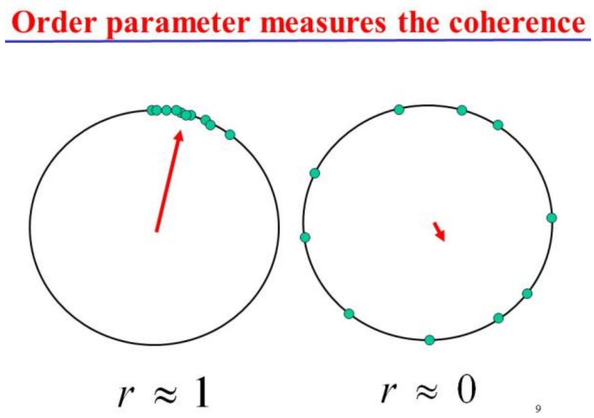

Figure 13: this chart illustrates the intuition behind $\boldsymbol{r}$ obtained from Eq.**8**. Here each point on the phase-circle represents the phase of an individual variable, the red arrow the mean vector. $\boldsymbol{r}$ is thus given by the magnitude of this arrow, and $\boldsymbol{\phi}$ by its angle. This hopefully makes intuitive how $\boldsymbol{r}$ achieves its maximum $\boldsymbol{r} = \mathbf{1}$ when all phases are identical and its minimum $\boldsymbol{r} = \mathbf{0}$ when phases are balanced around the circle.

3.3.2 Power spectrum and mean power

I will employ the average wavelet power spectrum in order to identify common areas of high power across different series (wavelet power spectra (Eq.2) (scale normalized following (Y. Liu et al., 2007) - these methods and definitions are introduced in Sections 2.2.1 and 2.2.2 above).

The average wavelet spectrum provides a simple approach to studying the phase-independent similarity in cycle components over time. This will allow me to identify areas of common high power across all markets.

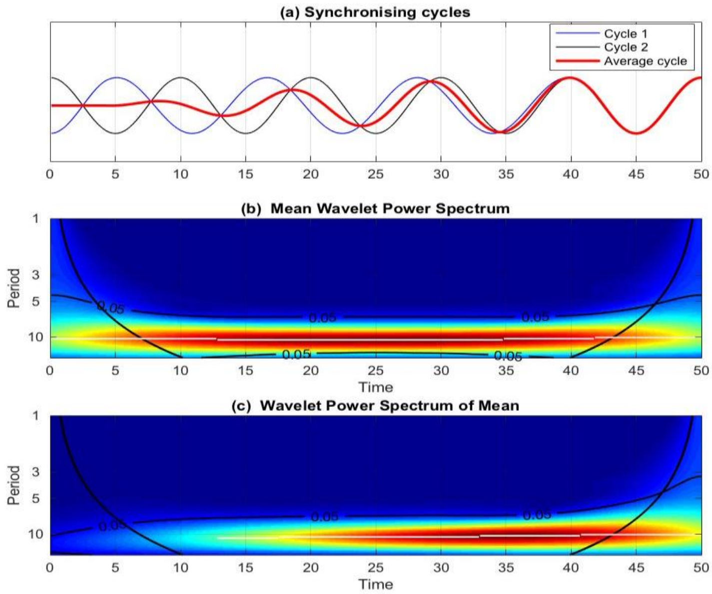

Figure 14: This illustrates the use of average wavelet power spectrum in order to assess common cycle components ignoring phase-differences between cycles, using the simple example of just two cycles (with the same amplitude and frequency) that synchronise over time.

Other standard methods for comparing spectra of different signals are not useful in this context. For example wavelet coherence is a function of both phase and amplitude similarity between signals. What is more because it is a measure of similarity between spectra, areas of common low power can show up as areas of high-coherence and it does not provide information on the spectral distribution of power for the underlying signals.

Figure 14 demonstrates in a stylized example of the synchronisation over time of just two simple cycles. This shows how the average spectrum is able to identify the common cycle component over the entire time period providing a phase-independent analysis.[60]

3.4 Empirical analysis and results

3.4.1 Mean amplitude envelope of state level cycles over time

Figure 15 compares (a) the power spectrum (Eq.2) of the mean of state level house price series to (b) the mean power spectrum of state level house price series. In both cases the power spectra are scale normalized to allow cross scale comparisons of power (Y. Liu et al., 2007).

[60] Note that while these are narrow band signals, wavelet coherence would show strong coherence across the entire spectrum.

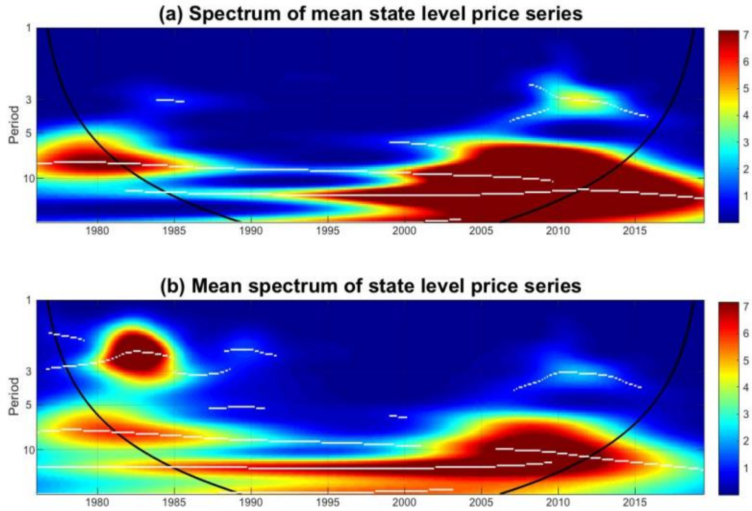

Figure 15: this chart presents (a) the wavelet spectrum of average house prices across all 51 states and DC; (b) the average power spectrum of all 51 states and DC. This analysis clearly reveals common features of local house price series dynamics that are lost or obscured in the aggregated (average) time series. Of particular interest is the much more pronounced spectral ridge (cycle) that shows up in the mean spectrum (b) and narrower band of high power even during the national boom-bust period. Another striking feature of the mean spectrum in (b) is the very clear common shock showing up in the 2-4 year periodicity band during the early 1980s – something that entirely averages out according to the spectrum of mean house prices in (a).

In both analyses the spectral ridges at 8-10 and the 12-14 year bands that were prominent in state level spectra are to some extent visible. However two striking differences stand out:

In particular (i) The 12-14 year ridge is very clear and prominent over the entire sample period in (b) the mean spectrum, clearly identifying a common cycle component at this frequency across US markets. However this cycle only becomes distinct in (a) the spectrum of the man, after 1995.

The second striking difference (ii) is the common shock apparent in the 2-4 year periodicity band during the early 1980s (cantered on approximately 1982) that shows up very clearly in the mean spectrum, but not at all in the spectrum of the mean.

Since these spectra reflect the real part of the wavelet transform, the difference between the two charts can be interpreted in terms of the contribution phase-relationships are making to average house prices suggesting differences in timing across different markets were such that the early 1980s shock entirely averaged out in aggregation, and sufficient to dramatically moderate the mean cycle for the 10-14 year cycle.

More detailed investigation of the high frequency shock of the early 1980s I leave to future research, but overall phase relations for the 10-14 year cycle I will investigate further in following section based on phase coherence analysis.

3.4.2 Phase-coherence of state level housing cycles over time

Figure 16 (b) Presents the raw phase series extracted for all 51 state level price indexes (as per Eq.5) for 8-15 year periodicity band. Figure 16 (a) presents the empirical phase coherence (Kuramoto's r as per Eq.8) for all 50 US states plus the District of Columbia over the 8-15 year periodicity band (based on results in Section 2.3.2) from 1975:01-2020:06.

These clearly show a dramatic de-synchronisation of this cycle component after 1984 (marked by first vertical dashed line), reaching a minimum in 1994 (marked by the second vertical dashed line) after which cycles re-synchronised rapidly reaching a new high in 2000 (marked by the third vertical dashed line) since when phase synchronisation has remained extremely high up to the present time.

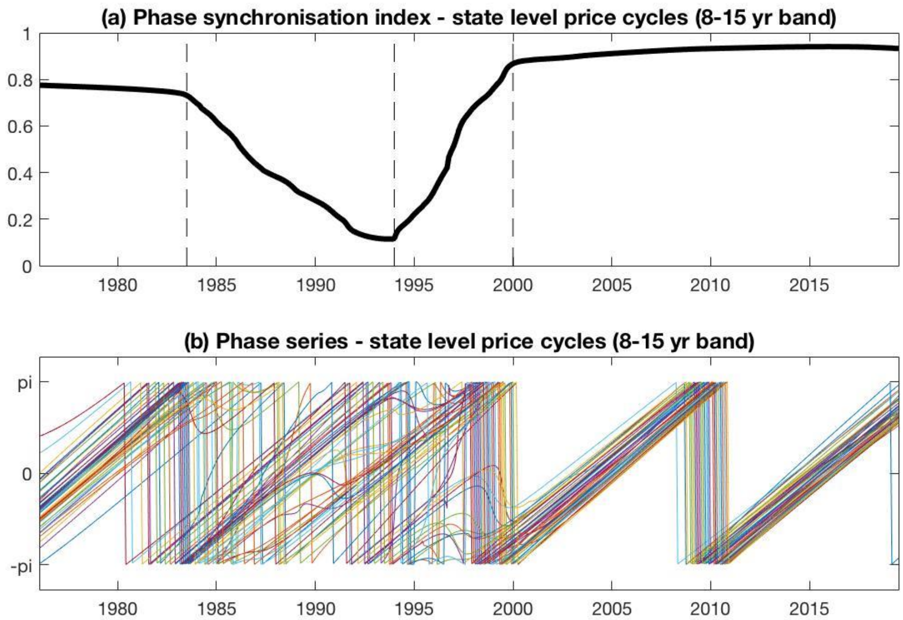

Figure 16: this chart presents (a) the empirical phase coherence (Kuramoto's r as per Eq.**8**) for 50 US states plus the District of Columbia over the 8-15 year periodicity band from Jan 1975 to Jun 2020. (b) The raw phase series extracted for all 51 state level price indexes (as per Eq.**6**). This clearly shows a dramatic de-synchronisation of this cycle component after 1984 (marked by first vertical dashed line), reaching a minimum in 1994 (marked by the second vertical dashed line) after which cycles re-synchronised rapidly reaching a new high in 2000 (marked by the third vertical dashed line) since when phase synchronisation has remained extremely high up to the present time.

As a further perspective/illustration, Figure 17 plots the individual phase angles (black dots) and mean vector (blue bar) (Eq.8) as at different points in time (1994, 2000 and 2010) on the phase/unit circle (this is thus an empirical version of Figure 13).

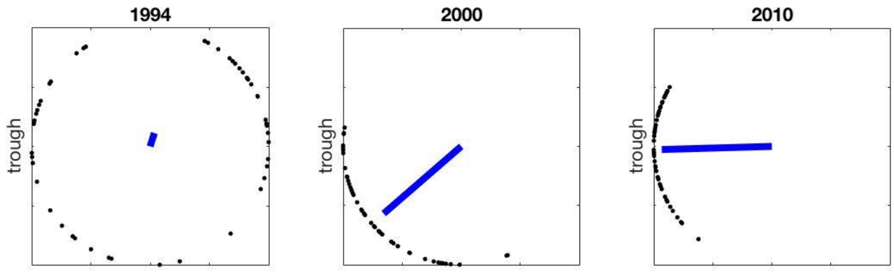

Figure 17: these charts show the distribution of phase-angles for all 50 states plus the District of Columbia at three different points in time. Here the black dots on the unit circle each represent the individual phase angle for a single market, and the blue bar the mean parameter (Eq.**8**) (Such that its magnitude/length corresponds to $\boldsymbol{r}$ and its angle is given by $\boldsymbol{\phi}$). The phase angles rotate anti-clockwise around this circle (e.g. the aggregate cycle had already troughed in 2000).

It is important for the purposes of this sort of phase analysis, to be extracting phase information from a meaningful signal component (Chavez, Cazelles, & Ird-upmc, 2014). Here this is ensured by the work in Section 2 and in 3.4.1 above, which demonstrate the significant contribution these scale bands make to individual and collective variation.

3.5 Discussion

These results beg interesting questions regarding (i) the source of the cyclicality of sate level data; (ii) the cause of the de-synchronisation from the mid 1980s and (iii) the cause of the dramatic re-synchronisation starting in 1995.

It is interesting to note that the significant common shock indicated by the mean power spectrum in the early 1980s coincides with the introduction at this time of a whole raft of regulatory changes aimed at boosting savings and loans (S&L) companies, that also opened the door to increasingly risky behaviour (culminating the Garn-St. Germain Depository Institutions Act of 1982 which, among many other things, eliminated restrictions on loan-to-value ratios (Chaudhuri, 2014, p. 105)) resulting in a dramatic expansion in S&L lending and assets (1982-1985 assets grew 56% (Federal Reserve Hisotry, 2013)).

Meanwhile the entire transient de-synchronisation period from the mid 1980s-1995, coincides closely with the period of S&L failures (Resolution Trust Corporation (RTC) established to resolve troubled S&Ls was closed in 1995) (Green & Wachter, 2005; Snowden, 1997). This raises the question whether and how the S&L crisis may have somehow driven the observed de-synch episode?

In this respect, it is interesting to note, that while on the one hand the S&L crisis and the large number of S&L failures over this period (c.50% of S&Ls failed between 1986 and 1995 (Curry & Shibut, 2000)) was arguably a financial shock driven by developments at the national level,[61] on the other hand most states

[61] Steep increases in inflation and interest rates at this time wiped out S&L industry net worth and profits. Regulatory limits on the deposit rates S&Ls could offer initially led depositors to withdraw funds and seek higher returns elsewhere. However once these restrictions were lifted the sharp rise in deposit rate S&Ls had to offer in order to attract funds in the environment at that time, pushed short term funding costs above the return on their long-term fixed rate mortgage books.

experienced some time-localised *spike* in S&L failures over this c.10 year period, the timing of which differed considerably between states.

Given these failures must have been highly disruptive for markets, the differences in the timing of S&L failures at the state level may have acted to de-synchronise state level cycles[62] - note that spatial type coupled cycle systems[63] can exhibit a cross-over from synchronized state at low noise-strength to de-synchronized state at high noise-strength (Sarkar, 2020).

Moving on, the beginning of the dramatic phase synchronisation from 1995 coincides not only with the closure of the RTC but also with the deregulation of interstate banking (the Interstate Banking act of 1995) - e.g. Landier (2017) has linked housing market comovement to interstate banking - and follows a fundamental restructuring of housing finance in the US following the S&L crisis, with mortgage finance shifting from being dominated by local 'balance sheet lending' by depositories, to a national market based system of securitized mortgage finance (Schnure, 2005).

Interestingly while Schnure (2005) argued in an IMF working paper on the eve of the sub-prime and housing crisis, that these changes in financial structure had "smoothed out the boom-bust cycle in lending flows, real activity, and prices" associated with the S&L based system, and that "Lower volatility of residential investment also appears to be a factor in the decrease in macroeconomic volatility over the same period." (Schnure, 2005, p. 3), it may be that the impact of these changes in financial structure was the synchronisation of these cycles.

It is notable that the period 1985-2000 in which de-synchronisation of local markets significantly moderates aggregate house price volatility (i.e. house price volatility does not so much go away as average out during this period), coincides closely with the "Great Moderation" period (especially in light of the strong links by now widely believed to exist at the national level between housing and the macroeconomy).

These are speculative observations and links, the detailed investigation of which is beyond the scope of this study and left to other or future research.

More broadly, these results pose a number of challenges to established narratives on the source of the 2000s housing boom-bust, and the localness vs. national character of housing market instability.

In particular the existence of a common cycle component spanning the entire sample period is at odds with the widely documented result that a significant common component to U.S. housing market fluctuations did not emerge until 2000s, prior to which housing cycles were believed to be local (in the sense of idiosyncratic).

While the apparent association of time series events with significant financial shocks and innovations suggests the possibility that these may have played a significant role in the level of synchronisation across cycles, nevertheless the contribution to the national boom-bust from the synchronisation of this common cycle challenges the widespread search for a smoking gun entirely at

[62] Of course this begs the question why the differences in timing between states – this question may no be easily answered and does not appear to have been studied in the literature (Warf & Cox, 1996).

[63] Such as 2D lattice and planar graphs.

the national level in terms of some common national driver and a switch from local to national housing market instability.

3.6 Conclusion

In this chapter I have studied the overall co-cyclicality of U.S. house prices across state level markets.

I identify a striking common cycle component spanning the entire sample period (clearly visible in the mean power spectrum across all states) that largely averaged out of mean price developments at the national level prior to 1995.

This result is clarified by a further analysis made of the evolution of overall phase coherence among U.S. states associated with this common cycle component over the historical sample period.

I show evidence of a marked de-synchronisation of state level cycle (from moderate levels) after the mid 1980s, following a significant common shock identified by the mean power spectrum (but that entirely averages out in mean house prices at the national level further emphasising the value of a disaggregated perspective), until 1995, coinciding with a period of savings and loan company failures.

This is followed by a dramatic transition from low to high phase-synchronisation of cycles occurred after 1995, with phase-synch reaching new heights before 2000.

With this analysis I am thus able to show that prior to the mid 1990s, and in particular between 1984-2000, asynchronicity moderated the impact of a common cycle on aggregate house price volatility, but that after 1995 a dramatic phase synchronisation of this existing cycle across markets made a significant contribution to the national housing boom-bust over the subsequent period.

It is interesting that the period over which de-synchronisation of local markets significantly moderates aggregate house price volatility (1984-2000) also coincides closely with the "Great Moderation" period in which macro-volatility was low.

These results provide rich new insight into the dramatic housing market gyrations of the 2000s, and challenge existing narratives on the sources of this episode and debate over the localness vs. national character of house price instability.

4 Essay 3: The spatial dynamics of permanent cycle co-movement: evidence of traveling spatial-waves in local housing cycle timing

Summary: In Essay 1 (Section 2) I show using monthly state level data from 1975:01-2020:06, that the majority of subnational markets across the US exhibit a permanent cycle component of a similar 8-10 year periodicity over most or all of this sample period. In Essay 2 (Section 3) I present evidence that states across the U.S. shared common cycle components over the entire sample period, but show how the contribution to aggregate house price variation was moderated, prior to the mid 1990s, by low overall synchronisation among cycles, as well as how a dramatic transition from low to high overall phase-synchronisation among these existing cycles occurred after the mid 1990s, contributed to the large national run up and subsequent downturn in national house prices after this time. In this Essay, I study (i) the question whether spatially local links between markets matter for the synchronisation among local cycles, or whether only national factors matter? And I also ask (ii) whether there are any significant spatial patterns in the timing of the 8-10 year cycles identified. I introduce a statistic to quantify spatial phase-synchronisation based on the instantaneous pairwise phase-differences (obtained here via continuous wavelet transform) between spatially contiguous markets and compare this to the overall level of synchronisation across all markets. I then employ the spatial projection of instantaneous phase and relative phase analysis in order to assess whether there are any significant spatial patterns in the relative timing of housing cycles across the country. This framework provides a time-varying, well time-resolved, frequency specific measure robust to non-stationarity and unbiased by temporal or cross-sectional variation in cycle amplitudes. I find clear evidence that the cycles in spatially adjacent markets are considerably more synchronous over the entire sample period; meanwhile relative phase analysis reveals a striking and remarkably stable spatial pattern resembling a traveling-wave over the c.50 year sample period. These results provide clear evidence of the significance of spatial links between markets. While a number of previous studies have reported evidence of spatial diffusion in US housing markets, this is the first time these striking spatio-temporal dynamics have been documented. What is more the '*traveling-wave'* phenomenon revealed is more consistent with the interaction of intrinsically cyclical markets, than with the sort of idiosyncratic shock or bubble type dynamics hypothesised in the existing literature.

4.1 Introduction

Motivation

The US sub-prime and subsequent global financial crisis that followed the national housing downturn starting in 2006-7 has stimulated interest in the study of the sources and propagation of housing market busts. While the national character of these events have motivated huge interest in *aggregate* factors in national house price fluctuations, a more careful look at disaggregated housing market data may be called for in order to assess the mechanisms underlying housing market instability.

In Essay 1 (Section 2) I document persistent housing cycles of similar frequency in state level data; in Essay 2 (Section 3) I clarify the existence of an important common cycle component across markets, and identify a period of marked de-synchronisation after the early 1980s, followed by dramatic synchronisation of these cycles after 1995 contributing, respectively, to low aggregate housing market volatility during the Great Moderation era, and the dramatic national housing boom-bust of the 2000s.

An interesting and important question arises, whether low levels of overall synchronisation prior to 1995, may have concealed local synchronisation among markets (e.g. geographical clusters of synchronised markets), what is more whether the global synchronisation that occurred after 1995 was principally driven by common national factors, or whether local (in the sense of direct bilateral) links between individual markets have played a role.

In this essay, I study the spatio-temporal character of the common cycle component in state level house price data 1975:01-2020:06. Specifically I address the questions:

Research questions

1. Does spatial contiguity matter for the synchronicity of the common cycle component as observed at the state level? (I.e. are neighbouring markets likely to be more synchronous?). (How) has this changed or varied over the available historical sample period (1975:01-2020:06)?
2. Are there any particular spatial *patterns* in the relative timing/the synchronicity of cycles across markets (such as e.g. evidence of spatial spreading processes consistent with shock diffusion or contagion effects; or of clusters of synchronised markets)? (How) has this changed or varied over the available historical sample period (1975:01-2020:06)?

Methods

In order to assess whether or not contiguous states are more synchronous, I introduce an instantaneous measure of *local network phase synchronisation* that I combine with a spatial adjacency matrix for contiguous US states.

To assess any spatial patterns that may have existed in the synchronisation and relative timing of cycles across markets over the sample period, I use the spatial projection of instantaneous *phase* and *relative-phase* information. The spatial projection of state level data allows me to assess not just whether neighbouring markets are more synchronous, but global patterns across markets, such as spatial segmentation (e.g. spatial clusters of synchronised markets or other spatial distribution of markets with similar phase); and the geographical distribution of leading and lagging markers and any propagation patterns of housing cycles across markets. In all cases instantaneous phase information is obtained via continuous wavelet transform (Eq.1) of the state level time series.

For the task at hand of detecting spatio-temporal patterns in cyclic housing markets, these techniques have a number of distinct advantages over traditional correlation based methods currently relied upon within the spatial econometric literature.

For example a phase based approach to studying comovement is unaffected by relative or time varying amplitude and not subject to the spurious impression of a time varying relationship suffered by rolling correlations (see Section 3.2.2 for discussion and references).

Also the time-frequency decomposition can be used to study specific and/or multiple periodic patterns in the data even in the presence of noise. This allows me to focus on the dynamic component of interest (the common cycle in 8-15 year periodicity band) as well as distinguish and compare the spatio-temporal patters associated with short run fluctuations vs. long cycles in the data.

Meanwhile the instantaneous character of the methods permits a truly dynamic analysis that allows for and should have the ability to reveal dynamic variation in the spatial pattern of housing cycle propagation thus capable of capturing transient and evolving phenomena such as the spatial propagation of particular local shocks or contagion episodes (note the optimal time-frequency resolution provided by the continuous wavelet transform provides a superior dynamic measure of comovement than rolling correlation based methods and a far more continuous measure than methods that rely on estimating discrete events to approximate phase (see Section 3.2.2)).

Despite their various advantages, these methods have not – to the best of my knowledge – been previously employed in the study of U.S. housing markets, or for that matter in any other application in economics (although similar methods have been employed in a range of analogous applications outside of economics).[64]

Results

Comparing local vs. global phase synchronisation shows clearly that spatially adjacent markets have always been highly synchronous over the entire c.50 year sample, even over the historical period when overall synchronisation levels were very low.

However a small increase in synchronisation after 1995 at the local level, added up to the dramatic shift in overall synchronisation among markets documented by Essay 2 (see Section 3.4.2).

The projection of instantaneous phase and relative phase analysis onto geographical space reveals a striking spatial pattern in the timings of cycles in different markets resembling a “traveling-wave” (analogous to a “Mexican wave”). This pattern is remarkably stable across the c.50 year sample period, across multiple cycle periods, and between the low and high overall synchronisation eras.

There is also some evidence of geographical clusters/segmentation the detailed investigation of which is beyond the scope of this paper.

[64] It is worth noting that whilst not previously used (to the best of my knowledge) in the study of housing markets or any other applications in economics, related methods have been employed for spatio-temporal analysis in other applications. See for example Liebhold et al (2004) and Sherratt & Smith (2008) for discussion of the merits of wavelet based approaches to the study of the analogous problem in ecology of identifying spatio-temporal patterns in cyclic population fluctuations.

Significance

Where much effort has been expended on the search for a smoking gun at the national level - a common national factor or shock - this evidence of the local synchronisation and global spatial pattern in the development of the common cycle component strongly suggests a significant role for local interactions in the form of spatial links between markets in the emergence of mean field house price fluctuations at the national level.

What is more the specific spatial pattern revealed, may also provide further important clues to the character of the underlying dynamics: this empirical pattern resembles a 'traveling wave' – synchronisation at first decreases with spatial distance along one projection angle (the direction in which the wave is travelling) before increasing again as the geographical separation approaches one wavelength, but not along the projection angle orthogonal to this.

This pattern is more consistent with the interaction of significant cyclical intrinsic dynamics, than with either the sort of spatial diffusion of local shocks, or contagious bubbles hypothesised within the existing literatures concerned with housing "ripples" and spillovers: whether shock diffusion or bubble contagion, the hypothesis in either case is that a local disturbance spills over from one neighbouring market to the next, thus we might expect in either case an *epicentre* pattern in which the disturbance radiates out in all directions from its initial source.

We might, what is more, expect to see *epicentres* (shocks or corrections spilling over to neighbouring markets) arising in different markets at different points in time. This is at odds with the unidirectional traveling wave and stable pattern of phase-relationships over multiple cycle episodes that I empirically observe.

These results are thus consistent with and reinforce the evidence of significant intrinsic dynamics reported in Essay 1 (Section 2) based on the wavelet power spectra of state level price series. They also raise the possibility local interactions between markets could have played a role in the national synchronisation of cycles, although it remains possible this was driven by a common factor or shock.

Contribution and relation to existing literature

Spatial dependence and spillovers are a well-established theme in the real estate literature, which has studied the hypothesis that house price relationships between contiguous markets might be stronger than between non-contiguous regions (S Holly et al., 2010); possible "ripple effects" due to the spatial diffusion of local shocks (Barros et al., 2012; Holmes et al., 2011); or contagion between spatially adjacent markets (DeFusco et al., 2013; Nneji et al., 2015; Riddel, 2011).[65] "Local" spillovers based not on spatial distance but some other form of

[65] See also e.g. Greenaway-Mcgrevy and Phillips. **(2015)** for study of Australian markts.

direct economic links have also been studied (Hernández-Murillo et al., 2017; Malone, 2017; Zhu et al., 2013).[66]

Spillovers between housing markets have also become a policy concern since if local spillovers are significant, then a house price correction in one market could have macro-financial implications (IMF, 2018; Vansteenkiste, 2007) (see e.g. concern over the potential for problems in the London market to spill over to the rest of the UK (IMF, 2014; UBS, 2017)).[67]

Many studies for the US have reported evidence that geography, and spatial-distance matter (Baltagi & Li, 2014; Brady, 2011, 2014; Karl E Case & Shiller, 1990; Chudik & Pesaran, 2010; J M Clapp & Tirtiroglu, 1994; John M Clapp, Dolde, & Tirtiroglu, 1995; DeFusco et al., 2013; Dolde & Tirtiroglu, 1997; S Holly et al., 2010; Kuethe & Pede, 2011; Pollakowski & Ray, 1997; Vansteenkiste, 2007).

However despite the huge interest in spatial aspects of U.S. housing, to the best of my knowledge this is the first time the striking spatio-temporal patterns revealed by my analysis have been documented. Indeed while there is much evidence on *spatial dependence*, work on the *spatio-temporal dynamics* underpinning this spatial correlation is surprisingly scarce.

The spatial coefficients yielded by spatial econometric methods provide an overall measure of local co-movement averaged across adjacent pairs (based on the exogenous introduction of an adjacency matrix), and over time, not spatio-temporal dynamics.

The considerable existing "ripple" literature that relies on cointegration tests for convergence,[68] asks whether markets share a common stochastic trend – whether they move together over time or exhibit mean-revering "spreads" (and rely on restrictive assumptions on the order of integration of time series).

Note however that the existence of a "ripple effect" - in the simple sense of spatial propagation of disturbances - might occur even in the absence of convergence; what is more even where convergence occurs cointegration tests do not reveal the synchronisation or spatial structure of short run adjustments or provide a dynamic view of the data, but a test of long-run comovement over the sample period.

Studies for the US in fact report mixed but limited evidence of convergence for U.S. markets and this has been argued to cast doubt on the existence of a ripple effect (Clark & Coggin, 2009; Gil-Alana et al., 2014; Gupta & Miller, 2012; S Holly et al., 2010; Holmes et al., 2011; Pollakowski & Ray, 1997; Zohrabyan et al., 2008).[69]

[66] E.g. Zhu et al. (2013) put forward the argument that linkages across geographical regions should not be restricted to connectedness across adjoining spatial units, but rather, they should also include connectedness predicating upon similar economic conditions.

[67] Although these have been downplayed/shrugged off by the BoE's latest inflation report (Bank of England, 2018).

[68] Since Meen (1999) argued that the transmission of shocks across regional markets will result in house prices in different markets converging in the long-run.

[69] Pollakowski and Ray (1997), Zohrabyan et al. (2008), Clark and Coggin (2009), Holly et al. (2010), Gupta and Miller (2012), Barros et al. (2012) and Barros et al. (2014) question the presence of overall convergence in regional housing prices and existence of a ripple effect, whereas Holmes et al. (2011) incorporates distance between states to show the existence of long-run convergence among U.S. states.

Unlike this convergence literature I directly investigate within a dynamic framework the geographical pattern in the timing of cyclical housing market fluctuations. The time-frequency methods I employ are less restrictive than the cointegration and error correction framework, and provides a richer unfolding both of time-scales (allowing the study of specific and multiple cycle components not just the long vs. short-run) and of the geography of house price developments, without any need for restrictive assumptions on the data/process.

Of course none of the time-domain methods relied upon in the existing literature provide spectral information or allow the study of the specific or multiple cycle components. All correlation-based methods are sensitive to amplitude and phase variation in the data, unlike these I separate fluctuation magnitudes and the phase-relations between the fluctuations in different markets.

It is common in studies of spatially *disaggregated* housing market data to emphasise a distinction between *idiosyncratic* 'local' dynamics and variation that can be captured by a *common component* assumed to reflect common national drivers (e.g. monetary policy, credit conditions and financial innovation, international capital flows, a national 'mania') (see e.g. Del Negro (2007) and papers that have followed). Some empirical studies of links between regional markets, first strip out the common component across all house price series (in order to control for strong cross-sectional dependence argued or assumed to reflect common national factors) before studying weak cross-sectional dependence in the residual variation (assumed to capture local spillovers - examples are e.g. Holly et al. (2010) and Baltagi et al. (2014)). By contrast, I study spatio-temporal dynamics in the relative timing of a periodicity band associated with a common cycle component across state level house price variation.

Organisation

Section 4.2 presents my analysis and results. Section 4.3 discusses my results and their interpretation. Section 4.4 puts these in the context of the existing literature. Section 4.5 concludes.

4.2 Analysis and results

4.2.1 Local phase-coherence of adjacent markets

While the mean field order parameter $R(t) = \frac{1}{N}\sum_{j=1}^{N} e^{i\theta_{x_i}(t)}$ (Eq.8) I used to assess the overall level of phase synchronisation across all markets (introduced in Essay 2 section 3.3.1) gives a good summary at the national level, it does not provide local information. It measures the average of the phase differences across all pairs of cycles

$$R(t) = r(t)e^{i\phi(t)} = \frac{1}{N}\sum_{j=1}^{N} e^{i\theta_{x_i}(t)}$$

$$R(t)^2 = \left|r(t)e^{i\phi(t)}\right|^2 = r(t)^2 e^{i\phi(t)} e^{-i\phi(t)}$$

$$R(t)^2 = \left|r(t)e^{i\phi(t)}\right|^2 = r(t)^2 e^{i\phi(t)} e^{-i\phi(t)}$$

$$= \frac{1}{N^2}\sum_{i,j=1}^{N} e^{i\left(\theta_{x_i}(a,t)-\theta_{x_j}(a,t)\right)}$$

$$= \frac{1}{N^2}\sum_{i,j=1}^{N} \cos\left(\theta_{x_i}(a,t) - \theta_{x_j}(a,t)\right)$$

This all-to-all relationship in the mean field setting can be thought of as implicitly considering a fully connected network. By explicitly introducing an adjacency matrix $A_{i,j}$ encoding the specific structure of links between elements, and averaging over these (rather than over all pairs) we can construct a parameter that can consider specific network topologies (but reduces to the standard Kuramoto order parameter for a fully connected (all-to-all) network) (Schroder, Timme, & Witthaut, 2017). Following Schroder et al (2017) I define an alternative order parameter

$$r_{uni}(t) = \frac{1}{\sum_{i=1}^{N} k_i}\sum_{i,j=1}^{N} A_{i,j}\Re\left(e^{i\left(\theta_{x_i}(t)-\theta_{x_j}(t)\right)}\right)$$

$$= \frac{1}{\sum_{i=1}^{N} k_i}\sum_{j=1}^{N} A_{i,j}\cos\left(\theta_{x_i}(t) - \theta_{x_j}(t)\right) \qquad (9)$$

where k_i is the degree of each node and $A_{i,j}$ the adjacency matrix defining the specific topology of the network. The main difference with respect to Eq. 8 is that r measures the degree of synchronization among all nodes with respect to the average phase ϕ, while r_{uni} considers only phase differences between neighbouring nodes (respecting the topology of the interaction network)[70]. This parameter is able to track transitions to partially and fully phase-locked states as well as convergence to complete synchrony (several adaptations have been introduced to study synchronization on a network (see e.g. (Arenas & Albert, 2008; Restrepo, Ott, & Hunt, 2006; Schroder et al., 2017)).

By introducing a spatial adjacency matrix A_{states} constructed based on the spatial contiguity of US states into Eq.9, I am able to quantify phase-synchrony considering only the phase-differences between price cycles in neighbouring states. In order to assess local synchronisation relative to the overall level of synchronisation among markets, I compare it to the same analysis run based on all-to-all network (i.e. the mean field analysis already presented in Ch.2 (see

[70] Thus reduces to Eq.8 for a completely connected network.

Section 3.4.2). Figure 18 presents the results from applying this, calculated over the 8-9 year periodicity band identified by my results in Ch.1 and further analysed in Ch.2. These results provide clear evidence that spatial adjacency matters for synchronisation.

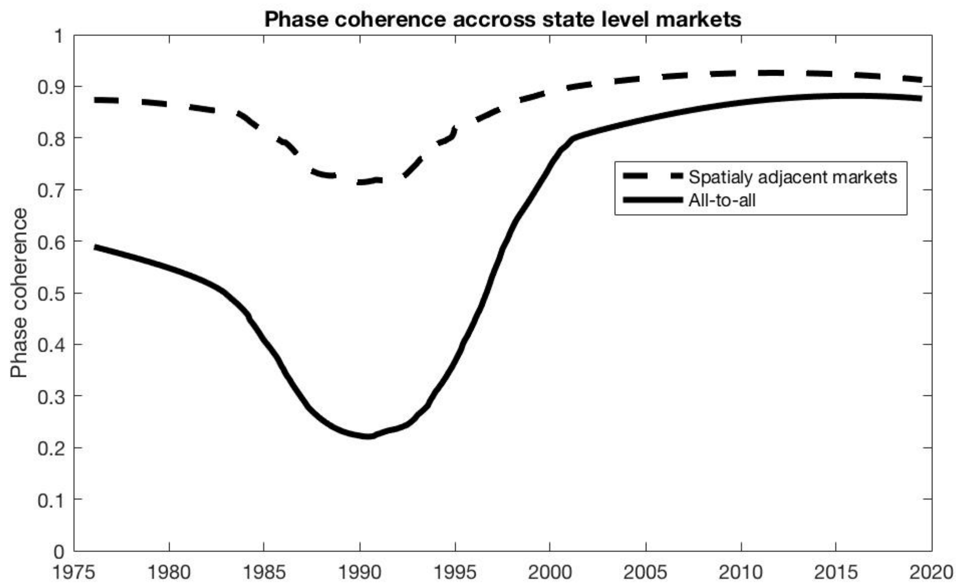

Figure 18 Phase-synchronisation (according to Eq.**9**) among (i) spatially adjacent markets (dotted black line) compared to (ii) overall synchronisation across all markets (black line). The blue shading represents the same statistic calculated based on lower and upper confidence limit (angle) of the scale averaged mean phase-difference.[71]

As a further check I also run the same analysis based on a series of random pairings of state level markets (I generate 1,000 random (ER) graphs with the same number of links as in the spatial adjacency matrix, and obtain the phase-coherence for this graph. Then take the 95% percentile of these. This tests the hypothesis that spatial adjacency is no more synchronised than a random set of links.

4.2.2 Spatial structure of relative-phase of cycles

The strong evidence in 4.2 that spatial adjacency matters, raises the question what sort of spatial patterns in the timing of state level housing cycles underpin this result? While Eq. 9 provided a useful means of assessing the *average* level of synchronisation between price cycles in neighbouring states, it does not help us to understand the specific *pattern of relationships* between markets across the US.

[71] These are obtained using meanPHASE function of Aguiar-Conraria and Soares (2014) following Zar (1999) and Matlab implementation in CircStat by Berens (2009) (see 10.1.4 for detailed explanation).

As a simple approach to assessing this question, I obtain the instantaneous phase (Eq.6) θ_{x_n} series averaged over the for each of $n = 1, \dots, 48$ contiguous states level house price series then visualise the evolution of the instantaneous phase of state level cycles as a dynamic heatmap of the US. The instantaneous phase is generally obtained either via wavelet or Hilbert transform of the data (see 3.3.1.1). Here (as for Ch.2 – see Section 3.3.1) I use periodicity band averaged local wavelet phase (Eq.6) based on the continuous wavelet transform (Eq.1) with Morlet wavelet (Eq.4). (I use a 10-15 year band reflecting the mean power spectrum results in Section 3.4.1 - see Figure 15).

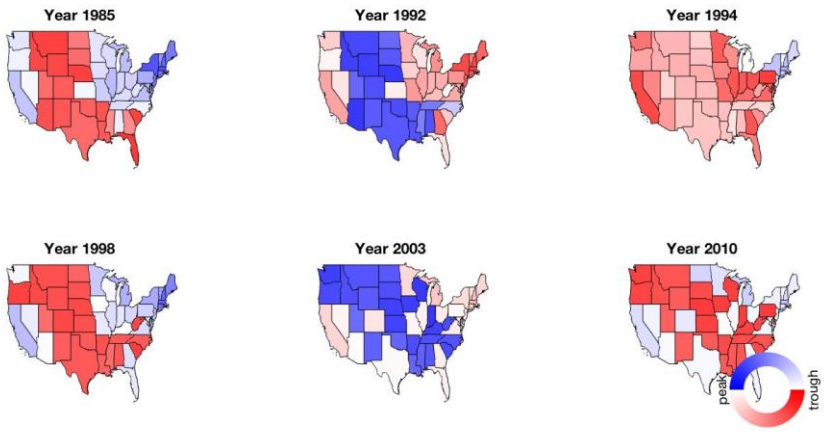

Figure 19 These heatmaps present the instantaneous phase of cycles in state level data across the US at six different points in time over the sample period. Here peak to trough is red increasing in intensity towards the trough, and trough to peak is blue, increasing in intensity towards the peak. This colour scheme makes a stark contrast between expansionary phase vs. contractionary phase cycles, but we also see e.g. in 1994 how the phase changes over space with coastal states close to troughing while central states are only just turning down. While these charts demonstrate the spatial patterns in relative phase, striking in the dynamic version (available here),[72] is how turning points ripple from adjacent state to adjacent state (e.g. another striking feature of the pre-2000s period in particular is the distinct segmentation of the northeast states).

It is perhaps worth emphasising, that there is nothing explicitly spatial about this analysis (unlike e.g. the spatial phase-coherence conducted in Section 4.2.1 no spatial adjacency matrix is introduced) I simply obtain the phase series separately for each state, but by projecting the results of this analysis into geographical space through heatmap visualisation, I am able to assess the spatial structure of the timing of cycles across the US.

The resulting dynamic heatmap reveals striking repeating 'travelling waves', with cycle peaks rippling across the US from east and west coast states into the centre. The full dynamic heatmap visualisation is available at (link) (see footnote 72) and also provided in in supplementary materials, meanwhile here **Figure 19**

[72] The link is:
https://drive.google.com/file/d/1BurjI7nm_2EjSpkusTZ0Qd4ZBF3K7u1T/view?usp=sharing

illustrates the observed pattern with some point in time stills from different dates over the sample period. Phase differences in price cycles in neighbouring states generate a periodic wave travelling across the US (analogous to a "Mexican wave").

Prior to the 2000s cycle peaks in some states occurred simultaneously with troughs in others (see e.g. 1985 and 1992 in **Figure 19**). We also see that this resembles a unidirectional traveling wave: in pre-2000s cross-state synchrony initially declines relatively steeply with distance in one direction (roughly east<->west) and then rises again as the geographical separation approaches one wavelength; meanwhile synchrony hardly changes with distance at all in the other direction (roughly north<->south) which is perpendicular to the direction in which the wave is travelling. We also see that the increased synchronisation after 1995 (Figure 16) has lengthened the spatial wavelength relative to spatial domain - the width of the US - so that simultaneous peaks and troughs no longer occur, but the travelling wave pattern is preserved.

In order to help assess the stability of/changes in this spatial pattern in the phase relationships between cycles, I use a continuous measure quantifying the phase shift of each individual market with respect to the overall mean phase across all states. I calculate the mean phase series across all markets from $R(t) = \frac{1}{N}\sum_{j=1}^{N} e^{i\theta_{x_i}(t)}$ (Eq.8) as

$$\phi(t) = atan2\big(R(t)\big) \qquad (10)$$

I then calculate the phase of each state relative to the mean phase across all sates (or *relative phase angle* (RPA)) as

$$\theta_{x_n,\phi}(t) = \theta_{x_n}(t) - \phi(t) \qquad (11)$$

This provides a continuous measure quantifying the phase shift of an individual market with respect to the overall collective development across states. This is defined for every state at every time step. In order to provide a more succinct summary of the relationships identified, I obtain the time averaged relative phase

$$\bar{\theta}_{x_n,\phi} = \frac{1}{T}\sum_{t=1}^{T} \theta_{x_n,\phi}(t) \qquad (12)$$

for all states for a series of (non-overlapping) sub-periods (using a 10 year window). Note that while as far as I am aware not previously employed in economics, these sort of relative phase differences have been used in a number of other applications (Brouwer et al., 2013; Lamb & Stöckl, 2014; Richardson, Garcia, Frank, Gergor, & Marsh, 2012; Varlet & Richardson, 2011).

The relative phase maps in **Figure 20** present these results. This also provides a succinct summary of the spatial patterns observed in spatial projection of phase data.

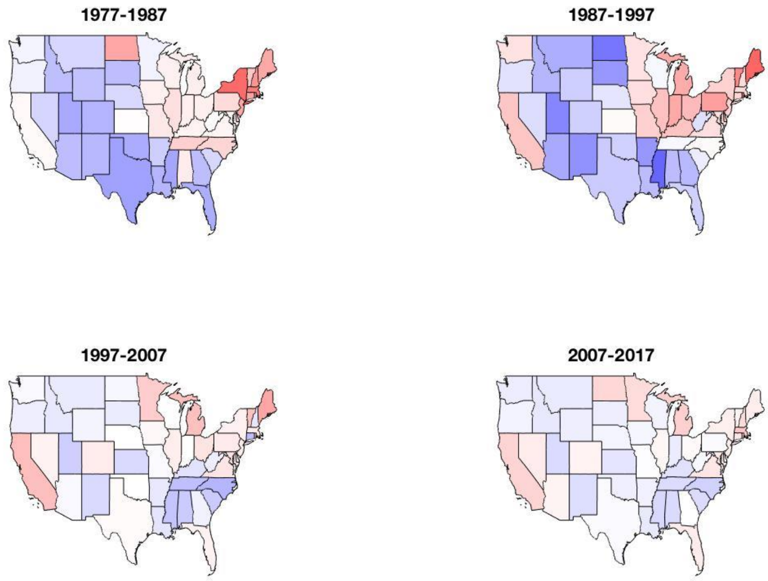

Figure 20 These heatmaps plot the relative phases of each state averaged over four non-overlapping 10 year windows spanning most of the sample period. Here red means ahead of the mean phase and blue lagging the mean phase, meanwhile stronger colours indicate a larger lead or lag (colours are consistent between maps). We see the general pattern is relatively stable over time with coastal states leading. However a number of changes are also apparent: (i) the distribution around mean phase tightens in the second half of the sample (hence the lighter colours in 1997-2007 and 2007-21017 charts); (ii) the spatially segmented strongly leading cluster of states in the north east weakens in the second half of the sample period.

We see that the overall spatial pattern of cycle phases relative to the mean phase across all states is relatively stable over time (with east and wet coast states leading the cycle. The increase in overall synchronisation is also clear (the lighter colours in later sub-periods reflect the smaller differences from mean). The spatial segmentation of leading northeast cluster of states (and how this segmentation weakens somewhat with time) is also recovered by this analysis.

4.3 Discussion

The clear spatial structure and patterns revealed provide a clear indication that the methods I employ are successfully picking up salient features of the housing market dataset, since no information on the spatial location of, or relationship between markets was employed in the data processing and analysis (only in the subsequent visualisation of my results).

While this spatial projection clearly shows smaller phase-differences in cycles between spatially adjacent markets and the relatively smooth variation of cycle phase over space, however the spatial projection on the whole emphasises the *spatial pattern* in relative phase of cycles in different markets (and the stability of this pattern over time). The local-phase coherence statistic meanwhile helps to provide a more precise quantification – thus view - of the time evolving average degree of synchronisation between adjacent markets.[73]

Moreover both the consistently high levels of local synchronisation (even when overall synchronisation was low) and the clear spatial patterns revealed, imply that sub national housing markets have not followed their own independent cycles, even when national synchronisation has been low, providing strong evidence that spatial links matter for the propagation of state housing cycles in the U.S. and for average house price dynamics at the national level.

Where the current literature for the US is inconclusive on the existence of "ripple effects" (Barros et al., 2012; Clark & Coggin, 2009; Gil-Alana et al., 2014; Gupta & Miller, 2012; S Holly et al., 2010; Pollakowski & Ray, 1997; Zohrabyan et al., 2008)[74] and spatial patterns in US housing market instability, moreover a number of studies have argued that other forms of economic links/distance are (more) important than spatial links (Hernández-Murillo et al., 2017; Malone, 2017; Pollakowski & Ray, 1997; Zhu et al., 2013), I clearly show that US markets are characterised by significant empirical "ripple effects" in the timing of price cycles demonstrating the significance of spatial links in U.S. housing.

However, while this spatial-wave revealed in the data resembles the sort of "ripple effect" widely discussed and studied in the real estate literature (from Meen (1999) to Tsai (2014)), by which a disturbances in house prices in a given location may spill over to other locations, leading to a global (yet potentially diminishing) effect on house prices in all other regions; it may be more consistent with the (spatial) coupling of relatively autonomous cyclical local house price dynamics:

Whether spatial diffusion of a local shock or a spatial contagion process, in either case we might expect "*epicentre*" dynamics/patterns where a local disturbance radiates out from its original source (as in fact observed using similar methods in e.g. the study of spatial epidemiological datasets (Grenfell, Bjùrnstad, & Kappey, 2001)).

Meanwhile the particular empirical pattern I document for U.S. house prices rather resembles the sort of traveling-wave than can arise in systems of coupled elements with non-trivial intrinsic cyclical dynamics - a dynamic possibility as yet unconsidered or explored in the real estate or wider economics literature but that has been widely explored by a large theoretical literature (M. Rosenblum, Pikovsky, Kurths, Schafer, & Tass, 2001; Strogatz, 2001) and widely documented in a range of spatial (D. M. Johnson, Bjørnstad, & Liebhold, 2004; Sherratt & Smith, 2008) and network systems.

[73] Here the use of spatial contiguity based matrix for *A* in the local phase coherence statistic (rather than other connectivity matrix) is strongly justified by the results of spatial-projection of phase series and travelling spatial wave documented. Future work might try to take a suitable data driven approach to empirically identifying coupling matrix and coefficients between markets. Under the hypothesis that individual markets are characterised by limit-cycle dynamics we must employ methods suitable for identifying (possibly time-varying) weak couplings between cycles (Cadieu & Koepsell, 2010; Casadiego et al., 2017; A. Pikovsky & Mrowka, 2007; M. G. Rosenblum & Pikovsky, 2001; Stankovski et al., 2012; Tirabassi et al., 2015) – see also section 8.2).

[74] Pollakowski and Ray (1997), Zohrabyan et al. (2008), Clark and Coggin (2009), Holly et al. (2010), Gupta and Miller (2012), Barros et al. (2012) and Barros et al. (2014) question the presence of overall convergence in regional housing prices and existence of a ripple effect, whereas Holmes et al. (2011) incorporates distance between states to show the existence of long-run convergence among U.S. states.

If markets have their own cycle, it seems easy to imagine how developments in neighbouring markets might cause small *delays* or *accelerations* to a state's own price cycle moving neighbouring cycles more into synch – e.g. if prices turn down in one market, this may influence confidence in neighbouring markets causing price cycles in those markets to turn a *little* earlier than they would have otherwise; or if rising prices cause migration and capital to spill over into neighbouring markets accelerating expansionary phase in their cycles. The non-stationarity of intrinsic cycle dynamics means that these adjustments have a permanent impact on co-movement – and in this way synchronisation could easily accumulate over time. Although for this reason, while the existence of a spatial-ripple strongly implies spatial coupling/diffusion, the degree of synchronisation does not provide a direct measure of dependence.

The combination of (i) the sort of local spillovers between neighbouring markets (such as are widely studied by the spatial diffusion and contagion literatures - which suggest a rich array of possible sources of spatial dependence between markets (Meen, 1999)) and (ii) local endogenous boom-bust dynamics (such as those that arise for example in the growing heterogeneous agent housing market literature (Dieci & Westerhoff, 2016)), might thus potentially generate both spatial-waves and increased synchronisation - thus amplifying national fluctuations over time (in Essay 5/Section 6 I will demonstrate this in a concrete model based setting, extending an endogenous expectations switching model from heterogeneous agent housing market literature to spatially extended setting).

Both the evidence of significant intrinsic dynamics reported in Essay 1 (the clear spectral ridges in the wavelet power spectra of state level price series); as well as the apparent stability of the spatio-temporal ordering of cycles across markets, and the traveling-wave spatial pattern revealed (the possibility of predicting not only the timing but also the geographical location of a shock seems inconsistent with the notion of an exogenous shock); seem to suggest the hypothesis that the local spatial interaction of relatively autonomous local cycle dynamics may underpin observed spatio-temporal dynamics.

While the spatial pattern provides clear evidence of spatial dependence - there is no reason to expect a spatial wave in the absence of local dependencies. However the question of whether common/national factor(s) may also have played an important role in the observed de-synchronisation and synchronisation events remains open.

Indeed the respective coincidence between the de-synch and synchronisation time series events and the S&L crisis, then Interstate Banking Act respectively (see previous work on interstate banking and housing market co-movement from Landier (2017)), provide at least circumstantial evidence that national financial shocks may have been significant in these events.

4.4 Relevant literature

Investigating the role of local links in co-movement presents some methodological challenges. Local dependencies between markets - especially spatial dependence - are well-established themes in real estate economics. However standard spatial econometric models may fail in the presence of strong cross-sectional dependence (generally requiring weak forms of cross-sectional dependence, in the sense that dependence decreases sufficiently quickly along the spatial dimension (Chudik et al., 2011; Pesaran & Tosetti, 2011)).

What is more, the spatial coefficients yielded by these models provide only a measure of contemporaneous local correlation averaged across links (adjacent pairs based on the introduction of a spatial adjacency matrix) and across the sample period or window.

Even where *dynamic* spatial effects are considered through the inclusion of a time-lagged spatial correlation (Baltagi & Li, 2014; DeFusco et al., 2013), the resulting spatial coefficients in either case provide only a measure of average spatial dependence, and do not provide any information on spatial patterns.

Some studies employ methods designed to accommodate both common factors and local links between markets as a sources of correlation (Pesaran, 2006; Pesaran & Tosetti, 2011): first using variation that can be captured by a common component to control for strong cross-sectional dependence, then studying residual spatial dependence across the idiosyncratic components using a standard spatial econometric model (e.g. spatial autoregressive model) (applications in U.S. housing market context include (Baltagi & Li, 2014; S Holly et al., 2010)).

Although studies employing this approach still find significant spatial dependence (Baltagi & Li, 2014; S Holly et al., 2010), this methodology starts from the assumption that covariance that can be captured by common components is driven by common factors. What is more, the standard spatial model estimated based on residual covariance, again only provides a test of spatial dependence based on average correlations.

The considerable existing empirical "ripple-effect" literature - which researches spatial propagation of house prices - has mostly relied on cointegration tests for convergence (Meen, 1999), asking whether markets move around/share a common stochastic trend in the 'long-run' (whether they move together over time exhibiting mean-revering "spreads") and rely on restrictive assumptions on the order of integration of time series.

The existence of a "ripple-effect" (in the simple sense of spatial propagation of disturbances) might occur however even in the absence of long-run convergence; what is more even where convergence occurs cointegration tests do not measure the synchronisation or reveal the spatio-temporal pattern of short run adjustments or provide a dynamic view of the data.

Indeed studies for the U.S. in fact report mixed but limited evidence of convergence for U.S. markets and this has been argued to cast doubt on the existence of a ripple-effect (Barros et al., 2012; Clark & Coggin, 2009; Gil-Alana et al., 2014; S Holly et al., 2010; Pollakowski & Ray, 1997).[75]

While these methods all provide time-averaged estimates of co-movement, some studies have employed rolling-windows or recursive estimations in order to address the question of how the co-movement of U.S. markets has changed over time.[76]

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[75] By far the largest literature on the "ripple-effect" is for the U.K. (Meen, 1996, 1999), but ripple-effects have been tested for in many countries.

[76] Simple correlation analysis (Kallberg et al., 2014; Landier et al., 2017); cointegration and error correction methods (Yunus & Swanson, 2013); latent factor models (Del Negro & Otrok, 2007) or simple

However, not only are there a number of potential issues with employing rolling-windows with many of these approaches,[77] but also none of these time domain methods provide the spectral information or phase-amplitude decomposition possible with wavelet analysis.

By contrast with a latent factor model approach, I study the phase-adjusted similarity between cycles in different markets (given by the wavelet power spectra in Essay 1 (Section 2) and the mean wavelet power spectra presented in Section 3.4.1 above); then study the phase synchronisation (Section 3-4) and pattern of phase-differences between markets (this Essay) for an empirically identified cycle component[78] associated with a common frequency band across markets. I am thus able to study the role of amplitude vs. phase in changing correlation among markets over time.

Given my focus on the pattern of phase-lead lags, strong cross-sectional dependence does not pose a problem (as it does for spatial econometric models) and the simple spatial projection of the instantaneous phase of the common cycle component that I introduce allows a rich elucidation of the exact pattern of relationships.[79]

Unlike the existing ripple-effect literature that has focused on convergence of house price levels, I thus directly study the temporal pattern in house price fluctuations.

What is more, the instantaneous phase based approach that I introduce allows me to study the development of overall synchrony and of spatial patterns with good temporal resolution (thanks to the optimal time-frequency resolution provided by the adaptive windowing of the continuous wavelet transform (see methods Section 2.2)).

These methodological innovations I introduce reveal striking spatio-temporal patterns not previously documented in the literature, despite the huge interest in spatial aspects of U.S. housing (U.S. housing markets are of course among the most closely and widely studied in the world).

Table 1 below sets out a brief summary of the relative capabilities and suitability for different data generating processes of the wavelet based approach I take in this essay, compared with dominant methodological strategies for studying ripple effects and spatial diffusion of house prices in the existing empirical literature - principally cointegration tests; and spatial panels and VARs.

By the wavelet based approach I take in this essay, I refer in particular to the estimation of empirical phase of a specific semi-periodic time-series component and spatial projection of this phase information in order to inspect for local or

multivariate regression frameworks (Cotter et al., 2011) as a way to try and estimate the relative importance of common (respectively latent or observed) national (vs. idiosyncratic local) factors in house price movements; and spatial econometric models (Abate & Anselin, 2016) in order to assess the co-movement of contiguous markets.

77 Rolling correlations based methods may generate nonsense results in the presence of persistent cycle components (oscillate even for stationary data and vary as a function of choice of window length relative to cycle period - see e.g. Yule (1926) on problems with rolling window correlations of oscillatory signals.

78 Note no assumptions are required as for turning point based methods widely used in the business cycle literature, and to some extent housing cycle analysis.

79 Although I also consider the phase-coherence of adjacent markets which provides an amplitude independent measure of spatial correlation.

global spatio-temporal patterns in phase lead-lags between markets (covered by third column of **Table 1**).

Arguably, since Meen (1999), the hypothesis that the spatial transmission of changes in house prices implies short-run divergence (lead-lag) but long-term convergence in regional house price levels, and studies using a range of pairwise and joint cointegration tests to search for long-run relationship between markets have dominated the "ripple effect" literature (and this strand remains an active literature (e.g. Hudson et al. (2017), Montagnoli & Nagayasu (2015), Tsai (2018) are just some recent examples) (covered by first column of **Table 1**).

More recently effort has increasingly focussed on using spatial panels and VARs to model spatio-temporal diffusion of house prices (Bailey, Holly, & Pesaran, 2016; Baltagi & Li, 2014; Blot, Creel, Hubert, Labondance, & Saraceno, 2015; Cohen, Ioannides, & Wirathip Thanapisitikul, 2016; S Holly et al., 2010; Yang & Yang, 2021) (where there has been some convergence in methods (Elhorst, Gross, & Tereanu, 2018) and the joint modelling of dynamic relations, spatial or network interactions, and common shocks is an area of active developments (Bai & Li, 2021; Meetings & Booth, 2020) likely to contribute further to study of housing market ripple-effects) (column two of **Table 1**).

Table 1: Comparison of methodological strategies

Capability	**(i) Tests for convergence**	**(ii) Spatial panels and VARs**	**(iii) Wavelet based approach**[80]
Test for spatial transmission?	No (Testing hypothesis of short–run divergence but long-run convergence[81] – thus despite being dominant strategy in the literature for testing housing market ripple effect, not a test of spatial diffusion).	Yes (Studies spatio-temporal correlation – using coefficients on spatial lag, temporal lags of spatial lag - directly relevant to hypothesis of spatial transmission/diffusion of shocks. May struggle to disentangle common shocks vs. spatial effects/endogenous comovement as source of strong cross-sectional dependence.[82] Relies on the introduction of spatial weights).	Yes (By estimating empirical phase and phase-differences between price changes in different markets, reveals any spatio-temporal patterns in phase lead-lags across markets – providing direct evidence on whether there are wide-scale "spatial-ripple" phenomena. While unobserved common factors may drive spatial correlation and reduce overall dispersion in cycle phases across markets, they cannot explain widescale ripple pattern in phase-lead lags between markets).

80 By this I refer only to the methods introduced in this Essay, but it is important to note that the potential to exploit wavelet transform in study of spatio-temporal phenomena is far from exhausted by the work presented here, and the wavelet transform could provide the basis for a whole range of further methodological strategies and extensions.

81 Variety of pairwise and joint cointegration tests.

82 Methods that control for strong cross sectional dependence through some de-factoring procedure (using principal components, or cross-sectional averages such as the two-stage approach taken by Bailey et al. (2016) that extracts the common factors in the first stage and then estimates the spatial connections in the second stage) make the *assumption* that strong cross-sectional dependence driven by some unobserved common factor (and not endogenous comovement).

Reveal spatial pattern of lead-lags between markets?	No (Tests whether prices in regional markets share the same contemporaneous stochastic trends – neither considers long-run lead-lags, nor the patter of lead-lags in short-run fluctuations around equilibrium).	Partly (Slope coefficient on spatial regressor does not reveal spatial pattern of lead-lags.[83] However within VAR framework GC[84] tests and FEVD[85] can provide information on average direction of information/key sources of shocks).[86]	Yes (This approach directly estimates spatial pattern of temporal lead-lags. Spatial projection of estimated phase then provides rich information on spatio-temporal patterns at different scales).
Reveal time-evolving pattern of relationships?	No (Tests time-averaged dynamics).	No (Time-averaged relationships).[87]	Yes (*Instantaneous* phase and amplitude decomposition provided allows viewing lead-lag pattern at a given time and time-scale, and *how this evolves/unfolds over time* – thus can provide information on specific shocks or time-evolving relationships/dynamics).
Provide frequency/scale specific test for spatial ripple/transmission?	Partly (Ripple effect - if it exists - is assumed to be in short-run lead-lags. "Short-run" vs. "long-run" defined in terms of trend vs. equilibrium adjusting dynamics).	No	Yes (Frequency decomposition means relevant time-scales can be identified in the data and scale-specific/varying spatio-temporal patterns studied).
Study spatial-ripple arising in coupled (quasi)-periodic dynamics setting?	No (Concerned with stochastic trend processes and not oscillatory processes. Study existence of equilibrium relationship between markets/ *contemporaneous* common *stochastic* trend(s)).	No (A well-specified model - with appropriate lag structure - might successfully capture cyclic dynamics,[88] but not (time evolving) phase-relations and their contribution to correlation. Meanwhile de-factoring based approaches ignore/destroy pattern of phase-shifts between cycles in different markets).	Yes (Combined time-frequency and phase-amplitude decomposition allows data driven identification of cycles and cycle period; study changing phase relationships between identified cycles – highly suited to empirical study of coupled deterministic cycle dynamics).
Forecasting/ prediction?	*No (*But cointegration implies the presence of a valid error correction model that could be exploited for forecasting purposes).	Yes ((Well) specified model could be used to directly forecast price developments over space and time.).	Partly (In coupled deterministic cycle setting, instantaneous phase + amplitude may help to predict direction and magnitude of future cyclic developments both at market and aggregate/mean field level).[89]

4.5 Conclusions

In this chapter I have investigated the spatio-temporal character of the common cycle component in state level house price data identified in Essay 1 and 2.

Through the introduction to the economics literature of time-frequency methods for spatio-temporal analysis, I am able to reveal and document for the first time, not only the high level of synchronisation among adjacent markets,

[83] Market specific slope coefficients in VAR settings (and some spatial panel specifications) can provide spatial information on comovement but not pattern of lead-lags.
[84] Granger causality.
[85] Forecast error variance decomposition.
[86] As for example Chiang & Tsai (2016).
[87] Sub-sample estimates can be used to deal with structural breaks.
[88] But struggle with multiple periodic components.
[89] This might be best exploited by combining with more conventional parametric methods for time-series modelling – something I leave to future work.

but a striking spatial pattern in the timings of cycles in different markets resembling a ‘traveling-wave’ (analogous to a “Mexican wave”).

This pattern is remarkably stable across the c.50 year sample period, across multiple cycle periods, and between the low and high overall synchronisation eras. Where the existing literature has cast doubt on the existence of a “ripple effect” my analysis clearly shows the spatial propagation of US housing cycles.

However whilst these results will be of considerable interest to the “ripple effect” literature, the ‘traveling-wave’, rather than ‘epicentre’ pattern may be more consistent with spatial interaction among markets with significant intrinsic cyclical dynamics (consistent with the evidence presented in Essay 1 – see Section 2), than with shock diffusion or contagion dynamics hypothesised in the literature.

Meanwhile both consistently high local-synchronisation and the striking spatial pattern make clear that local housing markets have not followed their own independent cycles, even when overall synchronisation was low at the national level. These results raise the questions whether local synchronisation among markets could have been at play in the global synchronisation event. However the manner in which this maps to changes in mortgage finance seems to suggest finance played some important role.

5 Essay 4: Local cycle and bubble dynamics: evidence permanent cycle phase modulates temporary bubble formation and collapse

Summary: econometric studies of U.S. house prices at the sub-national level present compelling evidence of a long history of temporary explosive episodes consistent with bubble dynamics. These were common prior to the 2000s consistent with a history of local bubbles, and geographically widespread during the 2000s housing boom, consistent with a national bubble at this time. Meanwhile in Essays 1 to 3 I document evidence of repeating c.10-year cycles, and of traveling spatial waves over the available historical sample period Jan 1975 - Jun 2020. These results are more consistent with spatial dependence among intrinsically cyclical markets, than with time localised explosive episodes in an otherwise stable process. Given the compelling evidence of both explosive episodes, and of persistent cycles, a question arises whether these are connected or independent phenomena. In this Essay I investigate the relationship between the bubbles and cycles observed in U.S. house prices using monthly state level house price data since 1975. I find a systematic relationship between the *timing* of the onset of explosive bubbles (dated using the PSY test by Phillips, Shi and Yu (2015a, 2015b) - now popular in the literature) and the instantaneous phase of the slow cycles (obtained by wavelet transform (as per analysis presented in Essays 2-3/Section 3-4)). This result suggests low frequency repeating housing cycle fluctuations may have played an important role in the occurrence and timing of housing bubbles, shedding new light on a problem we have so far made little progress on: how can we explain where and when bubbles occur? It also suggests slow fluctuations may have significance for housing market dynamics beyond their own amplitude contribution since the slow cycle seems to modulate shorter-run housing market volatility.

5.1 Introduction

The central role the U.S. housing market price run-up and collapse seem to have played in the global financial crisis and recession, have generated renewed interest in the dynamics of house prices (see Sections 2 to 4). A view widely shared among academics and policymakers is that the 2000s boom period saw US house prices depart from their fundamental values, leading to distortions and ending in the price correction that eventually precipitated the crisis (Ben S Bernanke, 2010).

While economic theory suggests many reasons housing markets may overshoot, and the character and causes of this episode remain hotly debated, the enormous increases and subsequent crashes in house prices have led many researchers to test for the presence of speculative bubbles:

Where property prices are determined not only by economic fundamentals, but driven either by the rational expectation of a future gain from future price increases (Flood & Hodrick, 1990),[90] or by irrationally optimistic expectations

[90] Rational expectations hold so no arbitrage opportunities. A recent review of theory of rational bubbles for macroeconomics is provided by Martin & Ventura (2018). Gurkaynak (2008) provides a previous overview of different empirical tests on rational bubbles.

(Shiller, 2000; Vissing-jorgensen, 2004), house prices will follow an explosive process.

A substantial empirical literature exploits this feature of non-fundamental asset price components as the basis for formal bubble tests - framed both within the well known present-value model ((Diba & Grossman, 1988a; Hall, Psaradakis, & Sola, 1999; Homm & Breitung, 2012; Efthymios Pavlidis et al., 2016; Phillips & Yu, 2011) and e.g. trend-following behaviour ((Bolt et al., 2014)) hypothesised in the behavioural asset market literature.

Bolt et al. (2014) make empirical tests based on an argument that house price dynamics and deviations from fundamentals will become temporarily explosive where the average extrapolation factor in house price expectation formation exceeds one. Zhou and Sornette (2005) look for faster than exponential growth (power law super-exponential acceleration) as evidence of an unsustainable bubble. The recursive unit root test recently introduced by Phillips (Phillips, Wu, & Yu, 2011) and Phillips Shi and Yu (2015a, 2015b) (henceforth PSY test) in particular has been deployed in a wide variety of applications,[91] including a large and growing number of studies of real estate markets (Engsted, Hviid, & Pedersen, 2016; Greenaway-mcgrevy & Phillips, 2015; Hu & Oxley, 2018a; Jiang, Phillips, & Yu, 2015; Efthymios Pavlidis et al., 2018, 2016; Phillips & Yu, 2011; Shi, 2017; Yusupova, Pavlidis, Paya, & Peel, 2016).

Econometric studies of US markets find national house price series followed an explosive process during the 2000s boom period, consistent with e.g. a temporary rational bubble or period of "irrational exuberance" (Kivedal, 2013; Phillips & Yu, 2011; W. Zhou & Sornette, 2005).

While many studies focus on aggregate U.S. house price developments, similar studies of regional house price series (i) further identify a long history of such explosive episodes at local market level (consistent with significant "local" speculative bubbles prior to the 2000s); and (ii) also confirm that explosive episodes were geographically widespread during the 2000s (providing additional support for the 'national bubble' interpretation of this period (see e.g. Shi (2017), Hu & Oxley (2018a), Pavlidis et al. (2018))).

While the bubble identification literature presents compelling evidence of significant *temporary* explosive episodes in regional house price series consistent with a non-stationary process switching between stable and temporarily explosive dynamics, in Essay.1 (Section 2) I present evidence that U.S. regional housing markets have exhibited repeating cycles (with a period of roughly 10 years) consistent with permanent or persistent fluctuations around an unstable or weakly stable equilibrium – i.e. limit cycle or near limit cycle dynamics such as those that arise in some e.g. behavioural housing models (Dieci (2016) is a recent example).

I further show, moreover, that the synchronisation of these repeating cycles across US markets made an important contribution to the national boom-bust of the 2000s.

These results suggest a novel alternative interpretation of the national housing market instability of the 2000s in terms, not of a temporary bubble, but

[91] Some examples covering various financial and commodity markets are: Bohl (2003); Etienne et al. (2014a, 2014b); Gutierrez (2012); Adammer & Bohl (2015); Figuerola-Ferretti et al. (2020); Hu & Oxley (2018b); Phillips & Shi (2017).

the synchronisation of existing cycles (something that could have occurred endogenously or as the result of a common shock or increased coupling between/integration of markets (something I will explore further in Essay.5 (Section 5)).

This evidence that: (i) temporary explosive ('bubble') episodes – now well documented, and (ii) on-going low frequency cyclicality both make significant contributions for understanding U.S. house price instability, raises the question: whether there is any important relationship between these two distinct phenomena? In order to address this question I study the relationship between the *timing* of (i) temporary house price bubbles, and (ii) repeating house price cycles. Specifically: using monthly state level house price data for the period Jan 1975 - Jun 2020, following the recent empirical bubble and housing bubble literature I use the PSY test (which provides a technology for identifying explosive episodes with consistent dating of their origination and collapse) to date-stamp both the *onset* and *bursting* of bubbles; then I obtain the instantaneous phase of the low frequency cycle at bubble onset dates (i.e. the instantaneous phase of the low frequency cycle in the same months as the 'bubble' started and burst as dated by PSY procedure).

First I use a simulation based exercise to test whether the novel procedure I introduce and employ is able to (i) identify bubbles and cycles, and (ii) distinguish between the case where bubble formation depends on the cycle phase, and the case where it does not. The procedure works well on simulated data.

I then apply the procedure to US housing market data. I find a systematic relationship between the onset and bursting of explosive bubbles, and the phase of the slow cycle with bubbles systematically associated with phase-angles corresponding to the late stage of the expansionary phase of the 10-year cycle, and collapse episodes occurring after the slow cycle has peaked. This result holds for pre-2000 bubble episodes (when bubbles were 'regional' not national and before local cycles synchronised) as well as for the full sample.

A defining aspect of temporary bubble based theories of house price instability, is that dramatic market swings are seen to be driven, not by major changes in economic conditions, but rather by random capricious shifts in market psychology (Martin & Ventura, 2018; Shiller, 2000, 2015). As a result it is hard to say much on predicting when or where temporary bubbles are likely to arise - note that while e.g. the PSY procedure provides a *real-time monitoring strategy* (for example the PSY approach is now employed by the Federal Reserve Bank of Dallas, providing an exuberance indicator for 23 international housing markets)[92] thus potential for early identification of a bubble once it starts, it does not help to predict in advance where or when bubbles are likely to occur.

By contrast the work I present in Essays 1-3 (Sections 2-4) is able to document striking temporal and spatial patterns in the data and the synchronisation of local cycles.

[92] The Dallas FED publishing recursive unit-root test based housing market exuberance indicators for 23 national housing markets based on the bubble test of Phillips, et al. (2015a,b) and the methods developed in Pavalidis et al. (2016). This indicator can be found here: https://www.dallasfed.org/institute/houseprice/

Given these results, the systematic relationship I demonstrate here, between bubble timing and cycle timing, implies bubbles may be far from random, and clearly has implications for our understanding and possible interpretations both of the evidence of some spatial patter in the historical timing of booms in different markets identified by some analysts (refs), and of the more nationally synchronised booms across the U.S. during the 2000s.

Meanwhile this result suggests that the low frequency cycles (even where these oscillations may be weak considering their amplitude relative to explosive episodes) have a significant influence on house price instability at shorter time scales and overall house price volatility beyond their own direct amplitude contribution due to their role in influencing the timing and likelihood of explosive episodes.

The paper proceeds as follows: In 5.2 in introduce my methodology in some detail, and provide simulation based demonstrations and validation (Section 5.3.3). Section 5.4 presents my analysis and results including some examples of state level house price series that exhibit (i) evidence of both cycles and bubbles, (ii) evidence of cycles but no significant evidence of bubbles (Section 5.4.1) as well as my systematic analysis of the relationship between cycle and bubble timing (Section 5.4.2). I make some discussion of my results in Section 5.5 Finally Section 5.6 concludes.

5.2 Housing bubble literature and choice of bubble test

Bubbles are defined as periods characterized by asset pricing that deviates from market fundamentals. Unsurprisingly there is a very large literature both on asset bubble detection in general (with a focus on stock markets and other traded securities and commodities), as well as on housing market bubble detection specifically.

Research has addressed both the (possible) *sources* of bubbles, and empirical methods to *test* for them. The literature on bubbles include research within the present-value pricing framework on rational speculative bubbles (Blanchard, 1979; Diba & Grossman, 1988a) which have nothing to do with fundamentals[93] (Kashiwagi, 2014); or intrinsic bubbles (Froot & Obstfeld, 1991) which depend exclusively on over-reaction to exogenous fundamental shocks (Nneji, Brooks, & Agency, 2013); as well as research on non-present value pricing such as momentum and extrapolative expectations (Glaeser & Nathanson, 2017; Granziera & Kozicki, 2015), herd behaviour, and irrational exuberance (Shiller, 2000, 2015; Vissing-jorgensen, 2004).

Since a bubble is defined as deviation of price from that justified by fundamentals, many studies seeking to assess the presence of housing bubbles have examined the relationship between house prices and housing market fundamentals[94] (Abraham & Hendershott, 1993, 1996; Meese & Wallace,

[93] When investors share the belief that variable(s) not related to fundamentals influence prices, it is rational to include this information into price expectations (Diba & Grossman, 1988a).

[94] The set of fundamentals typically includes variables such as income, housing stock, demography, credit availability and interest rates.

1994).[95] What cannot be explained by fundamentals may represent a bubble component in house prices.

However the question of fundamental value is not easy to pin down with any certainty or consistency and in these sorts of studies it remains unclear whether deviations from estimated fundamental values are due to a "bubble" or to model misspecification – a general problem for strategies based on measuring bubbles as a residual (Gürkaynak, 2008).[96]

This has motivated another strand of research which takes an alternative strategy, seeking to identify bubbles based on *dynamics*: bubbles are explosive (Diba & Grossman, 1988a) and subject to periodic collapse (Blanchard, 1979).

Evans (1991) showed that the conventional right-tail unit root test (Diba & Grossman, 1988a) is incapable of detecting explosive bubbles that collapse periodically (Blanchard, 1979) – these sorts of tests have difficulty distinguishing periodic collapse from mean reversion. However this has given rise to a number of econometric approaches based on testing the presence of time-localised explosive dynamics which are suitable not only for testing for, but also for *dating* bubble episodes given a periodically collapsing explosive process.

Econometric test for *identifying* and *dating* bubble episodes include: (i) regime switching models such as the Markov-switching augmented Dickey–Fuller (MSADF) test developed by Hall et al. (1999) (see also extension by Shi (2013));[97] and the infinite hidden Markov model proposed by Shi and Song (2016); (ii) the cumulative sum (CUSUM) test by Homm and Breitung (2012); (iii) rolling window unit-root tests (Chong & Hurn, 2017; Shi, 2007);[98] and (iv) measures constructed by recursively testing whether or not a time series variable is in a regime characterized by explosive behaviour such as the recursive right-tailed unit root test by Phillips, Wu and Yu (2011) (PWY) generalised by Phillips, Shi and Yu (2015a, 2015b) (PSY).[99]

In this essay, I choose to employ the PSY test in order to identify and date stamp bubble episodes, for: its power to consistently date *multiple* periodically-collapsing episodes of mildly explosive behaviour; its ability to accommodate various bubble generating mechanisms[100] – thus relative agnosticism with respect to the bubble-generating mechanisms; as well as its recent popularity in the literature for studying house price dynamics (see following references) (note other tests listed here have not as far as I can tell found application in the study of housing markets).[101]

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[95] Meese and Wallace (1994) examine whether the real expected return on home ownership is close to the real homeowner cost of capital by studying the relationship between price, rent, and the cost of capital. Abraham and Hendershott (1993, 1996) study the relationship between housing prices and construction cost, real income growth and interest rate. They find that these factors explain half of the historical variation in house price appreciation. The bubble, then, manifests itself in the "sustained serially correlated deviations," yet, it remains unclear whether these deviations are due to a "bubble" or to a misspecification of the econometric model (Escobari & Damianov, 2015).

[96] Bubbles will create a residual but so will any misspecification of the model.

[97] See also Norden (1996) for related approach.

[98] See also Taipalus (2006).

[99] Other strategies proposed in response to the "Evan's critique" include: the momentum threshold autoregressive (MTAR) test of Enders and Granger (1998) and Enders and Siklos (2001). Bohl (2003) showed that this test provides a sufficiently powerful test to detect periodically collapsing bubble behaviour and the test has been used to test bubbles in REITs markets (Jirasakuldech, Campbell, & Knight, 2006; Payne & Waters, 2006; Waters & Payne, 2007; Xie & Chen, 2015).

[100] Shi (2011) provides a partial overview of the literature. See also Phillips Shi and Yu (2015a, 2015b).

[101] Although the MSADF test was used by Qin and Tan (2006) to test for bubbles in Seoul property market.

Consistency of the PSY estimated bubble start and end dates under various data generating processes was established in Phillips et al. (2015b) and Phillips and Shi (2018a); and Phillips and Shi (2017) proved consistency of dating for crises. For bubble detection it has been shown to outperform the forward recursive algorithm (Phillips et al., 2011), rolling window unit-root testing approaches (Chong & Hurn, 2017; Shi, 2007), and the CUSUM monitoring strategy of Homm and Breitung (2012) - in particular when, as here, the sample period is likely to include multiple episodes of explosive bubbles.

Although studies employing the PSY test for bubble identification have tended to be framed in terms of present-value model and theory of rational speculative bubbles (Blanchard, 1979; Diba & Grossman, 1988a), the reduced-form empirical approach of the PSY test also accommodates other bubble-generating mechanisms such as intrinsic bubbles (Froot & Obstfeld, 1991) (for studied of intrinsic bubbles in housing market context see e.g. (Nneji et al., 2013)), and herd behaviour and extrapolative price expectations (Abreu & Brunnermeier, 2003; Avery & Zemsky, 1998) (in housing market context e.g. Bolt et al. (2014) make empirical tests based on an argument that house price dynamics and deviations from fundamentals will become temporarily explosive where the average extrapolation factor in house price expectation formation exceeds one); as well as time-varying discount factor fundamentals (Phillips & Yu, 2011).

This flexibility with respect to the underlying bubble process makes it suitably agnostic for my purpose: rather than distinguishing between alternative bubble mechanisms, my purpose here is to investing the relationship between the sort of explosive episodes identified by the existing literature, and the permanent cycle dynamics I document in Essay 1 (Section 2).

Moreover the PSY test has become widely used for detecting bubbles in a variety of different markets,[102] including a growing number of applications to the detection of housing market bubbles: based on the PWY test Phillips and Yu (2011) find U.S. national house price series followed an explosive process during the 2000s boom period (see also Das et al. (2011)); Hu and Oxley (2018a) and use the PSY procedure to test for bubbles in U.S. state level price series, finding a long history of explosive episodes at this subnational level (see also Pavlidis et al. (2018) and Shi (2017) for applications to U.S. subnational markets). The PSY procedure has also been widely used to test for housing bubbles in a number of other markets around the world (both national price series (Anundsen, Gerdrup, Hansen, & Kragh-Sorensen, 2016; Deng, Girardin, Joyeux, & Shi, 2017; Gomez-gonzalez, Gamboa-arbeláez, Hirs-garzón, & Pinchao-rosero, 2018; Hu & Oxley, 2016; Martínez-garcía & Grossman, 2020) and studies of sub-national markets (Gomez-gonzalez & Sanin-restrepo, 2018; Greenaway-mcgrevy & Phillips, 2015; Shi, Rahman, & Wang, 2020)).

Note some other strategies for identifying (housing) bubbles without relying on estimating fundamental values include: Zhou and Sornette (2005) who look for faster than exponential growth (power law super-exponential acceleration) as evidence of an unsustainable bubble. Watanabe et al. (2006) – extended by

[102] Wider applications include (but not limited to): stock markets (some examples are (Chuliá & Uribe, 2017; Deng et al., 2017; J. H. Lee & Phillips, 2016)); commodity markets (for instance, Etienne, (2017); Alexakis et al., (2017)), energy markets (Narayan & Kumar, 2017); and exchange rates (Maldonado, Tourinho, & Abreu, 2018).

Hui et al. (2010) - introduce a mathematical definition of bubbles and crashes by exponential behaviours, and use of this for detection. Escobari and Damianov (2015) exploit the idea that low tier home prices increase at a faster pace during the boom than the high tier home prices if cheap credit is available to consumers predominantly at the low end of the distribution of houses and estimates the beginning and the burst of bubbles as structural breaks in the difference between the appreciation rates of price tiers. They study 15 U.S. MSAs during the 2000s. In an earlier study Mizuno et al. (2011) also proposed making use of information on the cross-sectional dispersion of real estate prices and study not price movements but changes in the price dispersion.

5.3 Methodology

In order to study the relationship between the timing of bubble episodes and the timing of underlying cycles, I combine (1) the procedure introduced by Phillips, Shi and Yu (2015a, 2015b) for detecting and date-stamping temporary bubble episodes; with the time-frequency methods already introduced in previous chapters – power spectrum and instantaneous phase.

5.3.1 'Bubble' identification and timing

For the purpose of bubble identification and dating I employ the procedure introduced by Phillips, Shi and Yu (2015a, 2015b) (PSY procedure) which has become popular in the study of house price bubbles (Engsted et al., 2016; Greenaway-mcgrevy & Phillips, 2015; Hu & Oxley, 2018a; Jiang et al., 2015; Efthymios Pavlidis et al., 2016; Phillips & Yu, 2011; Yusupova et al., 2016) as well as wider asset price bubble literature;[103] with the bootstrapping procedure proposed in Phillips and Shi (2018b).[104]

The PSY procedure provides a method for detecting and dating multiple explosive bubble (Phillips et al., 2015a, 2015b) and/or crisis episodes (Phillips & Shi, 2017) in the same sample series.[105] This procedure is based on the implementation of right-tailed augmented Dickey-Fuller (ADF) type unit root tests via a backwards recursive evolving algorithm (See 10.2.1 of methods appendix).

The hypothesis of a mildly explosive process is tested against the null of a 'martingale' process with asymptotic drift

$$H_0: p_t = dT^{-\eta} + p_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim NID(0, \sigma^2) \qquad (13)$$

$$H_1: p_t = \delta_T p_{t-1} + \varepsilon_t \qquad (14)$$

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[103] Some examples covering various financial and commodity markets are: Bohl (2003); Etienne et al. (2014a, 2014b); Gutierrez (2012); Adammer & Bohl (2015); Figuerola-Ferretti et al. (2020); Hu & Oxley (2018b); Phillips & Shi (2017).

[104] This procedure was introduced in order to simultaneously addresses both heteroskedasticity (Harvey et al., 2016) and multiplicity issues in testing.

[105] The method is a generalized version of the sup augmented Dickey–Fuller (ADF) test of Phillips et al. (2011).

The term $dT^{-\eta}$ captures any mild drift that may be present in prices but which is of smaller order than the martingale component and is therefore asymptotically negligible (Phillips & Shi, 2018b, p. 5), where d is a constant, T sample size, and the localizing coefficient η is greater than $\frac{1}{2}$. $\delta_T = 1 + cT^{-\theta}$ with $c > 0$ and $\theta \in (0,1)$.. The ADF test statistic is the t-statistic on the least squares estimate of the coefficient of p_{t-1} in the regression model chosen for the PSY procedure

$$\Delta p_t = \alpha + \beta p_{t-1} + \sum_{k=1}^{K} \gamma_k \Delta p_{t-k} + \varepsilon_t \qquad (15)$$

which includes the intercept α but no time trend and nests the null hypothesis as a special case with $\alpha = dT^{-\eta}$ and $\beta = 0$. The K lag terms are included to account for serial correlation.

The PSY procedure calculates the ADF statistic recursively from a backward expanding sample sequence. If t_{start} and t_{end} are the start and end points of the regression sample, the ADF statistic calculated from this sample is denoted $ADF_{t_{end}}^{t_{start}}$. The starting point of the sample varies from the first observation t_0 to $t^{\dagger} - w_0 + 1$ where $t^{\dagger}$ is the observation of interest and w_0 is the minimum number of observations required in order to estimate Eq.34. The resulting ADF sequence is shown as

$$\{ADF_{t_{end}}^{t_{start}}\}_{t_{end}=t^{\dagger}}^{t_{start}\in[t_0,t^{\dagger}-w_0+1]} \qquad (16)$$

and inference regarding the explosiveness of observation $\Delta p_{t^{\dagger}}$ is based on the PSY statistic defined as the maximum value of the entire ADF sequence[106]

$$PSY_{t^{\dagger}}(w_0) = \sup \quad \{ADF_{t_{end}}^{t_{start}}\}_{t_{end}=t^{\dagger}}^{t_{start}\in[t_0,t^{\dagger}-w_0+1]} \qquad (17)$$

The supremum enables the selection of the 'optimal' starting point of the regression in the sense of providing the largest ADF statistic. This procedure can be repeated for each individual observation of interest ranging from w_0 to t_{end} generating the PSY statistic sequence $\{PSY_{t^{\dagger}}(w_0)\}_{t^{\dagger}\in[w_0,t_{end}]}$.

In Figure 38 I reproduce a visual representation of the recursive evolving algorithm provided by Phillips and Shi (2018b)).

[106] The backward supremum ADF.

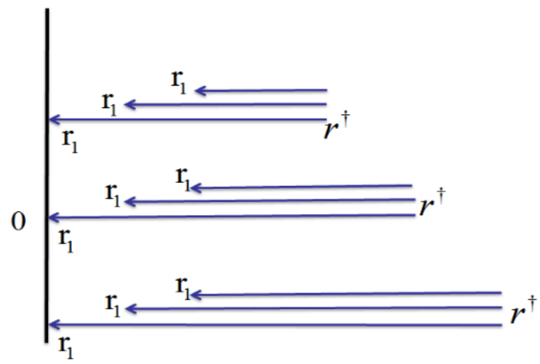

Figure 21: This figure reproduces illustration of PSY recursive evolving algorithm as presented in Phillips and Shi (2018b).

Consistency of the estimated bubble start and end dates under various data generating processes was established in Phillips et al. (2015b) and Phillips and Shi (2018a); and Phillips and Shi (2017) proved consistency of dating for crises. For bubble detection it has been shown to outperform the forward recursive algorithm (Phillips et al., 2011), the rolling window approach (Chong & Hurn, 2017; Shi, 2007), and the cusum monitoring strategy of Homm and Breitung (2012).

To assess statistical significance I rely on the procedure proposed by Phillips et al. (2018b) that combines the wild bootstrap introduced by Harvey et al. (2016) to address heteroskedasticity,[107] with a procedure to account for multiplicity in the test sequence recursion (a problem common to recursive testing procedures is that the probability of false positives rises with the number of hypotheses tested (Phillips & Shi, 2018b, p. 14)) (See Section 10.2.2 of methods appendix for details of this procedure as set out by Phillips et al. (2018b)).

5.3.2 Cycle identification

For cycle identification I rely on the analysis presented in Ch.1. Timing of cycle assessed based on instantaneous phase (Eq.6).

5.3.3 Assessing the relative timing of bubbles and cycles

Evidence house price series exhibit both significant 'bubble' and periodic components raises the question: what is the relationship between these phenomena? In order to answer this question we need to obtain information on the relationship between the *timing* of bubbles in relation to the *timing* of the cycle. The timing of the cycle can be described in terms of its *phase* (which evolves over time), thus the instantaneous phase of the cycle at the time of bubble onset, gives us the timing of the bubble in relation to the cycle. This is

[107] Harvey et al. (2016) show that the presence of heteroskedasticity can affect the performance of the forward recursive method of Phillips et al. (2011) and introduce a wild bootstrap to solve this problem which they show to have good performance asymptotically and in finite samples.

easily empirically quantified since the imaginary part of the wavelet transform gives us precise information about the instantaneous phase (Eq.6) of the cycle at each time step and frequency (See Section 3.3.1), while the PSY test gives us a precise onset date for the bubble episode (Section 5.3.1). I use simulation based approach to illustrate and validate this methodological approach.

5.3.3.1.1 Simulating combined bubble and cycle process

I simulate a time series that combines both (i) a repeating cycle component and (ii) a random-bubble with the overall process simply given by the sum of these two components. The cycle component I simulate as a simple sin wave with period 50 (corresponding to a 50 quarter, or c.12 year cycle). The temporary bubble process I simulate according to the model specified by Phillips et al. (2011) - based on Evans (1991) periodically collapsing bubbles model - allowing for regimes that switch between a unit root process and mildly explosive episodes. This is a data-generating process that allows for the possibility of a single explosive episode:

$$x_t = x_{t-1}1\{t < \tau_e\} + \delta_n x_{t-1}1\{\tau_e \leq t \leq \tau_f\} + \left(\sum_{k=\tau_f+1}^{t} \varepsilon_k + x^*_{\tau_f}\right)1\{t > \tau_f\} + \varepsilon_t 1\{t \leq \tau_f\}$$

$$\delta_n = 1 + \frac{c}{n^\alpha}, \quad c > 0, \alpha \in (0,1)$$

where $\varepsilon_{x,t}$ is i.i.d. $(0, \sigma^2)$, and the model is assumed to initiate at $t = 0$ from some $O_p(1)$ random variable x_0.

The autoregressive parameter $\delta_n = 1 + \frac{c}{n^\alpha} > 1$ for all n when $c > 0$ leading to mildly explosive behaviour in the data over the sub-period $t \in [\tau_e, \tau_f]$. The model starts with a unit root process but allows for switches in regime at τ_e (to the explosive episode) and τ_f (back to unit root behaviour).

When the explosive period comes to an end, the initial value of the new unit root period differs from the end value of the explosive period. So the specification captures both exuberance and collapse and involves re-initialization of the process under collapse - with re-initialization at τ_f the process jumps to a different level $x^*_{\tau_f}$. Following [] I define the new initial value $x^*_{\tau_f} = x_{\tau_e} + x^*$ for some $O_p(1)$ random quantity x^* - i.e. in terms of the earlier period martingale behaviour of the process with some random deviation.

5.3.3.1.2 Identifying bubbles and cycles in combined process

The top part of (a) of Figure 22 presents a plot of a time series obtained by simulating the combined cycle and bubble process set out in 5.3.3.1.1. I also mark the true onset and termination dates for the single explosive episode with vertical red lines. This chart further plots the results of the PSY procedure

(Phillips et al., 2015b, 2015a, 2011) (section 5.3.1) applied to this simulated series – bubble episodes identified by the procedure are shaded green. We see that the PSY procedure makes a good job of dating the onset and termination of the temporary bubble (and also picks up a couple of very short false positives that would be ruled out by minimum episode threshold).

Meanwhile the lower panel (b) presents the wavelet power spectrum (Eq.2) of the same simulated time series (see Section 2 for detailed presentation of this method and its interpretation). In the wavelet analysis the periodic component is clearly visible, appearing as a spectral ridge across all time (x-axis) at period-50 (y-axis) – this ridge is indicated by the narrow band of high power (expressed as hot colours) the peak of which is indicated by the white line in the centre of the ridge.

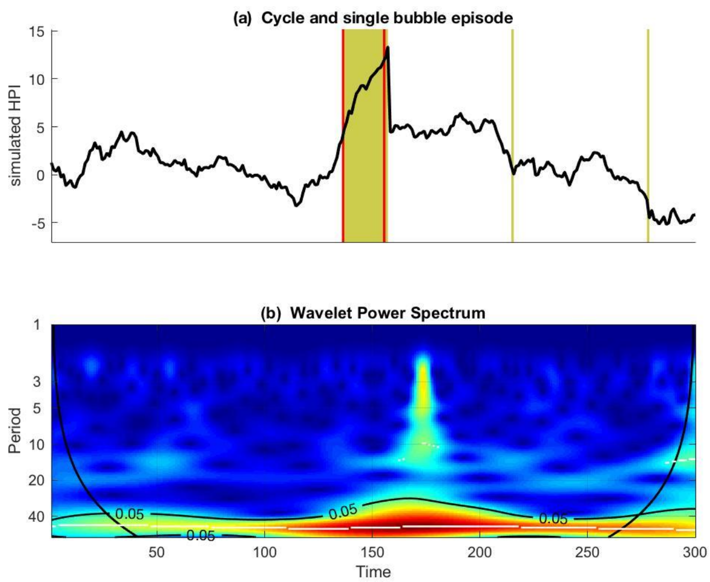

Figure 22: This figure presents (a) a time series simulated as a combination of a periodic cycle process (of 50 quarters so c.12 years) and a random walk process, with a single 'explosive episode'/'collapsing bubble', the true *onset* and *termination* dates for which are marked by vertical red lines. Meanwhile the green shading indicates the "explosive episodes" as identified by applying the PSY procedure (95% level) to the simulated data – we see the procedure dates the single explosive episode almost exactly (as well as suggests two extremely short false positives). Meanwhile (b) presents the wavelet power spectrum for the same simulated series. This change of perspective via transformation very clearly highlights the 12-year cycle - this shows up clearly in time-frequency representation as a spectral ridge, the peak of which - white line in the centre of the area of high power - identifies the true cycle periodicity almost exactly (something obscured in visual inspection of the time series plot by the martingale and explosive dynamics).

This simple simulated example illustrates: the usefulness of the PSY procedure for identifying temporary explosive dynamics; the usefulness of time-frequency methods for identifying cyclical components that may be obscured by other processes. While the bubble is clearly visible on inspection of the time-series plot, the PSY test provides an objective, consistent and accurate dating strategy.[108] Meanwhile the change of perspective provided by the wavelet transform of the series reveals the stable underlying periodic component (the 50 quarter or 12.5 year cycle) very clearly – something otherwise obscure in the combined signal and in fact making only a limited contribution to the overall variation in the series given its amplitude.

Figure 23 is based on the same simulated data as analysed in of Figure 22. This time: (a) plots the same simulated time series (thick line) and true bubble onset date, now along with the 12.5-year cycle component of this series (thin line). Meanwhile (b) plots the time evolution of the instantaneous *phase* of the cycle over the entire time period (based on the imaginary part of the wavelet transform of the time series)[109] and (c) the *phase angle* – in polar coordinates - of the cycle at the bubble onset date (the onset date as before – though now only the onset date - is marked both in (a) and now also in (b) by the vertical red line). This analysis makes clear what could not be assessed based on the power spectrum: the bubble began during the expansionary phase of the 12.5-year cycle. This did not have to be the case, however the question arises was this by chance, or due to some dependency between the cycle and bubble processes?

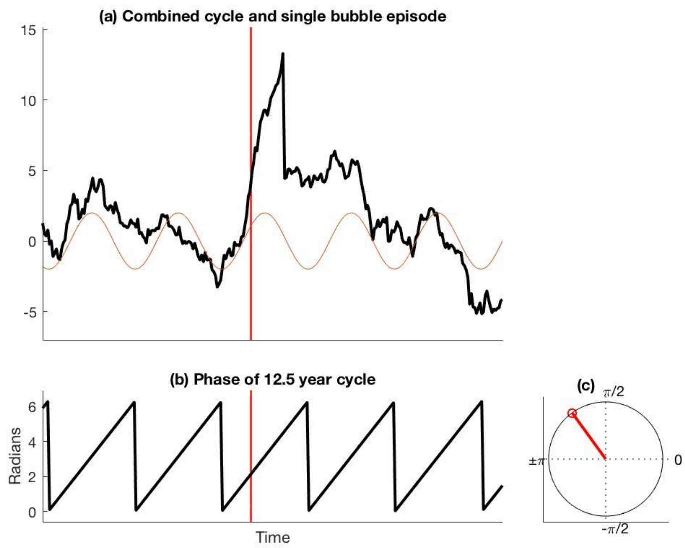

Figure 23: (a) plots the combined cycle, martingale and temporary bubble processes (heavy line), the cycle component (thin line) and the timing of bubble onset (red vertical line). (b) Plots the evolution of the instantaneous phase of the cycle component over time. (c) Plots in polar coordinates, the phase angle at bubble onset date (i.e. where vertical red line intersects phase series in (b)).

Without knowledge of the data generating process little can be said based on a single bubble. I simulate two sets of series (each 1,000 time-series with a length of 300 quarters) like that presented and Figure 23 and Figure 23, each time series combining both (i) a periodic cycle and (ii) a martingale process with a bubble

[108] Note one might e.g. easily (and incorrectly) have dated bubble onset earlier based on visual inspection.
[109] While power spectrum reveals stability of the periodicity of the cycle component over time, the phase of the cycle of course evolves.

episode. Both sets are simulated using the same data generating process set out in 5.3.3.1.1, however in one set of simulations the cycle and bubble processes are independent (bubble onset occurs randomly); in the other set of simulations, bubbles are influenced by the phase of the 12.5-year cycle (bubble onset only occurs during the expansionary phase of the cycle in the interval $[\frac{\pi}{2}, \pi]$ – but otherwise randomly).

For each simulated time series I obtain the phase angle of the cycle at bubble onset data as per the example presented in Figure 23 (c). Figure 24 presents circular histograms of the vectors of phase angle data thus obtained (a) for the coupled case; (b) for the un-coupled case (in each case 1,000 phase points are sorted among 12 phase bins). We see that the wavelet analysis of the combined signals is able to successfully distinguish these two different scenarios: in the un-coupled case (a) the distribution of the phase angles is relatively uniform around the circle and symmetric around zero; in the coupled case (b) the distribution of phase angles are appropriately clustered within the $[\frac{\pi}{2}, \pi]$ interval (within which interval bubble onset was simulated to be random).

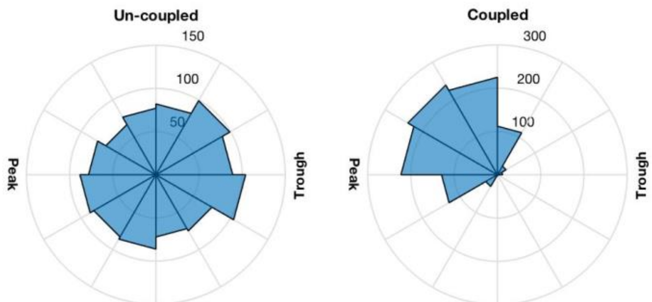

Figure 24: presents the results of methodology applied to simulated series (a) where the timing of bubbles is random and independent from timing of cycle; (b) where bubbles only occur during the expansionary phase of the cycle. The results show that the combined wavelet analysis and PSY procedure are able to distinguish between these two different generating processes.

5.4 Analysis and results

5.4.1 Evidence both of repeating cycles and of explosive 'bubbles'

5.4.1.1 Identifying and dating bubble episodes

I study log-changes in monthly house price data since Jan 1975 for 51 US states and the District of Columbia.[110] For each time series I conduct the PSY test.[111] These are implemented with a minimum window length of 18 following the

[110] I use seasonally adjusted monthly Freddie Mac House Price Index data. The availability of monthly data improves temporal but also spectral resolution. I take YoY log-differences. The data can be found at the following link: http://www.freddiemac.com/research/indices/house-price-index.page

[111] This is implemented with a minimum window size of 18, and lag-order selection was made using BIC order selector and maximum lag order of 6.

recommendation by Phillips et al. (2015a) to set the minimum window size close to $w_0 = 0.01 + \frac{1.8}{\sqrt{T}}$ as reduce the probability of size distortion. Optimal lag orders are selected based on BIC criteria and a maximum lag length of 6.[112]

For my analysis and following Gomez-gonzalez et al. (2018), after the bootstrapping test, I further define a restriction that an explosive "episode" should last at least 6 months. This procedure identifies a total of 230 episodes 103 (that is c.45%) of which occur before the year 2000 - from which time the literature roughly dates the beginning of the national bubble. The onset dates for these bubbles are plotted in Figure 25.

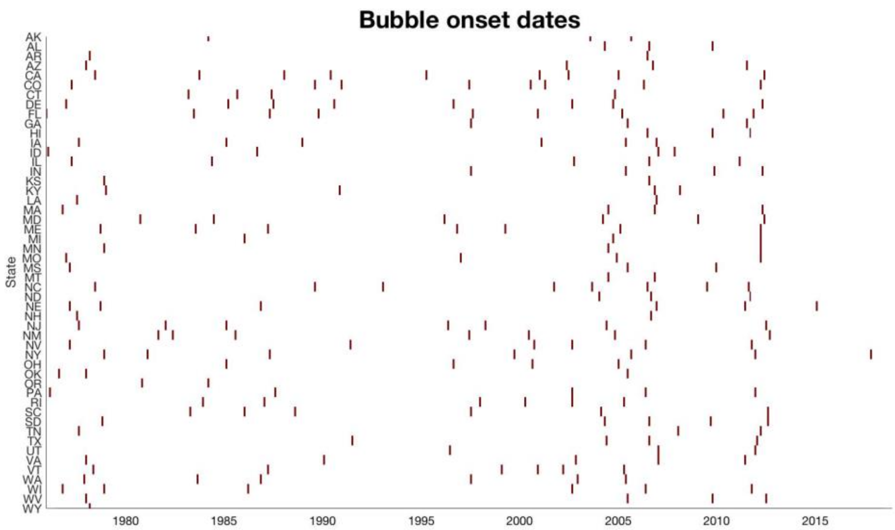

Figure 25: Bubble onset dates as estimated based on PSY procedure and minimum duration threshold of 6 months.

5.4.1.2 Evidence both of repeating cycles and of explosive 'bubbles'

While the general relevance of explosive 'bubble' episodes for U.S. regional housing market dynamics is established in the literature (see e.g. Shi (Shi, 2017), Hu & Oxley (2018a), Pavlidis et al. (2018)), and Essay 1 (Section 2) documents the importance of persistent cycles, it is useful to make a joint analysis of both phenomena for some specific examples. Figure 26 subjects house price data for Washington State[113] to precisely the same analysis as that made for the simulated time series in Figure 22, providing an empirical example of a market that exhibits evidence both of the c.10-year cycle identified by Sansom (2018), and important 'bubble' episodes of the type studied and documented in the bubble identification literature.

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[112] These procedures are implemented using Matlab code made available by Shuping Shi. This can be found at https://sites.google.com/site/shupingshi

[113] Log-changes in seasonally adjusted monthly Freddie Mac House Price Index data (see data appendix Section 11.1).

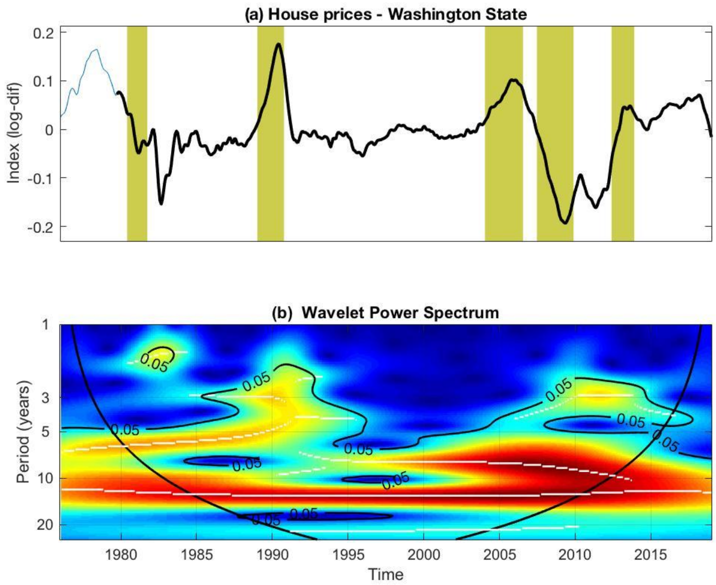

Figure 26: An empirical example of a market that exhibits evidence both of a cycle, and of important 'bubble' episodes (by PSY definition). (a) Plots log-changes (YoY) in the monthly house price index for Washington State since Jan 1975, and identified bubble episodes (shaded green). Note window length means first few observations are not covered by the PSY procedure (thin pale line). Significant bubbles are identified in the 1980s and mid-2000s. Meanwhile the wavelet power spectrum (b) exhibits evidence of a c.10 year cycle - the clear spectral ridge at this period.

(a) The PSY procedure identifies a significant bubble in the late-1980s (95% confidence interval based on the bootstrapping procedure proposed in Phillips and Shi (2018b)), and during the mid-2000s - bubble episodes are shaded green - as well as a collapse and recovery episode associated with the housing and financial crisis.

(b) The wavelet power spectrum meanwhile exhibits evidence of a c.10-year cycle (the clear spectral ridge near 10 year period – characteristic of a periodic not of an explosive process). This low frequency cycle, while low amplitude relative to the dramatic fluctuations during bubble episodes, is a striking feature of this time series.

Figure 27 presents the same analysis for Tennessee State (same data source and treatment) as an example of a market characterised by the c.10-year cycle, but that exhibits limited evidence of significant explosive 'bubble' episodes – the PSY procedure (a) only identifies the collapse and recovery associated with the housing and financial crisis of the late-2000s. However (b) the wavelet power spectrum of this price series (b) nevertheless clearly exhibits a spectral ridge consistent with a roughly 10-year cycle over the entire sample period.

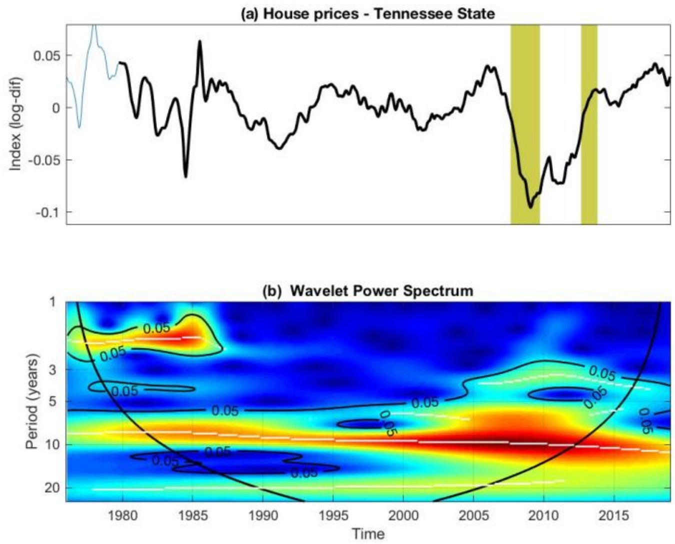

Figure 27: An empirical example of a series that exhibits evidence of a cycle, but limited evidence of 'bubble' episodes (by PSY definition). (a) Plots log-changes (YoY) in the monthly house price index for Tennessee State and bubble episodes (which are shaded green): only the collapse and recovery associated with the housing and financial crisis of the late-2000s is identified by the bubble test. Meanwhile the wavelet power spectrum of this price series (b) clearly exhibits a spectral ridge consistent with a roughly 10-year cycle over the entire sample period.

5.4.2 Evidence of a systematic relationship between cycle and bubble timing

5.4.2.1 Estimating phase of underlying cycle

Using the same set of house price time series (for all states in which the bubble detection procedure identified at least one bubble episode), I then estimate the instantaneous phase series of the roughly 10-year cycle identified by Sansom (2018). I perform this estimation with the continuous complex wavelet transform (CCWT) using the Morlet mother wavelet (Torrence & Compo, 1998) which yields instantaneous phase $\phi_f(t)$ for each wavelet central frequency f which I average – taking the circular mean - over the 8-12 year periodicity band of interest to obtain $\phi_{cycle}(t)$.[114]

5.4.2.2 Obtaining cycle-phase at bubble onset dates

Finally, I obtain the instantaneous phase of this low frequency cycle at bubble onset dates as estimated with the PSY procedure, $\phi_{cycle}(t_{onset})$ as a vector of phase angles which I will denote α_ϕ. This step allows me to answer the simple question: what phase was the 10-year cycle in when the bubble started? Under the null hypothesis of no relationship between the low frequency cycle and bubble episodes, the angles will have a uniform circular distribution, meanwhile a peaked distribution implies a systematic relationship between the phase of the

[114] A broadband signal of a multi-scale process needs to be filtered into a spectral band of interest.

low frequency cycle and the timing of the explosive episodes (as defined by the PSY procedure used in the empirical bubble literature).

5.4.2.3 *Results (full sample)*

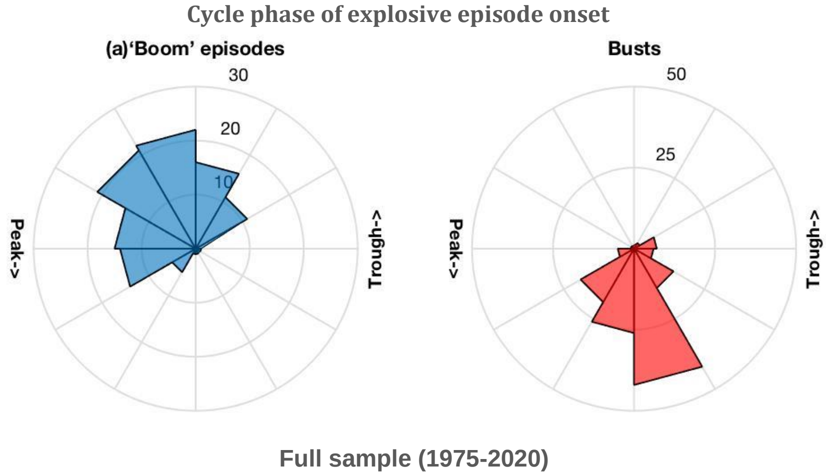

Figure 28: presents histograms in polar coordinates of the distribution of phase angles for the slow cycle (obtained based on the mean phase over 10-13 year periodicity band) at (a) explosive 'boom' episode onset dates and (b) 'collapse' episode onset dates (as identified with the bubble identification procedure of Phillips et al. (2015a, 2015b)). The slow cycle phase angles obtained at onset dates for a total of 230 identified explosive episodes are sorted between 12 angle bins on the interval $(\mathbf{0}, \mathbf{2}\boldsymbol{\pi})$. Both distributions show clear peaks near the "top" of the slow cycle suggesting a systematic relationship between the timing of bubble formation and collapse episodes, with bubbles developing during the expansionary phase and sudden collapses occurring after the slow cycle has peaked.[115]

Figure 28 plots a histogram of the vector of phase angles α_{ϕ}. The phase interval $(0,2\pi)$ (representing the full cycle) is divided into 12 bins. This empirically estimated joint distribution exhibits a clear peak in the bins between $(\frac{\pi}{2},\pi)$ (this is near the "top" of the 10 year cycle, during expansionary phase above its mean but before it peaks) suggesting a systematic influence from the rise of the slow 10-year cycle on the occurrence of explosive bubbles.

5.4.2.4 *Sub-sample analysis for eras of local vs. national housing instability*

Given that many of the bubbles in this analysis occurred during the "national" bubble episode of the 2000s when both bubbles and cycles were rather synchronised, it is interesting to make a separate analysis of pre and post-2000 episodes. The results of this analysis are presented in Figure 29. Before the 2000s both 'bubbles' and cycles were 'local' in the sense that they were not globally

[115] Booms and busts are distinguished based on comparison of series value at onset and termination dates.

synchronised. Even so, there is a systematic relationship between bubble onset and 10-year cycle phase.

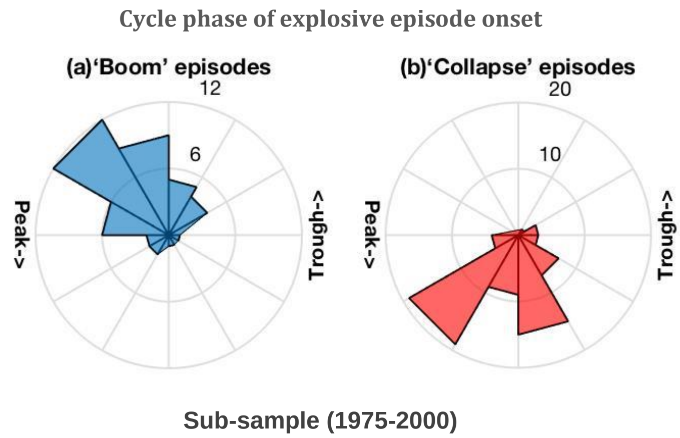

Figure 29: presents the same analysis as that presented in **Figure 28** (see caption for details) but for the restricted sample period 1975:01-2020:06 in order to exclude the more synchronised bubble and cycle dynamics of the 2000s national boom-bust. This leads to a sample of 103 explosive episodes for which slow cycle phase at onset dates are obtained. Although both 'bubbles' and cycles in this pre-2000 period were 'local' (in the sense of not globally synchronised), the distributions obtained are nevertheless similarly peaked (indeed boom episode onset dates are more narrowly distributed for the subsample) suggesting a systematic relationship between repeating cycles and bubble development across both the era of local and of national housing market instability.

5.5 Discussion

This study identifies a systematic empirical relationship between the *timing* of the sort of temporary explosive episodes documented in regional U.S. house price series by the empirical 'bubble' identification literature; and the repeating c.10-year cycle in state and city level price series I have documented in Essay 1 (Section 2).

One possible interpretation of this systematic relationship is that bubble episodes and low frequency cycles basically represent distinct processes, but cyclical expansions and contractions can, respectively, set off speculative bubbles, or trigger losses of confidence precipitating collapse episodes.

Another possibility might be that the explosive 'bubble' episodes picked up by the PSY procedure are nonlinearities in the cycle process.

While the latter possibility looks quite plausible in some markets (where the PSY procedure picks up 'bubbles' every cycle), in other markets explosive episodes - while systematically related to the phase of the underlying cycle - appear more sporadic and not a reliable feature of every cycle.

In any case the existence of a systematic relationship suggests that the low frequency cycles (even where these oscillations may be weak considering their amplitude relative to explosive episodes) have a significant influence on house price instability beyond their own direct amplitude contribution, due to their role in influencing the timing and likelihood of 'bubble' markets.

This systematic relationship also implies, of course, that 'bubble' episodes may be far from random – indeed the striking temporal and spatial patterns in underlying cyclicality that I document in Essays 1-3 (Sections 2-4) may be an important key to understanding both the apparent 'localness' of the widespread bubbles of the 1980s; as well as the 'national' character of the bubbles during the 2000s:

It is well known, after all, that the combination of explosive processes with other explosive, unit root, and/or stationary processes, generally results in an explosive process. This point is particularly important for unit root testing procedures because it implies that as long as one of the constituent series is explosive, so will the aggregated series be – this provides the basis for tests on individual time series hypothesised to aggregate a fundamental and a bubble component; but also applies in the geographical aggregation of housing market data. Nevertheless, explosive episodes, though widespread in the 1980s, have not shown up in PSY tests on aggregate US price series (Efthymios Pavlidis et al., 2016).[116]

Pavlidis et al. (2018) observe that "the effect of an upward explosive period in one of the constituent series *could* offset the effect of a simultaneous downward explosive period in another constituent series of the aggregate", (my emphasis) but comments that "Although theoretically possible, this scenario seems unlikely from a practical point of view in most conventional applications (a knife-edge case)" (Efthymios Pavlidis et al., 2018, p. 5).

Nevertheless, this seems to be what happened in the US during the 1980s.[117] While highly unlikely in a random bubble setting, this could be explained by the link between explosive episodes and underlying cycles given observed spatial wave in these cycles – the existence of a spatial wave implies highly correlated movements but phase-differences that increase with geographical distance. This makes the possibility that an upward explosive period in one of the constituent series *could* offset the effect of a simultaneous downward explosive period in another constituent series, rather plausible (something supported by the very low global phase-synchronisation at cycle frequency during the 1980s that I document in Essay 2 (Section 3) i.e. the fact that phase of cycles was balanced around the phase-circle implies that for every boom-phase there was an offsetting bust-phase).

This evidence that bubble episodes may be far from random is interesting since a huge problem when it comes to temporary 'bubbles', is of course how to identify them as they emerge, not just after they burst. This has lead to popular epithets such as "you know a bubble when you see one" and counter claims.

The PSY test provides a practical and objective quantitative method to identify bubbles as they emerge, and its potential as an early warning alert system for exuberance has been recognised by central bank economists, fiscal regulators, and others (for example the PSY approach is now employed by the Federal Reserve Bank of Dallas, providing an exuberance indicator for 23

[116] Although Pavlidis et al. (2016) do identify national bubbles in the UK and other national price series during this period.

[117] Pavlidis et al. (2018) use Case-Shiller 10 city index which only goes back to 1987. Given the window size needed for PSY procedure, this means 1980s bubbles will have been entirely excluded from this study.

international housing markets),[118] but it has nothing to say on the likelihood of a bubble emerging for any given market at a given time.

Overall, these results suggest that focussing exclusively on the more "pathological" dynamics of explosive episodes may miss the importance of housing cycles in both local and aggregate house price instability – not only can cycles help explain bubbles, but also some markets which did not experience significant bubbles, nevertheless do exhibit clear cyclicality (see the illustrating empirical example in Figure 27) which with the increased synchronisation fo markets has come to contribute to aggregate housing volatility.

5.6 Conclusion

I find evidence of a systematic relationship between the timing of the sort of temporary explosive episodes widely documented in regional US house price series by the 'bubble' identification literature, and the repeating c.10-year cycle I have empirically documented in state and city level price series in Essay 1 (Section 2).

This systematic relationship suggests that the cyclical component of these series - even where the contribution from these oscillations to house price volatility may in some cases be weak considering their amplitude - have a significant influence on house price instability beyond their own direct amplitude contribution.

What is more, it suggests 'bubble' episodes may be far from random - given the striking temporal and spatial patterns in underlying cyclicality that I document in Essay 3 (Section 4). Explosive episodes may (or may not) be driven by a distinct dynamical process (such as short periods of strongly speculative markets) from underlying low frequency cyclicality, however their timing – both their appearance of 'localness' during the 1980s and their 'national' character in the 2000s – seems to be well explained by the spatial-wave in phase development of underlying cycles prior to 1995 and their dramatic synchronisation after this time.

These results suggest that focussing exclusively on the more "pathological" dynamics of explosive episodes may miss the importance of repeating housing cycles in both local and aggregate house price instability: not only can cycles help explain bubbles, but also some markets which did not experience significant bubbles, nevertheless do exhibit clear cyclicality (see empirical example in Figure 27). What is more the more continuous cycle processes reveals spatial and temporal patterns that are obscured or lost in analysis of onset dates of explosive episodes - in which a lot of information is discarded.

[118] The Dallas FED publishing recursive unit-root test based housing market exuberance indicators for 23 national housing markets based on the bubble test of Phillips, et al. (2015a,b) and the methods developed in Pavalidis et al. (2016). This indicator can be found here: https://www.dallasfed.org/institute/houseprice/

6 Essay 5: A simple model of spatially coupled speculative housing cycles reproduces key spatio-temporal patterns in U.S. house prices

Summary: A variety of arguments have been put forward to explain the 2000s housing boom-bust in the U.S., however these hypotheses seem to have difficulty accounting for the restrictions implied by the accumulation of empirical evidence on the spatio-temporal dynamics of housing. Motivated by evidence in the existing empirical literature and in particular the empirical results presented in Essays 2 to 4 of this thesis, I argue that a persuasive account of U.S. housing market instability needs to explain or account for the following key empirical facts: (i) a long history of repeating boom-bust episodes in subnational markets; (ii) both the historic heterogeneity in timing of these local cycles as well as their more recent synchronisation; but also crucially (iii) the striking and persistent non-random spatial patterns in these dynamics over both the local and national instability eras. Collectively these seem to provide some rather strong restrictions and are not easily accounted for within the idiosyncratic shock or bubble frameworks in the existing literature. In this Essay I model a network of identical housing cycles locally bi-directionally coupled according to the spatial adjacency matrix for spatially contiguous U.S. states. I show that this simple framework of locally coupled housing cycles is able to simultaneously explain: repeating local boom busts; their synchronisation over time; and perhaps most interestingly neatly reproduces the east-west traveling spatial waves empirically observed in the historical data (see Essay 3. That this simple framework is sufficient to provide a unified explanation for these key spatio-temporal features of empirical house price dynamics suggests that the local coupling of intrinsically cyclical markets may offer a useful new framework and departure point for further empirical and theoretical work. The qualitative predictions of this framework are rather different from standard models, with important policy implications.

6.1 Introduction

The role of the national U.S. housing boom-bust of the 2000s at the centre of the sub-prime crisis - widely viewed as the trigger for the Global Financial Crisis and subsequent Great Recession - have made U.S. housing market developments and their wider economic linkages a key macro-financial concern for policymakers (Ben S. Bernanke, 2008; D. Miles, 2013; Praet, 2011).

Explaining the causes of this remarkable housing boom-bust has become the subject of a large and still expanding body of research: a wide range of explanations have been put forward including interest rates; mortgage credit and subprime lending; speculation and irrational bubbles; contagion and "fads"; and international capital flows.[119]

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[119] Interest rates (Campbell et al., 2009; Glaeser et al., 2013; Himmelberg et al., 2005); mortgage credit/market "innovations" and subprime lending (Dell'Ariccia, Igan, & Laeven, 2012; Favilukis et al., 2016; Levitin & Wachter, 2012; Mian & Sufi, 2009; Pavlov & Wachter, 2009; C. W. Wheaton & Nechayev, 2008); speculation and irrational bubbles (Barlevy & Fisher, 2011; Bayer et al., 2011, 2016; K E Case et al., 2005; Karl E Case & Shiller, 2003; J. M. Lee & Choi, 2011; Shiller, 2005; C. W. Wheaton & Nechayev, 2008);

Of course while the national boom-bust of the 2000s may have been historically unprecedented, earlier housing booms and busts had been previously widely documented at a geographically more local level in the US (Karl E Case & Shiller, 1993; Riddel, 1999; Shiller, 1990); and housing market observers had long puzzled over (i) the exaggerated cyclical behaviour of house prices relative to fundamentals; (ii) their significant short-term persistence; and (iii) longer-term mean reversion (see e.g. Case & Shiller (1989), Cutler et al. (1990), DiPasquale & Wheaton (1994); while more recent studies include e.g. Glaeser et al. (2014) Head et al. (2014)).

As Glaeser & Nathanson (2017) recently remark "These features were spectacularly on display during the great housing convulsion that rocked the U.S., and the world, between 1996 and 2010. Yet these three phenomena characterized house price dynamics even before this episode and continue to do so afterward." (Glaeser & Nathanson, 2017, p. 147).

Indeed not only does the U.S. appear to have a long history of housing market boom-bust (see e.g. Glaeser (2013), and Shiller (2005, 2007) for a review of various historical episodes) but systematic econometric studies of both metropolitan area and state level data suggest periodic "explosive" or "bubble" episodes had been geographically widespread in previous decades (Hu & Oxley, 2018a; Efthymios Pavlidis et al., 2018; Shi, 2017) – a result I confirm in my analysis of state level data in Essay 4 (Section 5, Figure 25).

Meanwhile a striking empirical feature of this widespread historic boom and bust are the non-random spatial patterns in the *amplitude* and *timing* of cycles: for example the states that experienced the largest boom-busts in the 2000s also experienced the largest boom-busts in the 1980s (Sinai, 2012).

Ferreira and Gyourko (2011) report (based on a proprietary MSA level dataset) that "the start of the boom was not a single, national event. Booms, which are defined by the global breakpoint in an area's price appreciation series, begin at different times over a decade-long period from 1995-2006." They note that "the geography of the timing of the start of housing booms is interesting in its own right" and report briefly that "the first booms at the metropolitan area level occurred in northern New England (Massachusetts and Connecticut) and coastal California. On the east coast, they then spread east and south from northern New England. They spread north and east from coastal California." arguing that this "is suggestive of a role for contagion in explaining the spread of the boom across markets." (Ferreira & Gyourko, 2011, p. 14).

DeFusco et al. (2013) highlight that local (MSA level) booms between 1993 and 2009 began initially in highly concentrated areas on the two coasts,[120] before spreading inland.

Hernández-Murillo et al. (2017) studying city level building permits data in in a Markov switching model allowing for idiosyncratic and national cycle regimes, find that national downturns always begin with the 'idiosyncratic' downturn in a cluster of cities (before growing to effect all cities).

These sorts of results suggest an important spatio-temporal dimension to housing market instability.[121]

contagion and "fads" (Bayer et al., 2016; Burnside et al., 2016); and international capital flows (Favilukis et al., 2013, 2016).

[120] In California and the mid-New England region.

My own results from the empirical phase of this thesis provide evidence (1) many sub-national housing markets across the U.S. have exhibited not just idiosyncratic explosive episodes but repeating cycles since data begins in the 1970s (Essay 1/Section 2); (2) these existing sub-national cycles synchronized dramatically in the mid 1990s (and this seems to have played a significant role in the national boom-bust of the 2000s) (Essay 2/Section 3); and document (3) striking non-random spatial patterns in the development of state level housing cycles: specifically clear and repeating 'ripples' running from coastal states (east and west coast) into the central states (Essay 3/Section 4). I also show a systematic relationship between the timing of bubbles (as identified in the econometric bubble test literature), and the local timing (local phase) of this permanent cycle component (Essay 4/Section 5).

My results on the spatial pattern of housing cycle developments confirm that developments in coastal markets spread inland. However I show that this pattern is much more continuous/smoother in both *space* and *time* than has been previously realised: since not relying on the timing of discrete events (e.g. turning point (peaks and troughs) or structural break in time series) I am able to show the stability of this pattern month-to-month since the early 1970s.

This pattern characterised not just the start of the 2000s boom, but equally characterises the "local" and "national" bubble periods and is consistent over all phases of the housing cycle (and continued to characterise 2000s bust, even though this was very simultaneous).

The systematic relationship between the timing of occasional bubble episodes also suggests that patterns previously noted in the timing of bubbles are likely to be driven by this smoother underlying spatio-temporal process.

Ideally potential explanations of the 2000s national boom-bust episode should account for, or at least accommodate, these characteristics of spatio-temporal dynamics. While Sinai (2012) for example has previously argued that potential explanations for housing booms need to generate differences in the timing of price changes across markets, I propose that it is important to account not just for differences in timings, but to specifically account for repeating coastal-to-centre ripples that have characterised U.S. housing market fluctuations over at least the last 50 years.

I will argue that theories of house price fluctuations in the existing literature may struggle to simultaneously account for (i) local cycles, (ii) the national boom-bust, and (iii) observed spatial waves and their stability across periods of apparently "local" instability (when phase of sub-national cycles are dispersed) vs. apparently national instability (when phase of sub-national cycles very clumped) - results which, taken together, seem to provide some powerful empirical restrictions on any explanation or model of U.S. housing dynamics.

On the one hand contributions in the literature that seek to identify national shocks to explain the national housing boom-bust (a very substantial literature) are not able to account either for the much longer history of instability at a local level, or for the spatial patterns in the data. Explanations based on a national 'mania' are similarly unhelpful in addressing the spatio-temporal facts.

[121] Not all studies agree on this. For example Pavlidis et al. (2009) date the onset of bubbles using the PSY test (Phillips et al., 2011); Freese (2015) using "Statistical Process Control". Both studies find no indications that the 2000s bubble evolved in a specific region and spread to another neighbouring region.

The spatial diffusion of *local* shocks, or contagion of *local* bubbles seems consistent with the existence of spatial "ripples" and might – were spillovers sufficiently large and spatial transmission sufficiently rapid and slow to decay over spatial distance - offer an account of both local and national level disturbance. However trying to account for evidence of repeating local cycles and stable spatial patterns over time within these local shock diffusion or contagious bubble frameworks seems – implausibly - to require similar shocks repeating at regular temporal intervals in the same leading markets. Moreover it does not provide an explanation for the temporal tightening of this spatio-temporal pattern over time.

An emerging heterogeneous agent housing market literature and the endogenous cyclical dynamics that often arise in these models (Bao & Hommes, 2015; Bolt et al., 2014; Defusco et al., 2017; Dieci & Westerhoff, 2012b, 2016; Geanakoplos et al., 2012) offers some plausible hypotheses for explaining the repeating cycles evident at a local market level. However they do not account for the national boom-bust, nor for spatial ripple phenomena – which have not, to the best of my knowledge, been addressed by this literature.

In this paper, I explore whether the *combination* of (a) local spillovers between neighbouring markets (such as those hypothesised both in the local shock propagation and local bubble contagion literatures); and (b) local endogenous boom-bust cycle dynamics (such as those often arising in the growing heterogeneous agent housing market literature), could provide a simple and unified qualitative explanation not only for the sort of repeating local boom-bust cycles already modeled in the literature, but also simultaneously account for both (i) the emergence of *national* housing boom-bust, as well as (ii) the spatial "ripples"/"waves" empirically observed in the data.

To this end I model 49 identical housing markets with autonomous cyclical dynamics (each characterised by the same endogenous speculative cycles in an endogenous expectations formation setting) but coupled according to the empirical spatial adjacency network for the 49 spatially contiguous US states (such that neighbouring markets have some influence on price expectations).

I conduct a number of simulation-based experiments to understand the influence of the local coupling parameter introduced, on the *spatio-temporal* dynamics on the network. I find that the local coupling (mutual influence among spatially adjacent markets) of local endogenous expectations driven quasi-periodic housing cycles, is sufficient to explain both the observed coasts-to-central waves, and the emergence over time of national boom-bust. No shocks to; heterogeneity across; or global factors are necessary to reproduce these phenomena.

While I simulate local housing dynamics based on the extension of a specific endogenous expectations formation mechanism driven cycle process borrowed from the existing literature (Dieci & Westerhoff, 2012b), my results are very unlikely to be specific to this particular process but rather are likely to hold for any specific model consistent with the more general framework I set out of locally interacting markets characterised by intrinsic cycle dynamics.

This work thus leads to a novel simple and plausible unified explanation for a collection of key empirically documented phenomena not easily resolved by recourse to existing theories. The sufficiency and parsimony of this minimal framework does not of course mean we should discard or discount other explanations and factors. It does seem to suggest however, that locally coupled locally unstable housing market dynamics may offer a valuable new theoretical framework, the relevance of which deserves further exploration.

This new framework, whilst it represents nothing short of an alternative paradigm, at the same time is broadly aligned with an important strand of thought in the real estate literature that argues housing markets may be best represented as a series of interconnected regional and local markets (Meen, 1996) - implying that we can neither consider housing in terms of a national aggregate, nor in terms of entirely local markets as housing markets are likely to be linked. It also provides a new direction and extends the potential empirical relevance for the growing behavioural housing market literature (as well as other work interested in intrinsic cycle dynamics in housing market behaviour). It suggests the relevance of, and contributes to a complex systems view of economic processes and suggests the potential relevance of existing literature of synchronisation phenomena in complex networks.

The interpretation of the 2000s housing boom-bust in terms of the synchronisation of unstable local markets not only provides a more ready explanation for key historical facts, it also has significant implications for what we might expect from the future, and distinct policy implications.

The paper is organized as follows: Section 6.2 provides a more careful discussion of relevant existing literature; section 6.3 introduces my general model (framework); section 6.4 introduces a specific model for the purpose of simulation; section 6.5 presents analysis of this model and simulation based results; in 6.6 I discuss some of the implications and questions thrown up by my key results. Section 6.7 concludes.

6.2 Relevant literature

6.2.1 Endogenous housing cycles literature

While the literature on endogenous housing market cyclicality is relatively small, following the wider behavioural asset market literature (B. Y. W. A. Brock & Hommes, 1997; W. A. Brock & Hommes, 1998) a number of behavioural housing market models have been proposed and estimated and a small literature has developed. The potential for endogenous periodic or semi-periodic dynamics tends to arise in these type of heterogeneous agent based models.

Sommervoll, Borgersen, and Wennemo (2010) model the interplay between consumption and investment/speculative motive in housing demand for budget constrained agents under an *adaptive* expectation scheme (Muth, 1960). The dynamics of the model are described by a high-dimensional nonlinear system. Simulations show the model generates periodic fluctuations in house prices and volumes. They further extend the model to include mortgage lending, and find that introducing credit constraints change the dynamics of the model generating periods of mild oscillations interrupted by violent collapses.

Dieci & Westerhoff (2012b) develop a model in which speculative agents are assumed to rely on a combination of *extrapolative* and *regressive* forecasting rules in forming their price expectations. The relative importance of these competing heuristics depends on the magnitude of the deviations of housing prices from long run fundamental steady state (in their model prices adjust to excess demand in each period in dis-equilibrium). The dynamics of the model are described by a two-dimensional non-linear map. Their model can generate irregular housing cycles endogenously (see also Dieci & Westerhoff (2013)).

Similarly Bolt et al. (2014) develop a model of the dynamic interplay of regressive and extrapolative beliefs in demand formation, in which agents switch endogenously between mean-reverting (regressive) and trend-following (extrapolative) beliefs based on their relative performance. Where Dieci & Westerhoff (2012b, 2013) employ a dis-equilibrium price adjustment rule based on excess demand, their model employs a temporary equilibrium. The model is described by a high-dimensional nonlinear dynamical system. Their simulations show cyclical fluctuations.

Kouwenberg and Zwinkels (2015) introduce and estimate a housing market model with a structure similar to Dieci & Westerhoff (2012b). As do Eichholtz et al. (2015).

Dieci & Westerhoff (2016) present a similar model of an endogenously evolving mix of extrapolative and regressive beliefs, but "nested into" a traditional stock-flow housing market framework (Denise DiPasquale & Wheaton, 1992; Poterba, 1984) connecting the house price to the rent level and housing stock. This is used in order to investigate how expectations driven house price fluctuations (such as those modeled in e.g.: Dieci & Westerhoff (2012b, 2013), Bolt et al. (2014), Kouwenberg and Zwinkels (2015), Eichholtz et al. (2015)) interact with supply-side conditions (housing supply elasticity and the existing stock of housing). Their model is described by a two-dimensional nonlinear map. Strong extrapolative behavior of housing market investors destabilizes the model's fundamental steady state, either via a pitchfork bifurcation and the emergence of multiple steady states or via a Neimark-Sacker bifurcation and the appearance of oscillatory dynamics, 'born' initially as a simple cycle, then irregular fluctuations (a complex attractor). In this model, the loss of stability may produce very different outcomes depending on the elasticities of the supply of new housing and the demand for housing services: in particular "price bubbles" tend to be shorter under a more elastic supply of new housing or a less elastic demand of housing services.

In a realted study, Bao & Hommes (2015) design an experimental housing market and study how the strength of negative feedback (framed in terms of supply elasticity), affects market stability in the context of positive feedback through speculative demand.

Defusco et al. (2017) model a housing market populated by extrapolative investors with heterogeneous investment *horizons*. In this model long-run and short-run investors play a role similar to that of fundamental and feed-back traders in models of asset price fluctuations arising out of the interaction of these two different expectations schemes (Cutler et al., 1990; De Long, Shleifer, & Summers, 1990). In their model the combination of extrapolative expectations and heterogeneous holding times generates cycles in prices and transaction volumes.

While there is thus a small theoretical literature using formal dynamical models in order to explore mechanisms by which housing market cyclicality may arise endogenously, to the best of my knowledge the implications from the interaction of multiple cyclical markets – the setting I explore in this Essay - has not been previously considered.

6.2.2 Interconnected local housing markets – theory and evidence

While the implications from the interaction of housing markets characterised by endogenous cyclicality has not been previously considered, the issue of local dependence between housing markets has been widely studied and theorised in real estate economics, where theory and evidence suggest the potential relevance of a range of different connectivity structures from local dependence between spatially adjacent markets; to a range of other forms of local dependence based not on spatial adjacency but e.g. economic links; to global (all-to-all) coupling among markets.

Empirical evidence of spatial 'ripple effects' (especially from the U.K.) has motivated a large literature on possible channels by which house prices may spill over leading to the spatial diffusion of house prices among neighbouring markets. It has been proposed that the underlying economic factors associated with the ripple effect may include e.g. migration flows, home equity conversion, or capital flows and spatial arbitrage between neighbouring markets (Meen, 1999).

While it remains unclear what channels operate and their relative importance, empirical evidence of local spatial dependencies among U.S. housing markets is quite strong. A number of studies of state level data find evidence of dependence among neighbouring states. For example:

Vansteenkiste (2007) in a global VAR framework finds evidence of significant interstate linkages for house prices and impulse response analysis suggests closer states tend to be more affected by a local shock than states which are located further away. Kuethe and Pede (2011) find evidence in a spatial VAR of spatial spillovers in their analysis of state level house price data for the Western USA.[122] Holly et al. (2010) in a spatial panel model find a significant spatial effect among contiguous states even after controlling for state specific real incomes, and allowing for a number of unobserved common factors. These results are confirmed by Chudik and Pesaran (2010) who additionally find evidence of significant dynamic spatial spillovers among contiguous states.[123] DeFusco et al. (2013) report strong evidence of housing market spillovers among U.S. cities and their nearest neighbour cities[124] but do not find evidence of significant spillovers arising from more distant markets. Brady (2014) using a single equation spatial autoregressive model finds significant evidence of persistent spatial diffusion of housing prices across U.S. states.[125] Similar results are reported for studies conducted at a more spatially granular level (see e.g.

[122] Spatial autocorrelation test, significant spatial cross-regressive lags in SpVAR, and significantly reduced mean square forecast error.
[123] With the dynamics from past price changes distributed between own and neighbourhood effects in a spatial panel
[124] Based on proprietary data on 99 MSAs.
[125] Estimates the spatial diffusion of housing prices across US states over 1975–2011 using a single equation spatial autoregressive model.

Dolde and Tirtiroglu (1997), Case and Shiller (1990), Clapp and Tirtiroglu (1994), Brady (2011)).

Many of the channels hypothesised to explain 'ripple-effect' type spatial diffusion, might also give rise to long-range connections between markets based on various forms of 'economic proximity' that are to some extent independent of spatial contiguity. For example migration flows, capital flows (internationally or regionally mobile investors - whether direct or indirect), and a range of relevant fundamental economic links between markets need not be primarily a function of geographical distance.

It has been argued for example that the similar timing of cycles in geographically distant markets (such as San Diego and Washington DC) implies local spatial diffusion of house prices cannot fully explain the spatio-temporal patterns of U.S. housing fluctuations and that some other explanation - e.g. the arbitrage of investment opportunities by national investors (Füss, Zhu, & Zietz, 2012; Zhu et al., 2013) - is required. Holly et al. (2010) whilst finding strong evidence of a role for spatial contiguity, also document in tests for spatial autocorrelation, a number of between-State correlations that appear to be independent of spatial patterns. Bailey et al. (2016) find evidence of significant non-local dependencies after controlling for common factors in house price data across U.S. metropolitan statistical areas.

Much as empirical evidence of spatial dependence seems to imply some form of local spatial coupling, nevertheless it seems highly likely that global connectivity structures are also relevant. While local spatial spillovers and strong non-local links between some markets imply spatial adjacency based - or otherwise *sparse* - connectivity structure, it is easy to see how e.g. common factors (national variables such as for example monetary policy, other aggregate shocks such as oil prices, or national credit supply-side conditions) may be an important source of global coupling (*dense* connectivity structure).

A wide range of possible mean-field couplings present a further potential sources of global coupling. A simple example would be that if price expectations of market participants are influenced or anchored by national house price indices, this feedback would result in all-to-all connection among the local markets underlying this index.

It is easy to think of many other likely - and potentially powerful - mean-field feedbacks including a range of possible financial channels. For example: a national housing volumes cycle will have an impact on total mortgage formation, and mortgage backed security (MBS) supply, but also on prepayment risk thus duration and spreads in fixed income markets impacting the cost of housing finance (as well as a wide array of other connected markets); due to the counter cyclicality of mortgage defaults with respect to house prices, a national housing cycle may imply a national mortgage default rate cycle leading to cyclicality in credit supply if lenders do not “look through the cycle” adequately or underestimate underlying correlations. Price and volumes cycles will also lead to wealth and housing equity withdrawal cycles with the potential to impact aggregate demand, thus feed back to housing markets via income and employment channels.

All of these channels and others besides imply that if/once a mean field emerges among local cycles, powerful feedbacks to markets across the country might well arise via channels that do not operate when local markets are in an asynchronous state.

In practice *local*, *non-local* and *global* couplings among markets all seem likely to operate to some extent. Although as I have already argued in this thesis, while explanations for national boom-bust have tended to emphasise common factors (e.g. monetary policy (Campbell, Davis, Gallin, & Martin, 2009; Glaeser, Gottlieb, & Gyourko, 2013; Himmelberg, Mayer, & Sinai, 2005), or aggregate credit shocks (Dell'Ariccia, Igan, & Laeven, 2012; Favilukis, Ludvigson, & Nieuwerburgh, 2016; Levitin & Wachter, 2012; Mian & Sufi, 2009; Pavlov & Wachter, 2009; C. W. Wheaton & Nechayev, 2008)); or arguments that may be consistent with mean-field coupling (e.g. if national house price trends inform house price expectations in the development of a national house price 'mania' (Shiller, 2000) local coupling seems to offer by far the more plausible explanation for the observed spatial dependence by now well established in the empirical literature and the spatial patterns that I documented in Essay 3 (see Section 4).

I am interested in the implications from different connectivity structures in an endogenous cycle framework – a question that has not been previously studied. In particular I am interested in whether local coupling of endogenous cycles could provide a more convincing explanation for the stability of spatial 'ripples' over multiple boom-bust episodes than the spatial diffusion of local shocks assumed in the existing 'ripple effect' literature; but also whether purely local coupling could plausibly account in principle not only for repeating ripples but also for the emergence of national boom-bust.

6.3 Local housing cycles with local spillovers: a general model

An important strand of thought argues that housing markets may be best represented as a series of interconnected regional and local markets (Meen, 1996). This framework implies that we can neither consider housing in terms of a national aggregate, nor in terms of entirely local markets as housing markets are likely to be linked.

I use a graphical framework in order to formalise this idea. I consider a graph $\mathcal{G} = \{\mathbf{V}, \mathbf{E}\}$ in which each node or 'vertex' v_i in $\mathbf{V}$ represents a geographically defined local market with its own autonomous intrinsic dynamics, and the interactions between these markets is represented by the *edges* in the graph $\mathbf{E} \subseteq \mathbf{V} \times \mathbf{V}$ (each edge written as a tuple (v_i, v_j)) which can be summarised by an adjacency matrix $\mathbf{A}$ - a square $|\boldsymbol{V}| \times |\boldsymbol{V}|$ matrix whose element $A_{ij} = 1$ where there exists an edge (v_i, v_j) and 0 otherwise.

In general the dynamics of different markets need not be the same, and coupling strength A_{ij} may also vary (with some markets more strongly linked than others) and be asymmetric (if influence is proportional to e.g. market size). However I consider the simple case of N markets with identical internal dynamics and assume they interact over a connected unweighted ($A_{ij} \in [0,1]$) undirected ($A_{ij} = A_{ji}$) graph. I define the underlying dynamics as

$$\boldsymbol{X_{i,t+1}} = \boldsymbol{F}\left(\left(1 - D\frac{w}{d_i}\sum_{j=1}^{N} A_{ij}\right)\boldsymbol{X_{i,t}} + D\frac{w}{d_i}\sum_{j=1}^{N} A_{ij}\,\boldsymbol{X_{j,t}}\right)$$

$$\boldsymbol{X}_{i,t(0)} = \boldsymbol{X}_i^0 \tag{18}$$

or by rearrangement

$$\boldsymbol{X_{i,t+1}} = \boldsymbol{F}\left(\boldsymbol{X_{i,t}} + D\frac{w}{d_i}\sum_{j=1}^{N} A_{ij}\,(\boldsymbol{X_{j,t}} - \boldsymbol{X_{i,t}})\right)$$

$$\boldsymbol{X}_{i,t(0)} = \boldsymbol{X}_i^0 \tag{19}$$

for $i = 1, \dots, N$, where $\boldsymbol{X_i} \in \mathbb{R}$ is the state vector denoting the state of the i-th node (i.e. market conditions), $\boldsymbol{F}(.)$ the dynamics by which these evolve (identical for all markets), $0 < w < 1$ a uniform coupling strength at all nodes governing the relative weight given to conditions in neighbouring markets, d_i is the degree of the i-th node[126] (this normalisation giving equal weighting to all linked markets) and A a symmetric adjacency matrix (influence between linked markets is mutual) defining the specific topology of the connectivity structure among markets. Finally D is an identity matrix allowing the introduction of restrictions on the coupling dimensions (markets may be coupled on some dimensions and not others, and may be positively or negatively coupled). The model reduces to $\boldsymbol{X_{i,t+1}} = \boldsymbol{F}(\boldsymbol{X_{i,t}})$ for any unconnected market, and for all markets $i = 1, \dots, N$ where $w = 0$.

The dynamics of the model will of course be crucially influenced by the intrinsic local dynamics $\boldsymbol{F}(.)$ of markets, the coupling parameter w, but also the connectivity structure A, and the interaction among these.

Reflecting documented empirical evidence for repeating boom-bust dynamics in local markets (Essay 1/Section 2), I am here interested in cases where individual markets are characterised by their own non-trivial local dynamics. In particular where the qualitative dynamics of $\boldsymbol{F}(\boldsymbol{X_i})$ are characterised by endogenous cyclicality – i.e. limit-cycle dynamics.

Meanwhile regarding the connectivity structure, although economic theory suggests the potential *a priori* relevance of a range of different connectivity structures - from spatially *local*, to non-local (in a spatial sense i.e. sparse connections based on some form of non-spatial economic linkage) to global (all-to-all) coupling among markets (See section **Error! Reference source not found.** for a more detailed discussion) – motivated by my the spatial ripple patterns I find in Essay 3 (Section 4), I am interested to study *local spatial coupling* in an endogenous cycle framework.

Specifically I am interested in whether local spatial coupling of endogenous local cycles could provide a more convincing explanation for the stability of spatial 'ripples' over multiple boom-bust episodes than the spatial diffusion of local shocks assumed in the extensive existing 'ripple effect' literature; but also whether purely local coupling could plausibly account not only for spatial patterns but also for the emergence of national boom-bust. A is thus a sparse matrix representing a spatial contiguity based planar network.

[126] The degree of node i denoted d_i is the number of links that connect node i to other nodes in the network.

6.4 Simulating speculative housing cycles in a spatial network setting

For simulation purposes we will require a specific model. Since the economic processes underlying the observed cyclicality of local markets remains poorly understood, the appropriate choice of functional form of $\boldsymbol{F}(.)$ and state vector $\boldsymbol{X}$ in the general model introduced in Eq.19 is not obvious. However as already discussed one important class of models in the existing literature that do provide plausible hypotheses regarding the source of cyclicality in housing markets, are heterogeneous agent based behavioural models of housing market dynamics (a mostly recent literature - see for example Dieci & Westerhoff (2012b, 2016), Geanakoplos et al. (2012), Bolt et al. (2014), Bao & Hommes (2015), Defusco et al. (2017). I make some review in section 6.2.1).

I employ and extend the simple speculative housing cycle model developed by Dieci & Westerhoff (2012b) as a workhorse with which to explore the implications of spatial spillovers for housing markets within an endogenous cycle setting. Unlike many of the models in the existing literature the dynamics are described by a low dimensional system (two dimensional non-linear map).

In their original model (which I will formally introduced in section **Error! Reference source not found.**) the demand for houses is influenced by expectations about future house prices. In forming their expectations about future prices, agents rely on a combination of '*extrapolative*' and '*regressive*' forecasting rules (i.e. they expect both momentum and mean reversion in prices). The relative importance of these competing views evolves endogenously over time in response to market conditions. The interaction between speculative and fundamental forces in the model can - under some parameterisations - give rise to quasi-periodic boom-bust cycles broadly consistent with the semi-regular housing boom bust cycles that can be observed in U.S. markets (in both city and state level data).

I extend this rather general theoretical model of a single market to that of a network of spatially connected mutually influencing markets according to the general framework described by Eq.19.

For those persuaded that the endogenous expectations dynamics studied in Dieci and Westerhoff's original model provide crucial insights into local housing market instability, this extension allows us to study and generate qualitative insights into how the spatial dimension to housing markets interacts with fluctuations initiated by local speculative forces, within a specific topological context – here the geography of the US.

Alternatively, maintaining a more agnostic approach with respect to the underlying mechanism behind the cyclicality of local housing markets, this work provides the concreteness necessary in order to explore the implications for positive spatial spillovers among quasi-periodic cycles in US housing markets. The qualitative insights generated by this analysis regarding wide-scale spatio-temporal phenomena, are unlikely to be specific to the particular cycle process described by this model, but rather have more general relevance to the locally coupling of any quasi-periodic house price dynamics.

6.4.1 Autonomous dynamics of individual market

The original model of Dieci and Westerhoff (2012b) is described by the two dimensional non-linear map

$$\pi_{t+1} = (1 - c - e)\pi_t + \frac{f\pi_t - gh\pi_t^3}{1 + h\pi_t^2} - d\zeta_t$$

$$\zeta_{t+1} = e\pi_t + d\zeta_t \qquad (20)$$

where the state variables π and ζ are, respectively, *house prices* and *house building* expressed as deviations from fundamental equilibrium.[127]

The parameter c is the price elasticity of demand for housing (fundamental demand depends negatively on the current price); $(1 - d)$ is the depreciation rate of the housing stock $(0 < d < 1)$;[128] e is the price elasticity of housing supply $(e > 0)$; meanwhile f and g govern the speculative housing demand components driven respectively by *extrapolative* and *mean-reverting* expectations. Finally the parameter h governs agents' endogenous switching behaviour between these *extrapolative* and *regressive* forecasting strategies - specifically the higher the parameter h, the faster agents abandon *extrapolating* behaviour in response to increases in mispricing $(P_t - P^*)$.[129]

Switching behaviour is assumed to be governed by the bell shaped curve

$$W_t = \frac{1}{1+h\pi_t{}^2} \qquad (21)$$

The transformed system Eq.(20) of course has a fixed point at the origin $(\pi^* = 0, \zeta^* = 0)$ (corresponding to the market fundamental equilibrium). This fixed point is stable under some parameterisations, but undergoes a supercritical Neimark-Sacker bifurcation when

$$f > c + \frac{e}{1+d} - 2 \qquad (22)$$

$$f < c + \frac{e}{1-d} \qquad (23)$$

but

$$f > c + \frac{1}{d} - 1 \qquad (24)$$

generating ongoing quasi-periodic cycles around the destabilised fundamental equilibrium (see Diecei and Westerhoff's original paper for full derivation of the model and more detailed stability analysis). Figure 30 illustrates with a

[127] $\pi_t = P_t - P^*$, $\zeta_t = Z_t - Z^*$ where P is house prices, Z lagged house building, and P^* and Z^* the fixed point of the untransformed model that represents the market fundamental equilibrium.

[128] Where the housing stock is given by $S_{t+1} = S_t - (1 - d)S_t + eP_t = dS_t + eP_t$.

[129] Since in my simulations I set $g = h = 1$ the equation of motion for π further simplifies.

numerical simulation, the dynamics of the model parameterized in this cyclical regime.

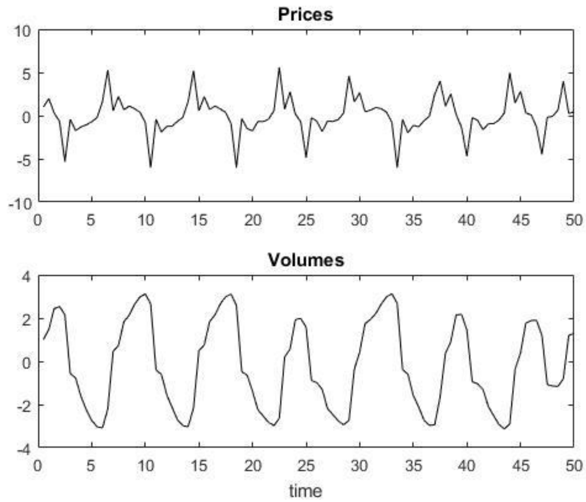

Figure 30: The signals generated by the speculative housing cycle model of Dieci and Westerhoff (2012b) parameterised to be in a cyclical regime. I use this model to characterise the autonomous dynamics of individual housing markets.

The intuition behind the derivation and ultimate functional form of the model is that: at the margin households will reduce their fundamental housing demand in response to an increase in house prices, unmet demand will bid prices up and upshifted supply will cause asking prices to be adjusted down, while excess demand may also be met by a positive supply response to price movements. However speculative investment motives can destabilize the equilibrium, as investors seeking to benefit from the capital gains offered by house price momentum themselves become a source of market momentum. The potential explosiveness this dynamic introduces is contained in the model by the fact that agents do not believe growth out of line with fundamentals can continue indefinitely. This combination of globally contained local instability gives rise to cycles.

6.4.2 Extension to network setting

In this specific example I extend Eq.20 according to Eq.19 in the sense that I assume that the *autonomous* dynamics of each market $\boldsymbol{F}(\boldsymbol{X})$ are driven by the Dieci and Westerhoff model (Eq.20). I further assume that while agents' price expectations for a given market may be mainly based on local market conditions, they may also be influenced to some extent by conditions in adjacent markets (for example if I live in x and I hear prices are falling in y, this may have some influence on my expectations regarding the outlook for house prices in x).

Specifically I assume that agents to some extent factor trends and mispricing in adjacent markets into their price expectations.

Formally I assume prices and volumes in the i-th market evolve according to

$$\pi_{i,t+1} = (1 - c - e)\hat{\pi}_{i,t} + \frac{f\hat{\pi}_{i,t} - gh\hat{\pi}_{i,t}^3}{1 + h\hat{\pi}_{i,t}^2} - d\zeta_t$$

$$\zeta_{i,t+1} = e\hat{\pi}_{i,t} + d\zeta_t \qquad (25)$$

where $\hat{\pi}_{i,t}$ is the weighted sum of own market and neighbouring market price deviations at time t

$$\hat{\pi}_{i,t} = \pi_{i,t} + \frac{w}{k_i}\sum_{j=1}^{N} A_{ij}\left(\pi_{j,t} - \pi_{i,t}\right) \qquad (26)$$

Local markets are thus directly coupled via the price expectations dimension only.

6.4.3 Spatial diffusion and local coupling scheme

The specific topology - i.e. choice of A - may be important for the dynamics of the model. As discussed in section **Error! Reference source not found.**, links among different housing markets may be *local* (markets influence and/or are influenced by nearby markets); non-local (long range economic links among markets that are not necessarily geographically close); or global (where mean field or common global factors generate an all-to-all dependency structure).

However as already discussed and introduced I am interested here in the case of sparse spatial contiguity based coupling motivated by the strong empirical evidence in the literature and from my results in Essay 3 (Section 4) for some form of spatial dependence of house prices in markets across the U.S. (something also found for other markets such as the U.K (Sean Holly, Hashem Pesaran, & Yamagata, 2011; Meen, 1996)).

For simulation purposes I introduce (for choice of A in Eq.26) the spatial adjacency matrix describing the *actual* spatial contiguity patter among the 49 contiguous US states (visually illustrated in Figure 31).

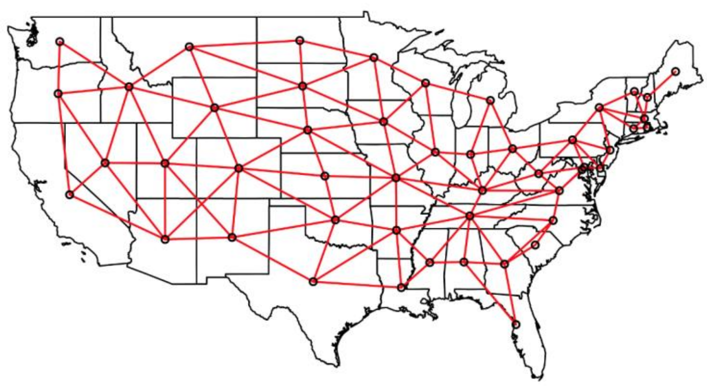

Figure 31: State-to-state spatial contiguity matrix for contiguous US states.

6.5 Simulation and results

To numerically investigate the mean field and spatial dynamics of the network model Eq.25 augmented with spatial adjacency matrix for US states, I set the vector of initial values $\boldsymbol{X}_i^0$ based on uniformly and randomly sampling of the signal generated by the simulation of a single market. Since the cycle is sampled at all different points in its phase-space this achieves a random and approximate uniform distribution of initial phases $\boldsymbol{\theta}_{X_i}^0$. I then evolve the system to obtain the trajectory of π_i and ζ_i over time for all markets $i = 1, \dots, N$.

6.5.1 Endogenous synchronisation of locally coupled cycles

The results of this simulation are presented in Figure 32, which plots the evolution of the state variables π_i and ζ_i (prices and volumes respectively) over time as well as the simple mean across all markets for each state variable (bold blue line).

Although the cyclical stance of cycles in different markets is initially dispersed, they clearly synchronise over time.

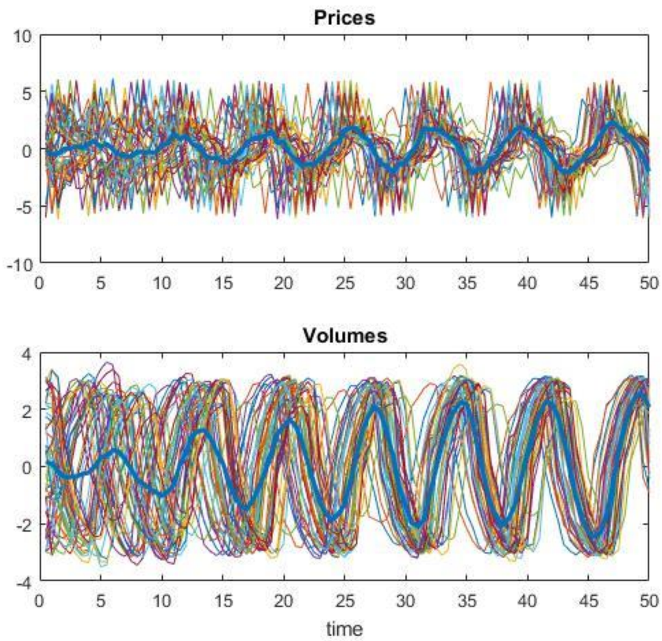

Figure 32: Illustration of the synchronisation over time of coupled cycles with initially randomised phase and $\boldsymbol{w} = \mathbf{0.3}$. Each of the thin lines plots the evolution of one of 49 markets; the thick blue line is the un-weighted mean value across all markets.

Figure 33 presents a phase-space trajectory of the mean field of the system (average prices vs. average volumes across all 48 markets) based on a longer run of the same simulation. This clearly shows the mean field converging to a quasi-periodic orbit i.e. the network of markets – although only *locally* coupled *local* cycles – is behaving like a single cyclical market.

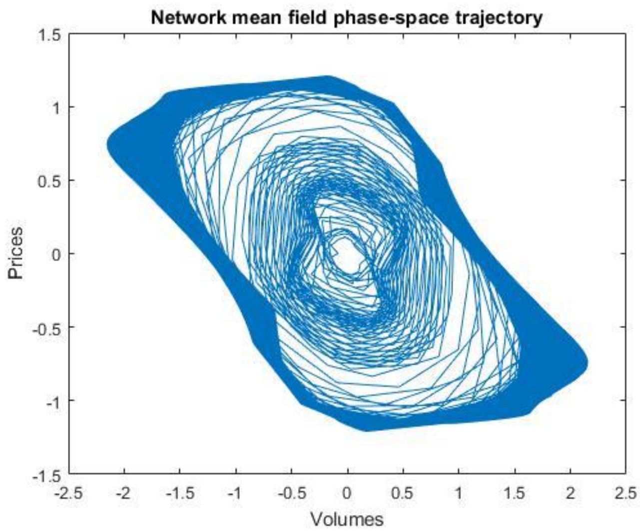

Figure 33: Plots the trajectory of the mean fields for prices and volumes in phase-space (randomised initial phase, $\boldsymbol{w = 0.3}$, 2,500 time steps) showing that starting from a small collective cycle in the almost incoherent state, the amplitude of the collective cycle grows as synchronisation proceeds, and the network apparently converging to what looks like quasi-periodic behaviour.

In order to study the relationship between the coupling parameter w (the parameter governing the strength of influence from neighbouring markets on own-market price expectations) and the synchronisation dynamics of the network, it is useful to quantify the overall state of the system.

In order to quantify the time-evolving overall degree of synchronization among markets $i = 1, \dots, N$, I employ the same order parameter (Eq. 8, re-stated here for convenience) as I employed in my empirical analysis of U.S. markets in Essay 2 (Section 3):

$$R_t = \frac{1}{N} \sum_{i=1}^{N} e^{i\theta_{x_i,t}} \qquad (27)$$

The modulus $r = |R|,\ 0 \leq r \leq 1$ measures the overall *phase synchronisation* among the different markets, achieving its maximum $r = 1$ when all phases are identical and its minimum $r = 0$ when phases are balanced around the circle.[130] Phase series $\theta_{x_i t}$ are obtained by complex continuous wavelet transform of the simulated time series.[131]

[130] Such as evenly spread or in clusters that balance each other out. For a detailed discussion of the structure/local order that may be missed by Kuramoto order parameter see e.g. Frank & Richardson (2010) , Richardson et al. (2012).

[131] This is a scale-band average over the narrow scale-band within which the cycles generated by the model reside.

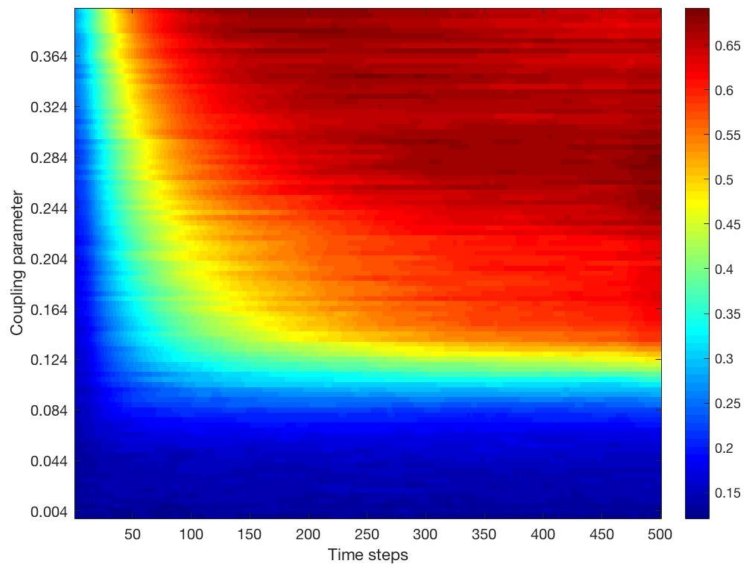

Figure 34: This figure plots average time sequences (time is on the x-axis) of the order parameter $\boldsymbol{r}$ (Eq.**8**) (represented by the colour of the heatmap) calculated at different strengths of the coupling parameter $\boldsymbol{w}$ (vertical axis). These are based on 500 simulations from different randomised initial conditions, each of 500 time steps.

Figure 34 displays the temporal evolution of $r = |R|$ averaged over 500 realisations from different randomised initial conditions, for different values of the coupling parameter w. For uncoupled markets or low levels of influence from neighbouring markets, synchronisation does not occur. For higher values of w ($w = 0.1$ and above) synchronisation occurs, and the level of synchronisation ultimately reached depends on w - synchronisation happens faster and reaches higher levels for higher values of w.

That the network does not fully synchronise reflects a competition between the synchronising influence of the spatial coupling and the de-synchronising influence from the quasi-periodic dynamics of individual market level cycle process.[132]

6.5.2 *Endogenous emergence of spatial-waves*

To study the spatial pattern of dynamics generated by the model, I follow precisely the same strategy as for my empirical analysis in Essay 3 (Section 4. See Section 4.2.2 specifically).

[132] Interestingly the network of interdependencies seem to stabilize the periodicity of the cycles compared to the autonomous dynamics of a single market without neighbouring influences.

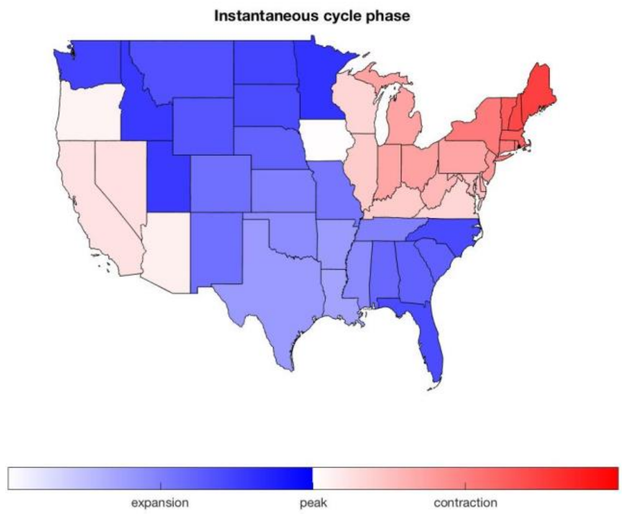

Figure 35: This figure presents a snapshot (the distribution of instantaneous phase angles at a single time-step) from the dynamic heatmap representation of a single realisation of the model (the full dynamic visualisation is available here).[133] (Note that space is not continuous in the model as each state is represented by a single node and the distances between sates is geodesic not Cartesian).

First I plot as a dynamic heatmap the individual phase series $\theta_{x_i t}$ for each market (based on a simulation of the model, and obtained as above by complex continuous wavelet transform of the simulated time series). This analysis (which can be viewed here (see footnote 133) and is provided as supplementary material) shows the endogenous emergence of a pattern very closely resembling the empirical pattern I show in historical house price data, with coast-to-centre ripples. Figure 35 presents a 'snapshot' from this dynamic view of the simulated data. From this we can see that even the appearance of a cluster of markets in the northeast of the country emerges endogenously from the spatial structure of the model.

I then use the mean relative phase of cycles (Eq.12) in order to summarise the overall spatial pattern in the relative timing of cycles in a static chart. I have previously introduced mean relative phase analysis for the purposes of my empirical analysis in section Essay 3 (See Section 4.2.2), but for convenience I restate definitions here:

I calculate the mean phase series across all markets from $R(t) = \frac{1}{N}\sum_{j=1}^{N} e^{i\theta_{x_i}(t)}$ (Eq.8) (which can be re-written $R_t = r_t{}^{i\phi_t}$) as

$$\phi(t) = atan2\big(R(t)\big) \qquad (28)$$

I then calculate the phase of each market relative to the mean phase across all markets (or *relative phase angle* (RPA)) as

133 Hyperlink is:
https://drive.google.com/file/d/1GVLsEvUXgb5JLNyuTyMTfL3gqcb5_uSF/view?usp=sharing

$$\theta_{x_n,\phi}(t) = \theta_{x_n}(t) - \phi(t) \qquad (29)$$

This provides a continuous measure quantifying the phase shift of an individual market with respect to the overall collective development across states. This is defined for every state at every time step. In order to provide a more succinct summary of the relationships identified, I obtain the time averaged relative phase

$$\bar{\theta}_{x_n,\phi} = \frac{1}{T}\sum_{t=1}^{T} e^{i\theta_{x_n,\phi}(t)} \qquad (30)$$

where $t = 1, \dots, T$ are the number of time steps and $\bar{\theta}_{x_n,\phi}$ are the mean relative phases in complex form (radian $[-\pi, \pi]$ form can be obtained as $atan2(\bar{\theta}_{x_n,\phi})$). These $\bar{\theta}_{x_n,\phi}$ capture the phase-shift of a given market n with respect to the collective or national cycle ϕ.

By using these mean relative phases $\bar{\theta}_{x_n,\phi}$ as input for a heatmap of U.S. sates (see Figure 36) I am able to see whether there is any stable spatial pattern over time in the relative timings of cycles across the spatial network. Figure 36 plots the results of this analysis for a single (500 time-step) simulation of the model.[134]

This analysis clearly shows that this simulation of the locally coupled spatial network generates clear east-west spatial 'waves' similar to those I empirically documented in Essay 3 (Section 4).

Figure 37 plots the same mean relative phase analysis, but now averaged over 1,000 different simulations of the model. This average over a large number of simulations allows me to assess whether there are particular patterns that tend to arise endogenously regardless of initial conditions (the initial distribution of cycle phase). While the pattern is less clear than for individual runs of the model, we see that there is a systematic tendency for coastal states (east and west) to lead the collective cycle. The less crisp traveling-wave pattern seems to be the result of some variation in the precise spatial projection of the traveling wave pattern, although a general east-west pattern is clearly confirmed.

[134] The first 100 time steps are excluded from the time averaged relative phase angles, since the phase of cycles in different states are initially randomized, before then pattern among cycles emerges endogenously out of their interaction.

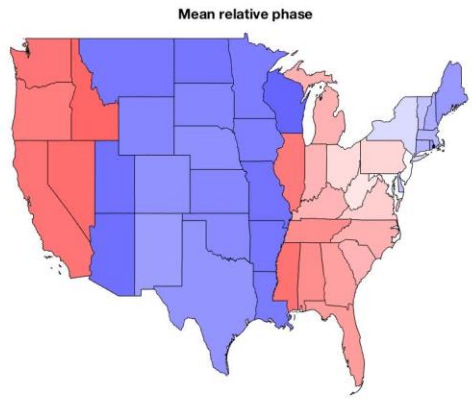

Figure 36: This figure plots the time averaged relative phases for each market $\overline{\boldsymbol{\theta}}_{x_n,\phi}$ (Eq.**30)**) (obtained as average over 1,000 time steps based on a simulation of the network model Eq.**25** as detailed above) as a heatmap of US states (space is not continuous as each state is a node and the distances between sates is geodesic not Cartesian). Spatial 'waves'/'ripples' are clearly visible with coastal states on east and west coasts leading and central states lagging the collective or 'national' cycle.

It is perhaps worth briefly noting, that the pattern of phase relations between markets is the same for the price dimension as it is for the volumes dimension of the model, thus I do not present a separate analysis of price and volumes.

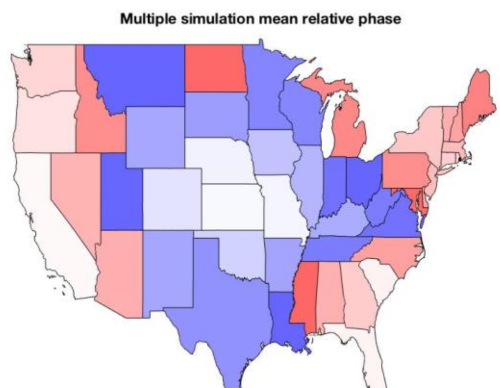

Figure 37: This figure plots the same analysis as **Figure 36** but now averaged over 1,000 runs of the model (where **Figure 36** presents the result of a single run).

6.6 Discussion and significance

The model developed for this essay is highly stylised: I employ a rather minimal model to characterise the intrinsic dynamics of individual nodes/markets; I assume not only the same model (in the sense of functional form), but also identical parameters across all markets and uniform coupling between markets ('unrealistic'); I also assume parameters are identical over time (also unlikely to be the case); I assume away all sorts of aggregate factors and feedbacks that are likely very important. No shocks – local or national - no heterogeneity across markets, no global factors go into the model.

This deliberate simplicity however sets up an interesting thought experiment.

The results of this experiment show that in a limit-cycle setting, even for quasi-periodic dynamics, purely *local* spatial spillovers among *local* markets; combined with the specific spatial topology of the geography of U.S. states, are by themselves sufficient to account for key aspects of the historic spatio-temporal dynamics of housing, including: *local cycles*,[135] *spatial ripples*, and *national boom-bust*. Perhaps most interestingly, it produces not just ripple patterns, but is able to neatly reproduce something very close to the empirical pattern of relationships observed in the data: the synchronisation of markets along one spatial projection; and traveling wave along that orthogonal to it; and the coasts-to-centre pattern of this wave (see Figure 35-Figure 37). Indeed even other details such as the appearance of a northeast cluster emerge from the model.

The ability of this model - despite its simplicity - to simultaneously account within a unified framework for a collection of key empirical aspects of the spatio-temporal dynamics of U.S. housing – features that cannot easily be resolved by recourse to existing theories - suggests locally coupled locally unstable housing market dynamics may provide an empirically relevant and valuable new framework within which to interpret and study U.S. housing market instability.

These results will be of relevance and interest for a number of different literatures.

Clearly it has significant implications for theory and modeling of housing market dynamics as well as for the forecasting of housing variables.

One common hypothesis is that a national cycle exists across all housing markets, but that housing cycles also have some local or regional element. Some empirical work seeks to parse these common vs. idiosyncratic components (Del Negro & Otrok, 2007; S Holly et al., 2010). Previous research into the national boom-bust has generally sought to identify the relevant common factors driving common price developments in markets across the country (a national loosening of credit, FED interest rate policies etc. (Campbell et al., 2009; Dell'Ariccia, Igan, & Laeven, 2012; Favilukis et al., 2016; Glaeser et al., 2013; Himmelberg et al., 2005; Levitin & Wachter, 2012; Mian & Sufi, 2009; Pavlov & Wachter, 2009; C. W. Wheaton & Nechayev, 2008)). Meanwhile theories of local

[135] Trivially so given cyclic character of model, although networks of oscillatory variables can lead to oscillation death and other interesting phenomena. Nevertheless the empirical results presented in section 2 supports the use of a model able to explain periodic behaviour.

market instability have seemed to lack relevance or explanatory power with respect to the national boom-bust.

At the same time spatial dependence has been an important theme in real estate economics and seems at odds with the view that house price fluctuations are a simple sum of independent *local* and of common *national* components. Here methods to separate out the relationship between spatial markets that is due to the effect of *common factors* from that which is *truly spatial* have been sought. One strategy introduced is to first strip out contemporaneous comovement across all markets, before then studying comovement between markets in the residual variation (e.g. Holly et al. (Baltagi & Li, 2014; S Holly et al., 2010)). Global comovement is thus assumed to be the result of common factors and spatial dependence only a source of weak cross-sectional dependence.

What is more within this shock diffusion framework, since a disturbance in one market directly drives adjacent markets, and more distant markets only indirectly, the spatial diffusion of local shocks cannot explain the synchrony of distant markets. It has thus been argued that the similar timing of cycles in geographically distant markets (such as San Diego and Washington DC) provides evidence of important non-spatial links between markets resulting from e.g. the arbitrage of investment opportunities by national investors (Füss et al., 2012; Hernández-Murillo et al., 2017; Zhu et al., 2013).

By contrast my theoretical framework and experiment suggests an alternative hypothesis, according to which we can neither consider housing in terms of a national aggregate, nor in terms of entirely local markets: both *spatial patterns* and *national housing market movements* may be understood as emerging endogenously from the *local* interaction among *local* markets.

It thus provides a novel and seemingly powerful alternative explanation and framework for thinking about housing market dynamics at different spatial scales and the sort of 'ripple effects' that have long been studied in the real estate economics literature (Holmans, 1990; Meen, 1999).

It suggests a need for care in interpreting everything that does not average out as driven by some unobserved common factor. Indeed this observation potentially has wider relevance in business cycle applications - whether the analysis of spatial or sectoral disaggregations of variables, or even different business cycle variables – and calls for methods that take account of temporal-relations between variables.[136]

The hypothesis developed in this essay and model is made plausible by the fact that these model results are consistent with the data. The traveling-wave pattern observed in the data (Section 4, **Figure 19**) and generated by this model (see Figure 36) is very hard to account for within a spatial diffusion of shocks framework, in which setting we might rather expect an *epicentre* pattern (in

[136] Methods that allow for phase differences between cycles, such as complex principal component analysis (Horel, 1984) (hardly exploited in economics). The phase-adjusted correlation methodology of Koopman & Azevedo (2008) based on unobserved components models explicitly assumes time-varying phase-shifts between signals. However, while the Koopman & Azevedo (2008) method allows for the convergence of cycles, the evolution of phase differences is governed by a monotone deterministic function of time. The empirical methods I introduce in the first 1-4 of this thesis make a contribution in this respect, towards methods suitable for time-evolving multivariate signals.

which shocks diffuse in all directions) as well as evidence of changing lead-lag patterns reflecting a succession of local shocks to different markets.

Indeed, it is also a particularly interesting feature of this model that the leading character of coastal states emerges endogenously (regardless of initial conditions – see Figure 37). This result should be of interest not only to the housing "ripple effect" literature, but to the wider spatial economics literature, since it implies an important role for space: the system of interconnected markets means that space needs to be explicitly considered and is important both for aggregate dynamics and for the role of particular markets within the economy – here giving influence to coastal markets:

For some markets to have a constant systematic lead over others within a spatial diffusion of local shocks setting, requires them to be a dominant market propagating shocks to other regions (Sean Holly et al., 2011). Here by contrast, given the identical parameterisation and uniform coupling scheme, the strong tendency for coastal states to lead the national cycle in the model must be driven by the topology of the network (i.e. spatial structure of the model - perhaps simply being coastal (at a boundary) gives them more influence).

This result suggests a need for caution over seeking heterogeneity based explanations for the apparent dominance of some markets, and interpreting leading markets as key sources of shocks (Chiang & Tsai, 2016).

Similarly, although e.g. stronger time-lagged correlations between adjacent markets after the 2007-8 crisis have been interpreted as evidence of increased spatial shock transmission (Cohen et al., 2016), the results of this modelling exercise suggest caution over this strongly causal interpretation, since increased local synchronisation between cycles would increase both contemporaneous and lagged correlations between markets.

While there may be good reason to expect possible non-local links between geographically distant markets, my results also suggest a need for caution in interpreting the synchronisation of non-adjacent markets: in a local shock diffusion setting, the synchrony of spatially distant markets implies non-spatial economic links (Füss et al., 2012; Hernández-Murillo et al., 2017; Zhu et al., 2013). However the synchronisation of spatially distant markets (such as San Diego and Washington DC) arises in the spatially coupled cycle I investigate here (even though links are purely spatial) due to the 'wave' patterns generated by the local synchronisation of markets.

These results are also relevant for a literature that seeks to explain observed increases over time in the co-movement across subnational markets. One highly plausible line of thinking pursued by a growing literature, asks whether increased integration among sub-national markets has been a driver of their increased co-movement (in particular increasing financial integration has been proposed as a possible factor in increased comovement across US housing markets (Loutskina & Strahan, 2015; Milcheva & Zhu, 2016)).

The nationalisation of housing finance in the US represents the emergence of a common factor across sub-national markets. While one possibility is that financial dynamics become a common semi-exogenous source of volatility, another possibility is that the common factor becomes a source of global coupling - increasing the coupling/potential for spillovers among markets. In a limit-cycle setting this increased coupling would certainly become a driver for increased comovement. As such in the context of endogenous cyclicality in sub-markets, market integration (whether general economic integration of housing fundamentals; or financial integration and the de-localisation of housing finance etc.) may lead to increased aggregate volatility. It is particularly interesting to note, for example, the possibility that e.g. interstate banking policies designed to take advantage of risk diversification opportunities presented by the heterogeneity in the timing of cycles across different markets (Amel, 2000; Rice & Johnson, 2007), could plausibly in this sort of setting contribute to the synchronisation of those markets. Some support for this hypothesis is provided by the fact that the global synchronisation event I empirically document in Essay 2 and 3 (see Section 3, Figure 18)

At the same time my results suggest a need for caution in interpreting trends in comovement since while a function of coupling, synchronisation may play out as a dynamic process over time. As a result incremental changes in the level of comovement in the system need not necessarily reflect incremental changes in the underlying connectivity structure or strength of links between markets.

What is more, increases in the sort of global coupling implied by the nationalisation of housing finance for example, does not provide an explanation for observed spatial patterns; meanwhile local coupling is *sufficient* to explain both spatial patterns and the trend to increased comovement nationally.

As such my results suggest an important need for further empirical work to identify the channels operating between markets and to unpick the contributions of local, non-local and global connectivity among them.

The coupling dimension matters: for example evidence presented here that synchronisation already experienced in the U.S. might in principal be consistent with *local* coupling, raises question to what extent national comovement has been driven by global factors such as e.g. financial regulation and innovation vs. channels of local diffusion that may not necessarily map clearly to obvious macro policy and leavers such as monetary policy.

Nevertheless it seems highly likely that *both* local *and* global (e.g. financial integration and innovation driven) factors have been at play in the U.S. historic experience, suggesting the need for empirical work to disentangle their contributions. Another important point here may be that once a national cycle develops (i.e. once some mean field emerges perhaps as a result of local spatial links) a host of *powerful* mean-field feedbacks/couplings (experienced acutely during the GFC) seem perhaps as good as inevitable and should be explored in detail. These are also likely to trigger behavioural and policy reactions with the potential to modulate the cycle process.

The potential relevance of a coupled intrinsic cycle framework in explaining the historic U.S. national housing boom-bust raises of course the question whether we should expect intensified housing cyclicality at the national level on an on-going basis.[137] The answer to this question is contingent not only on the relevance of the framework I have explored in this essay for explaining historical experience; but also whether e.g. institutional or behavioural responses to the

[137] In coupled cycle setting/my simulations once synchronisation built up in the network, all the sub-markets then continued to behave like one giant cyclical market. Synchronisation of on-going cycles thus implies potential for onset of on-going cyclicality of housing at a national level. This contrasts with the exogenous shock and temporary bubble views/paradigms in the existing literature, under which we would expect markets may normalise.

GFC (including structural and cyclical macroprudential tools) have moderated or qualitatively shifted instability in housing dynamics.

These questions point finally to the potential policy significance of the results presented here.

Historically the asynchrony of sub-national cycles meant that macro policy could not target housing effectively but also limited the role of housing as a significance source of macro-financial instability. It may also have limited the house price based credit channel (Iacoviello, 2004, 2005; Iacoviello & Minetti, 2008) for monetary policy transmission (Brady, 2014; Fratantoni & Schuh, 2003; Füss et al., 2012); it presumably meant the impact of monetary policy varied across regions and may have been sub-optimal for some (this relates to the literature on business cycle synchronisation as a criteria for an optimal currency area starting from the seminal work of Mundell (1961) and McKinnon (1963)).

Meanwhile the synchronisation of sub-national cycles whilst representing a potentially significant source of macro-financial risk, and increased transmission of autonomous/endogenous housing market dynamics to the wider economy and housing based transmission and amplification of a variety of shocks; may also imply housing becomes amenable to countercyclical policies, and indeed could sharpen housing based channels of national policy transmission to macroeconomic and financial aggregates (Hofmann & Peersman, 2017).

The distinctive implications of this setting for interest rate, non-interest rate and structural policies cannot be developed in detail here, but merit careful exploration.

The empirical evidence of permanent cycles in city and state level data (Section 2) provides strong empirical motivation for models able to explain endogenous cyclicality. This is reinforced by the results of my theoretical modeling exercise in this essay, where I show the potential explanatory power and empirical relevance of local housing market cycle models such as those that have been developed in the existing behavioural heterogeneous agent housing market literature, for explaining rich wide-scale spatio-temporal phenomena and national house price averages and aggregates.

It is perhaps worth pointing out however, that both the empirical results I present, and the model based results I derive here are nevertheless *agnostic* with respect to the fundamental cycle mechanism underlying the instability of local markets and unlikely to be specific to the particular model of endogenous expectations dynamics I employ (rather the qualitative dynamics are the key issue, with simple periodic dynamics synchronising more easily than quasi-periodic dynamics such as those of the model here employed). As such my results call for further effort to develop and empirically discriminate between and test competing explanations for local housing market cyclicality.[138]

The ideas and results presented in this Essay introduce a new paradigm within which to interpret and analyse housing market dynamics. This new view is broadly aligned with the idea articulated, now some twenty five years ago, by Geoffrey Meen: that "housing is better treated as a set of interrelated local or

[138] While the heterogeneous agent literature seems to provide perhaps the most promising starting point in the existing literature; however even within this literature a range of different mechanisms are proposed (section 6.2.1) and empirical motivation and validation is often cursory, suggesting a need to deepen our understanding of the generating process/fundamental source of instability.

regional markets" (Meen, 1996, p. 346). However allowing for non-trivial dynamics at the individual market level introduces the potential for much richer phenomena than within the spatial shock diffusion framework employed in the existing literature. Combining the sort of non-trivial market level dynamics hypothesised and studied within the behavioural housing literature (Bao & Hommes, 2015; Bolt et al., 2014; Dieci & Westerhoff, 2012b, 2013, 2016; Sommervoll et al., 2010) (see Section 6.2.1) with the interconnected market view of Meen (e.g. Meen (1996)) deeply embedded within the real estate literature (Baltagi & Li, 2014) results in the sort of oscillator network system extensively studied by complexity literature (Arenas & Albert, 2008; A S Pikovsky, Rosenblum, & Kurths, 2001; Rodrigues, Peron, Ji, & Kurths, 2015; M. Rosenblum et al., 2001; Schroder et al., 2017).

Directions for further work are numerous but include (i) exploring spatio-temporal synchronisation dynamics in coupled noise driven cycle settings (here I model coupled *limit-cycle* setting, but what if house price dynamics would converge in the absence of noise, but are nevertheless characterised by complex roots?); (ii) empirical and theoretical work into appropriate cycle models (from the perspective of empirical relevance); and (ii) empirical investigation of the coupling dimension between markets.

6.7 Summary and conclusions

In the first, empirical phase of this thesis (Essays 1-4), I present evidence of repeating sub-national housing cycles (Essay 1. See Section 2); spatial correlation and non-random repeating spatial waves in these cycles (Essay 3. See Section 4); and show that the synchronisation of these sub-national cycles played a crucial role in the national U.S. housing-boom bust that culminated in the GFC (Essay 2. See Section 3).

Taken together these empirical facts seem to provide non-trivial restrictions on any theoretical explanation. Indeed I argue they are not easily explained by existing theories in the literature.

In this essay, I ask whether the sort of spatial diffusion of house prices among local markets often assumed in the spatial 'ripple' effect literature; combined with the sort of endogenous cyclicality suggested by the data and that often arises in e.g. heterogeneous agent housing models; could provide a useful new theoretical framework within which to think about this collection of empirical phenomena.

I model 49 identical housing markets with autonomous dynamics characterised by the same endogenous quasi-periodic speculative price cycles but coupled according to the spatial adjacency network for the 49 spatially contiguous U.S. states - such that neighbouring markets also have some influence on price expectations (sections **Error! Reference source not found.**-**Error! Reference source not found.**).

I conduct a number of simulation-based experiments to understand the *spatio-temporal* dynamics on the network and the influence of the local positive coupling parameter (mutual influence among spatially adjacent markets) on these dynamics (section 6.5.1-6.5.2). I find for sufficiently weak coupling the national market (understood as the average price and aggregate quantities over all markets) is stable; but if coupling is increased a bifurcation occurs and markets: (i) synchronise over time (developing a collective or national cycle); and (ii) coast-to-center spatial 'waves' develop (consistent with those I document in Essay 3 (Section 4).

This work thus leads to a novel simple and unified explanation for a collection of key empirically documented phenomena not easily resolved by recourse to existing theories. The sufficiency and parsimony of this minimal framework does not of course mean we should discard or discount other explanations and factors. It does seem to suggest however, that locally coupled locally unstable housing market dynamics may offer a valuable new framework, the relevance of which deserves further exploration.

This approach combines familiar elements: (i) spatial dependence between adjacent markets - consistent with an important strand of thought in the real estate literature that argues housing markets may be best represented as a series of interconnected regional and local markets (Meen, 1996); and (ii) intrinsic cyclicality such as arises in behavioural house price models.

This combination of familiar elements leads to a new paradigm framework able to account for rich spatio-temporal phenomena, and provides a more ready account of the data than existing frameworks.

This re-conceptualizes the local vs. national character of housing market dynamics: we can neither consider housing in terms of a national aggregate, nor in terms of entirely local markets, and the sources of national instability may be found in local phenomena.

Since my results are very unlikely to be specific to the particular local cycle process I employ here, but rather are likely to hold for a general class of models consistent with the more general framework I set out of locally interacting markets characterised by intrinsic cycle dynamics (section 6.3), my results motivate further work on developing, and empirically discriminating between and testing theories of endogenous local housing market cyclicality.

The empirical relevance of this framework suggested by the ready explanation it provides for key historical facts, raises for example the question whether we should expect intensified national housing instability on an on-going basis. It also has distinct policy implications. The synchronisation of local cycles might imply on the one hand increased spillovers from autonomous housing dynamics to wider economy as well potentially as increased transmission and/or amplification by housing of policy and other shocks; meanwhile it might also make housing more amenable to countercyclical policies and sharpen housing based channels for national policy transmission.

7 Implications and relation to the literature

7.1 Implications for economic theory and the empirical literature

7.1.1 Characterising local housing cycle dynamics

Many sub-national housing markets in the U.S. exhibit a long history of repeated boom-bust. The dynamic character of these cycles represents an important question. A key debate in the literature has been whether house prices are stable but subject to *shocks*; or exhibit *bubble* episodes (Abraham & Hendershott, 1996; Clark & Coggin, 2011; Mikhed & Zem, 2009; Shiller, 1990). In either case this leads to a view of housing cyclicality as an irregular episodic process. I first ask whether the repeated fluctuations in state level house prices could instead reflect an endogenous mechanism, which produces recurrent boom-bust phenomena (Essay 1).

While economic theory suggests a variety of market imperfections and/or "alternative" behavioural assumptions that may amplify fundamental shocks,[139] enormous house price increases and subsequent crashes have led many researchers to test for the presence of speculative bubbles.

An empirical bubble literature reports evidence of temporarily explosive dynamics (argued to be the time series signature of an unstable bubble process rather than equilibrium adjustment in response to a shock (see Phillips et al. (2015a) for an overview)).[140] Econometric studies of U.S. markets find national house price series followed an explosive process during the 2000s boom period (Bolt et al., 2014; Phillips & Yu, 2011; W. Zhou & Sornette, 2005) consistent with e.g. a temporary rational bubble or period of "irrational exuberance". Meanwhile similar studies of regional house price series both (i) identify a long history of such explosive episodes at the local market level (consistent with multiple "local" bubbles prior to the 2000s); and (ii) confirm that explosive episodes were geographically widespread during the 2000s (consistent with a 'national bubble' during this period) (Hu & Oxley, 2018a; Efthymios Pavlidis et al., 2018; Shi, 2017).

Where this empirical bubble literature employs tests for time-localised zero frequency explosive behaviour (Bolt et al., 2014; Kivedal, 2013; Phillips & Yu, 2011; W. Zhou & Sornette, 2005) I use wavelet spectra in order to investigate the time-varying spectral characteristics of state level house price series since Jan 1975. The wavelet transform has power to distinguish periodic

[139] Key examples are credit-constraints (Ortalo-magné, 2006; Stein, 1995), search market externalities (Diaz & Jerez, 2013; W. C. Wheaton, 1990), (policy) constraints on the elasticity of supply (Glaeser & Gyourko, 2007), and e.g. backward-looking expectations schemes (Capozza et al., 2002; Karl E Case & Shiller, 1988).

[140] Where property prices are determined not only by economic fundamentals, but driven either by the rational expectation of a future gain from future price increases (Flood & Hodrick, 1990), or by irrationally optimistic expectations (Shiller, 2000; Vissing-jorgensen, 2004), house prices will follow an explosive process. A substantial empirical literature exploits this feature of non-fundamental asset price components as the basis for formal bubble tests - framed both within the well known present-value model (Diba & Grossman, 1988b; Hall et al., 1999; Homm & Breitung, 2012; Efthymios Pavlidis et al., 2016; Phillips et al., 2011; Phillips & Yu, 2011) and e.g. trend-following behaviour (Bolt et al., 2014) hypothesised in the behavioural asset market literature.

component(s) in time series (where present) even where these may be obscured within a noisy or complex dynamical process (Magrini, Oliveira Domingues, Macau, & Kiss, 2020; Torrence & Compo, 1995). It also has the distinct advantage over conventional spectral methods (Fourier analysis)[141] that it provides an (optimal) joint time-frequency decomposition.

Note that whether driven by successive shocks or bubbles, in either case under this episodic view housing cycles might recur, but would be fundamentally irregular and unpredictable (no preferred period).[142] The stable spectral ridges that I document for the majority of state level (and other subnational) markets, suggest on the contrary that housing cycles, while they may be subject to shocks thus exhibit some *noisy* behaviour, and while they may be "*bubbly*", they *also* have a cycle component with a preferred period (a c.10 year cycle) consistent with significant *intrinsic* cycle dynamics (i.e. persistent fluctuations around an either unstable or only weakly stable equilibrium).

Moreover, while the bubble identification literature presents compelling evidence of significant time-localised explosive dynamics in regional house price series (i.e. at the zero frequency), I document a systematic relationship between the onset and termination of "bubble episodes" (as dated by the econometric bubble literature (Phillips et al., 2015a, 2015b)) and the timing (as measured by the instantaneous phase)[143] of the permanent cycle component in the data. This implies that while prices may be *bubbly*, episodic bubble dynamics are crucially modulated by the more systematic intrinsic dynamics of the underlying cycle process.

This provides an important advance for our understanding of bubbles, since until now the bubble literature has focussed on how to identify a bubble when it happens, but has had little or nothing to say on when and where a bubble is likely to occur. Indeed a defining aspect of temporary bubble based theories of house price instability, is that dramatic market swings are seen to be driven, not by major changes in economic conditions, but rather by random capricious shifts in market psychology (Martin & Ventura, 2018; Shiller, 2000, 2015). However my results suggest that the timing of bubbles has been very far from random.[144]

While endogenous house price cycles are a dynamic possibility that *has* been shown to arise in a number of different *theoretical* house price model settings (such as Sommervoll et al. (2010), Dieci & Westerhoff (2012b, 2016)),[145] I am not aware of any serious *empirical* studies of whether house prices actually exhibit evidence of periodic dynamics (either for the U.S. or any other

[141] Used in recent studies such as high profile work by Beaudry et al. (2020) who address the same question of distinguishing noisy-limit cycle from persistent shock driven cycles but in a study of macro series, in particular unemployment data.

[142] Another possibility of course is that some markets are not switching but permanently in an unstable Evans bubble type regime (Evans, 1991). However if bubble period duration has some regularity, this would imply - unlike Evans bubbles - that bubbles not only build, but also end endogenously.

[143] Obtained here via continuous wavelet transform of the time series.

[144] Indeed in some markets the onset of such explosive episodes with the expansionary phase of every cycle raises the question whether these markets are really switching occasionally between stable and temporarily explosive dynamics as hypothesised, or are rather in an endogenous non-linear cycle regime with a locally unstable equilibrium. On the other hand for some markets explosive episodes are more occasional and do not occur every cycle.

[145] There really are not many relevant papers on this (Baptista et al., 2016; Bolt et al., 2014; Burnside et al., 2016; Chia et al., 2017; Defusco et al., 2017; Dieci & Westerhoff, 2012a, 2016; Diks & Wang, 2016; Eichholtz et al., 2015; Geanakoplos et al., 2012; He et al., 2015; Kouwenberg & Zwinkels, 2015; Lingling & Ma, 2009; Ryoo, 2015; Sommervoll et al., 2010; Uluc & Bank of England, 2015; W. C. Wheaton, 1990).

markets).[146] In a thematically related study, Beaudry et al. (2020) recently argue key macroeconomic time series - unemployment data - might be best understood as a noisy limit-cycle process (they present Fourier based analysis).

The evidence I present of endogenous cyclicality within a similar dominant cycle frequency range across U.S. markets, thus suggests we may need to make a significant shift in our understanding of housing market instability at the local level. This sort of qualitative dynamic regime has, up to now, received only limited theoretical attention and even less serious empirical motivation or validation. These results motivate calls for effort to develop theoretical models able to explain observed cyclicality, and strategies by which to empirically discriminate between alternative hypotheses regarding the underlying cycle mechanism.

7.1.2 Local vs. national sources of housing instability and spatial dynamics

The evidence I find of permanent cycle components in state level house price fluctuations also suggest however, a need to revisit our interpretation and analysis of housing instability both at different *spatial scales* and across space: our current understanding and interpretation of "*local*" or "*regional*" vs. *national* house price fluctuations; as well as our interpretation of *spatial patterns* in the timing of house price fluctuations in different markets, is fundamentally underpinned by the *idiosyncratic shock* and *bubble* hypotheses.

One common and natural hypothesis is that housing market fluctuations in any given market may reflect both *national* and *local* factors. Fluctuations in *national* house price indices and aggregates are assumed to reflect *national* shocks or bubbles, since local shocks or bubbles (given their idiosyncratic character) aught to largely average out.

Previous research into the national boom-bust has generally sought to identify the relevant common factors driving common price developments in markets across the country (a national loosening of credit, FED interest rate policies etc.) and some studies attempt to estimate unobserved common factors using a latent factor decomposition approach (Del Negro & Otrok, 2007; Vansteenkiste, 2007) - a panel of price growth rates is decomposed into loadings on a low-dimensional vector of latent factors, and a vector of market-specific variation (satisfying weak cross-sectional dependence) based on assumption that idiosyncratic components average out (Forni & Reichlin, 1998).[147]

However in the presence of permanent cycles (such as those I document in state level price data), a temporary global shock can potentially have a permanent impact on the degree of co-movement among cycles (thus aggregate volatility) meaning for example that the impact of a succession of common shocks on co-movement could plausibly accumulate over time. What is more, the coupling of markets via direct links or two-way causality between housing and the wider economy could result in the endogenous synchronisation of local cycle dynamics.

[146] And that has been missed in particular by Flor & Klarl (2017) despite similar methods due to the short sample period (thus narrower frequency window) they considered.
[147] This approach is also widely employed in the study of international house price cycles, see e.g. (Cesa-Bianchi, 2013; Hirata et al., 2013; Igan et al., 2009).

The latent factor model approach typically does not allow for phase-shifts between common components (that may e.g. naturally arise as a result of local propagation), and by assuming local components are independent from each other, preclude the meaningful study of bilateral linkages between markets as a source of co-movement across all markets. While such a variance decomposition is always possible, care must be taken in its interpretation as common shocks rather than the result of endogenous co-movement generated by the interactions between different markets (a concern raised for example in the analogous context of production networks by Carvalho & Tahbaz-salehi (2019)).

Indeed, by studying the phase-adjusted similarity in predominant frequency between cycles in different markets; then quantifying the time-evolving phase synchronisation among markets for these predominant cycles in the data,[148] I am able to show that the synchronisation of existing cycle components in state level house price variation contributed to national housing boom-bust (Essay 2). This result strongly suggests *local* endogenous dynamics contributed significantly and increasingly to national house price fluctuations over time.

At the same time spatial dependence has been an important theme in real estate economics and seems at odds with the view that house price fluctuations are a simple sum of independent *local* and of common *national* components. Spatial dependence and spillovers, or other (non-spatial) local links between markets may also be a source of co-movement across markets and are well-established themes in real estate economics.

Here methods to separate out the relationship between spatial markets that is due to the effect of *common factors* from that which is *truly spatial* have been sought. One strategy introduced is to first strip out contemporaneous comovement across all markets, before then studying comovement between markets in the residual variation (e.g. Holly et al. (Baltagi & Li, 2014; S Holly et al., 2010)). Global comovement is thus assumed to be the result of common factors, and spatial dependence only a source of weak cross-sectional dependence.

Interestingly the question of whether local dependence between cycles of this sort could be an important source not only of regional but also of national house price co-movement, seems not to have been widely or seriously considered (although this has increasingly featured as a policy concern since the GFC (see e.g. IMF (2014, 2018), UBS (2017), Vansteenkiste (2007)).

The existing literature on spatial patterns in house price movements, have assumed either the spatial diffusion of housing shocks (see especially the "ripple effect" literature) (Barros et al., 2012; Cook & Thomas, 2003; Drake, 1995; S Holly et al., 2010; Holmes et al., 2011; Meen, 1996, 1999) or (less often) some sort of spatial contagion process for the spread of bubbles (DeFusco et al., 2013; Nneji et al., 2015; Riddel, 2011).

However in the presence of permanent cycle dynamics (such as those I document in state level house prices), the spatial coupling of housing cycles could give rise to local synchronisation leading to spatial-pattern formations across markets. This thus provides an alternative conceptual framework within

[148] Note that no *a priori* assumptions are required on e.g. relevant band as for turning point based methods widely used in the business cycle literature, and to some extent housing cycle analysis. Relevant frequency range is identified from the time-frequency decomposition of the entire signal (a reversible transformation).

which to explain and interpret empirical "ripple-effect" type phenomena that has not previously been considered in the literature. There is also the possibility that a national cycle could arise via the endogenous synchronisation of spatially coupled cycles – another possibility has not, as far as I am aware, been considered before.

Local dependencies between markets - especially spatial dependence - are well-established themes in real estate economics. However standard spatial econometric models may fail in the presence of strong cross-sectional dependence (generally requiring weak forms of cross-sectional dependence, in the sense that dependence decreases sufficiently quickly along the spatial dimension (Pesaran & Tosetti, 2011)).

What is more, the spatial coefficients yielded by these models provide only a measure of contemporaneous local correlation averaged across links (adjacent pairs based on the introduction of a spatial adjacency matrix) and across the sample period or window. Even where dynamic spatial effects are considered through the inclusion of a time-lagged spatial correlation (Baltagi & Li, 2014; Chudik et al., 2011), the resulting spatial coefficients in either case provide only a measure of average spatial dependence, and do not provide any information on spatial patterns in the timing of cycles.

Some studies employ methods designed to accommodate both common factors and local links between markets as a sources of correlation (Pesaran, 2006; Pesaran & Tosetti, 2011): first using variation that can be captured by a common component to control for strong cross-sectional dependence; then studying residual spatial dependence across the idiosyncratic components using a standard spatial econometric model (e.g. spatial autoregressive model) (applications in U.S. housing market context include (Baltagi & Li, 2014; S Holly et al., 2010)).

Although studies employing this approach still find significant spatial dependence (Baltagi & Li, 2014; S Holly et al., 2010), this methodology thus also starts from the assumption that covariance that can be captured by common components is driven by common factors. What is more, the standard spatial model estimated based on residual covariance, again only provides a test of spatial dependence based on average correlations.

The considerable existing empirical "*ripple effect*" literature – motivated by the hypothesis of spatial house price propagation - has mostly relied on cointegration tests for convergence, asking whether markets move around/share a common stochastic trend in the 'long-run' (whether they move together over time exhibiting mean-revering "spreads") and rely on restrictive assumptions on the order of integration of time series. Studies for the U.S. report mixed but limited evidence of convergence for U.S. markets and this has been argued to cast doubt on the existence of a ripple effect (Clark & Coggin, 2009; Gil-Alana et al., 2014; Gupta & Miller, 2012; S Holly et al., 2010; Holmes et al., 2011; Pollakowski & Ray, 1997; Zohrabyan et al., 2008).[149]

The existence of a "ripple effect" (in the simple sense of spatial propagation of disturbances) in cyclical fluctuations might occur however even in the absence

[149] By far the largest literature on the "ripple-effect" is for the U.K. (following influential early contributions such as Meen (1996, 1999), but ripple-effects have been tested for in the housing markets of many countries around the world including an number of studies of U.S. markets.

of long-run convergence; what is more even where convergence occurs cointegration tests do not measure the synchronisation or reveal the spatio-temporal pattern of short run adjustments or provide a dynamic view of the data.

By contrast, I directly study the spatial pattern in the relative timing of cycle components, focussing on the c.10 year cycle identified as a shared predominant cycle frequency in the data (Essay 3). Given my focus on the pattern of phase-lead lags, strong cross-sectional dependence does not pose a problem (as it does for spatial econometric models) and the simple spatial projection of the instantaneous phase of the common cycle component that I introduce allows a rich elucidation of the exact pattern of relationships between individual markets.[150] Moreover the scale band I analyse – associated with the specific cycle component of interest – provides a far more concrete and explicit notion of temporal-scale than the 'long-run' and 'short-run' distinction in the cointegration approach.

The striking "*traveling-wave*" phenomena I document in the pattern of lead-lag relationships between cycles across U.S. markets (Essay 3), while very much resembling a "ripple effect", is much more readily interpreted within a coupled-cycle framework than it can be in terms of the spatial diffusion of shocks or contagion of bubbles.

For example: the synchronisation of markets along one spatial projection, and traveling wave along that orthogonal to it is characteristic of coupled cycle systems but hard to explain within a standard spatial house price *diffusion* or *contagion* framework (likely to generate "epicentre" patterns).

Likewise the rather consistent spatio-temporal pattern of lead lags over time (c.50 years of data and multiple cycle periods) is more consistent with coupled cycle dynamics, but hard to reconcile with spatial diffusion of random local shocks or contagious bubbles (likely to give rise to changing lead-lag patterns across markets in response to successive random local shocks or bubbles in different markets in different periods).

Not only does this provide an alternative framework within which to understand empirical "ripple effects", but the link I document (Essay 4) between the timing of the sort of temporary explosive episodes documented by the econometric 'bubble' identification literature, and the phase of the underlying permanent cycle component of price fluctuations, also have a direct bearing on contagions bubble hypotheses (DeFusco et al., 2013; Nneji et al., 2015; Riddel, 2011): since the episodic character of bubbles compared to the more systematic cycle processes,[151] suggests that any spatial pattern in the onset of bubble episodes might be better explained by the underlying pattern of phase-relations between cycles, without necessarily requiring a direct contagion process between bubbles.

The relevance of this hypothesis is strongly corroborated by the results of the modelling exercise I undertake (Essay 5) in which I show a the extension of a

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[150] Although I do also consider the average phase-coherence of adjacent markets, which is analogous to spatial correlation coefficient but only considers phase and not amplitude.

[151] The cycle component I document is present both in markets that do *not* exhibit bubble episodes (as well as those that *do*) and over historical periods in which bubble episodes did *not* occur (as well as those in which they *did*).

simple speculative housing cycle model to a network context is able to replicate all the key aspects of the spatio-temporal patterns I document in the data.

This modelling work also helps to highlight a few further areas where this new framework may have distinct implications for our interpretation of the data as compared with e.g. spatial diffusion of shocks setting.

For example, for some markets to have a constant systematic lead over others within a spatial diffusion of local shocks setting, requires them to be a dominant market propagating shocks to other regions (Sean Holly et al., 2011).

For example I show Massachusetts has a consistent and stable lead over some one-third of U.S. states over the entire sample period. Under a causal interpretation - consistent with spatial diffusion of shocks paradigm - this temporal hierarchy would imply the surprising conclusion that shocks in Massachusetts cascade across the U.S. ripping through larger markets and reaching as far as Kansas and Louisiana. Meanwhile this would be an un-remarkable outcome in a coupled cycle setting where it would not however, imply that fluctuations in Massachusetts directly drive fluctuations in New York and Louisiana.

This argument is confirmed by the results of my modelling exercise (Essay 5) in which I show given identical parameterisation, and a uniform coupling scheme, there is a strong tendency for coastal states to lead the national cycle (driven by the topology of the network i.e. spatial structure of the model). These results thus suggests a need for caution over seeking heterogeneity based explanations for the apparent dominance of some markets, and interpreting leading markets as key sources of shocks (Chiang & Tsai, 2016).

What is more within this shock diffusion framework, since a disturbance in one market directly drives adjacent markets, and more distant markets only indirectly, the spatial diffusion of local shocks cannot explain the synchrony of distant markets. It has thus been argued that the similar timing of cycles in geographically distant markets (such as San Diego and Washington DC) provides evidence of important non-spatial links between markets resulting from e.g. the arbitrage of investment opportunities by national investors (Füss et al., 2012; Hernández-Murillo et al., 2017; Zhu et al., 2013).

While there may be good reason to expect possible non-local links between geographically distant markets, my results also suggest a need for caution in interpreting the synchronisation of non-adjacent markets as evidence of non-spatial economic links (Füss et al., 2012; Hernández-Murillo et al., 2017; Zhu et al., 2013) since, as I show with my model of spatially coupled cycles - the synchronisation of spatially distant markets can naturally arise out of purely local spatial interactions in a coupled cycle setting.

It is also perhaps worth noting that although e.g. stronger time-lagged correlations between adjacent markets after the 2007-8 crisis have been interpreted as evidence of increased spatial shock transmission (Cohen et al., 2016), both my empirical results and the results of my modelling exercise suggest caution over this strongly causal interpretation, since increased local synchronisation between cycles would increase both contemporaneous and lagged correlations between markets.

Note that while these methods all provide time-averaged estimates of co-movement, some studies have employed rolling-windows or recursive estimations in order to address the question of how the co-movement of U.S.

markets has changed over time (Abate & Anselin, 2016; Cotter et al., 2011; Del Negro & Otrok, 2007; Kallberg et al., 2014; Landier et al., 2017; Yunus & Swanson, 2013).[152]

However, not only are there a number of potential issues with employing rolling-windows with many of these approaches (spurious time variation, sensitivity to time-varying amplitude etc.), but also none of these time domain methods provide the spectral information or phase-amplitude decomposition possible with the wavelet based methods I employ and introduce. These methods also inherit the optimal time-frequency resolution from the wavelet transform (which optimises the trade-off between temporal and spectral resolution) providing a well time resolved approach to studying time-evolving dynamics (non-stationary phenomena).

7.1.3 Relation to previous literature using wavelets methods

Wavelets analysis is widely employed in a range of applied sciences (it is extensively used in physics, neuroscience, epidemiology, ecology, climate science, seismology, signal processing, etc.) and has become increasingly employed in economics (Aguiar-Conraria & Soares, 2014; Crowley, 2007; Soares & Aguiar-Conraria, 2011), especially in studying cyclical properties of economic and financial time series, and their cyclical comovements.

A growing number of studies employ wavelet coherence (or related measures such as *'cohesion'* (Rua, 2010)) to provide a pairwise measure of correlation in the time-frequency domain (Aguiar-Conraria & Soares, 2011; Aloui & Hkiri, 2014; Crowley & Mayes, 2008; ECB, 2018; Flor & Klarl, 2017; Klarl, 2016; Li et al., 2015; Reboredo et al., 2017). These have been generalised to the multivariate context simply by averaging over all possible pairs (Kurowski & Rogowicz, 2018; Rua & Lopes, 2012). These measures provide a combined measure of *phase* and *amplitude* correlation.

One problem with this approach may be that areas of low power may be similar between spectra of different series.

What we really want to know about is common areas of high power. In a study of business cycle synchronisation Aguiar-Conraria & Soares (2011) first apply a dimension reduction approach (SVD) to extracted components corresponding to the most important common patterns (areas of high power) between the wavelet spectra, *then* they compute a measure of distance between the two spectra.

Their measure of distance again takes into account both the *real* and the *imaginary* part of the wavelet spectrum, thus provides a combined measure of *phase* and *amplitude* correlation and is based on a comparison of the whole time-frequency matrix. Similarity is thus maximised when two series share the

[152] Simple correlation analysis (Kallberg et al., 2014; Landier et al., 2017); cointegration and error correction methods (Yunus & Swanson, 2013) to test whether price differences between markets are mean reverting - thus whether regional housing cycles move around/share a common stochastic trend in the 'long-run'; latent factor models (Del Negro & Otrok, 2007) or simple multivariate regression frameworks (Cotter et al., 2011) as a way to try and estimate the relative importance of common (respectively latent or observed) national (vs. idiosyncratic local) factors in house price movements; and spatial econometric models (Abate & Anselin, 2016) in order to assess the co-movement of contiguous markets.

same high power regions and their phases are aligned consistently (over the entire sample period).

Pairwise instantaneous phase-difference provides a dynamic measure of phase lead-lag that has become increasingly used since introduced to economics by (Soares & Aguiar-Conraria, 2011). While economic applications have stress the size of the phase difference (smaller phase-difference -> more synchronous) the stability of phase-difference over time (phase-locking) also provides a relevant measure of synchronisation.

However the methodological question of instantaneous phase synchronisation in a multivariate context, although studied by the wider synchronisation literature (Arenas & Albert, 2008; A S Pikovsky et al., 2001; Rodrigues et al., 2015; M. Rosenblum et al., 2001; Schroder et al., 2017), has not to the best of my knowledge been previously addressed in economics.

It provides significant advantages however, over the *concordance index* methods (Bordon & Reade, 2013; Harding & Pagan, 2002, 2003, 2006; Mink et al., 2012) - based on the fraction of time that two series spend in the same binary (expansionary or contractionary) phase - widely employed to study phase-synchronisation in the business cycle literature (housing cycle applications include (L J Álvarez et al., 2009; Hirata et al., 2013; Jackson et al., 2008; W. Miles, 2015b)). Because only discrete distances between turning points are used to approximate underlying phase-differences, valuable temporal information is lost. What is more since the dating of turning points (based on commonly used algorithms such as Bry-Boshan (Bry & Boschan, 1971)) may also be imprecise in the presence of noise and complex spectral content, and require assumptions on cycle periods, these indexes also lack spectral precision.

Given increasing adoption of wavelet based methods for the study of co-movement, and wide interest in phase synchronisation in business cycle literature, it is surprising that the imaginary part of the wavelet transform has so far been largely overlooked. For example a recent report from ECB Working Group on Econometric Modelling (ECB, 2018) uses wavelet power spectra in order to assess cyclical properties of growth series; and wavelet coherence to assess bivariate comovements; but resorts (in the very same paper) to the binary indicator based *concordance* approach in order to measure bivariate and multivariate phase synchronicity.

The instantaneous measure of overall phase-synchronisation in a multivariate setting that I introduce in this paper seems likely to find wide relevance in a range of other applications.

In what is by far the closest study to my own, Flor & Klarl (2017) borrow the method introduced by Aguiar-Conraria and Soares (2011) in order to study U.S. regional housing market sychronisation (they study MSA level data).

They first perform the clustering routine (as per Aguiar-Conraria and Soares (2011): SVD based dimension reduction, then pairwise distances reflecting a combined measure of phase and amplitude similarity). They then look at (i) the power spectrum of the *average* price series for each cluster; and (ii) the wavelet coherence and instantaneous phase-differences between the *average* price series for each cluster and the the national house price index series.[153]

[153] Itself of course some weighted mean of regional series.

One simple but important difference between our studies is that they only study data between 2001-2013 (c.10 years of data compared to the c.50 years of data I study here).[154]

A sample of this length of course makes it impossible for them to study lower frequency dynamics, and is only really suitable for analysis of variance in a 2-3 year periodicity band. As a result the c.10 year cycles I identify and study here is out side the scope of their analysis.

As above, their measure of synchronisation used in the primary step of cluster assignment, is a measure of combined phase and amplitude correlation; and clusters markets that have both areas of similar power and phase over the entire sample period. They provide neither a measure of national synchronisation, nor detail on the spatio-temporal pattern in the timing of cycles.

In contrast to this, I estimate instantaneous cycle frequency and compare cycle frequencies across different markets over time; I study separately (i) areas of common high power (phase-adjusted similarity of cycles) and (ii) the phase-synchronisation among markets at this common cycle frequency with an emphasis on how these have changed or varied over time. Finally I study detailed time evolving spatio-temporal patterns in the timing of house price cycles across the U.S.

7.2 Policy implications

All of this leads to a range of significant policy implications that will be of interest in the context of a rapidly expanding literature investigating the housing/monetary policy nexus (both the impact of monetary policy on house price fluctuations, and the implications of house price fluctuations for monetary policy) (Adam & Woodford, 2013; Allen, 2011; Del Negro & Otrok, 2007; Glaeser, Gottlieb, & Gyourko, 2010; Goodhart & Hofmann, 2008; Jarociński & Smets, 2008; Jordà, Schularick, & Taylor, 2015; Kuttner, 2013; Williams, 2011).

On the one hand, the historical asynchrony of cycles prior to the late 1990s suggests that common national factors such as monetary policy were not the key driver of these cycles. On the other hand, one obvious implication of the work I present here is that policy shocks may be a potential source of synchronising impetus (when markets are not well synchronised). What is more, a series of policy shocks that would not themselves be large enough to generate significant house price movements, could - by incrementally shifting the phase of cycles across the country - nevertheless lead to the emergence of national house price boom-bust. This observation has significant implications for the debate over the link between monetary conditions, mortgage borrowing, and house price appreciation (e.g., Bernanke, (2010); Leamer, (2007); Taylor, (2007)).[155]

That the global synchronisation of cycles coincides with the Interstate Banking Act of 1995 and shift towards national credit based finance, suggests

[154] It is not clear why they do not use full available historical time-series dimension given on the one hand the problem of edge effects, and on the other hand the good temporal resolution provided by the transform.

[155] Many analysts and policy makers have wondered whether the low interest rate environment that prevailed in the years before the GFC contributed to the housing booms experienced in many economies over this period.

however that these institutional shifts may have played a significant role in the global synchronisation event. The intrinsic cyclicality of individual markets seems very likely to change the calculus of market integration: while integration may be a potential source of efficiencies and provide diversification opportunities, increased integration across markets exhibiting persistent or permanent cycle dynamics seems also highly likely to result in increased co-movement of these cycles - thus may also risk increased instability of relevant aggregates.[156]

Significantly the synchronisation of permanent cycles of course implies the potential for on-going aggregate cyclicality. However, whilst the synchronisation of sub-national cycles represents a potentially significant source of macro-financial risk, and increased transmission of autonomous/endogenous housing market dynamics to the wider economy and housing based transmission and amplification of a variety of shocks; it may also imply housing becomes amenable to countercyclical policies, and indeed could sharpen housing based channels of national policy transmission to macroeconomic and financial aggregates (Hofmann & Peersman, 2017):

Policies to counteract housing cyclicality in the synchronised regime would, if effective, not only benefit macro-financial stability (previously supported by the low synchronisation across unstable local markets), but also stabilise housing markets at the local level reducing the risk faced by (and speculation opportunities available to) micro-economic agents (households and investors).

However an important question arises whether policy can be effective, or what sort of policy can be effective, for this purpose. It seems likely that a magnitude of policy shock sufficient to synchronise cyclical markets, may be entirely inadequate to counter the dynamic forces driving the underlying cyclic behaviour. On the other hand, housing may be responsive to targeted interventions.

Indeed, while historical asynchrony of markets may have both moderated the macro-financial impact of housing instability and limited policy makers ability to target housing market developments, it may also have limited the house price based credit channel (Iacoviello, 2004, 2005; Iacoviello & Minetti, 2008) for monetary policy transmission (Brady, 2014; Fratantoni & Schuh, 2003; Füss et al., 2012); it presumably meant the impact of monetary policy varied across regions and may have been sub-optimal for some (this relates to the literature on business cycle synchronisation as a criteria for an optimal currency area starting from the seminal work of Mundell (1961) and McKinnon (1963)).

While a macro-prudential policy able to improve the efficiency of markets across the country (helping them to increase the stability of equilibrium prices) might be particularly appealing, were this infeasible given available policy tools or remit, a coupled cycle view of housing dynamics does suggest a range of possible *new* alternative stabilisation strategies not available within the shock

[156] An existing literature has linked banking integration and house price co-movement: for example Landier et al. (2017) argue that when banks face idiosyncratic lending shocks and operate across multiple markets, their mortgage lending activity induces house price co-movement across those markets (if the mortgage market is sufficiently concentrated). They present evidence that inter-state banking agreements led to increased house price comovement. However according to this argument, for banking integration to affect house price comovement, a few large overlapping banks need to be subject to substantial idiosyncratic shocks: common banking shocks impact all banks the same whether integrated or not.

diffusion or bubble settings. For example: rather than attempting to everywhere stabilise local cycle dynamics, could an alternative policy strategy be to deliberately aim at desynchronising markets, or disrupting synchronisation? These are questions that would need to be explored and developed in more detail.

The distinctive implications of this setting for interest rate, non-interest rate and structural policies cannot be developed in detail here, but merit careful exploration.

Besides implications for both the likely impact of policy interventions and the set of available policy strategies, notice that the findings presented and the methods employed here also potentially offer authorities valuable monitoring tools and strategies.

The spatio-temporal patters and cross frequency amplitude modulation that I document suggest some non-trivial predictability that could be exploited. The evolving magnitude of cycle components and degree of synchronisation among cycles can provide a useful measure of the existence and magnitude of aggregate housing cyclicality. Meanwhile the mean phase angle may be helpful for assessing the timing of shifts between more and less inflationary periods.

Meanwhile the spatial pattern of lead-lag relationships between markets clearly identifies which markets provide leading information, thus key markets to watch from a monitoring perspective.

Where e.g. PSY test based index provides one approach to identify a bubble once it has started; the systematic relationship between cycle phase and the timing of bubble episodes implies this approach can provide some indication of where and when bubbles are more likely to arise, thus could form the basis for a real time local and national bubble risk index.

8 Summary and conclusions

8.1 General conclusions

In this thesis I revisit U.S. housing market cyclicality.

In the first, empirical phase of my work, I use time-frequency methods and the phase-amplitude decomposition facilitated by complex wavelet analysis, to study spatio-temporal patterns in U.S. housing market fluctuations. These methods allow me to study how the spectral structure of house price fluctuations and spatial patterns in the timing of cycles in different markets have evolved with time. The power and flexibility of these methods combined with c.50 years of monthly state level house price data (Jan 1975 - Jun 2020) allows me to derive a series striking new results:

I document for the first time that house price fluctuations in markets all across the U.S. exhibit a clear spectral ridge (estimated as local maxima of wavelet power spectrum) consistent with a cyclical component with a preferred period (at odds with the idiosyncratic shock and bubble hypotheses in the existing literature) over this long historical sample. What is more, cycles in different markets share a similar c.10 year periodicity.

I show that historically phase-shifts between these cycles moderated aggregate house price cyclicality. However the global synchronisation after 1995 of these existing cycles contributed to the emergence of a national housing cycle - the national boom-bust of the 2000s that is widely believed to have played a central role in the onset of the Global Financial Crisis of 2007-8.

Focusing on the scale/spectral band around the relatively well-defined c.10 year cycle identified, I am able to generate a phase-angle for each market at each (monthly) time step. With this phase information I am able study the time-evolving relative phase of cycles in different markets. I show that there exists a striking *travelling-wave* pattern in the timing of U.S. housing market cycles that has not been previously documented. I show that this pattern has been relatively stable over time.

Travelling-wave patterns of this type typically arise in networks of locally coupled cycles. Taken together, these findings suggest an important role both for (i) local spatial coupling between markets and (ii) non-trivial intrinsic cycle dynamics leading to a possible re-interpretation of the character of U.S. housing market instability in terms of either emergent and/or common shock driven synchronisation of coupled cycles across a spatial network.

Changes in overall synchronisation seem to coincide with important developments in housing finance and the global synchronisation event coincides with the Interstate Banking Act of 1995 and move to national credit based mortgage finance. This suggests common shocks or increased integration among markets may have played a significant role in the national synchronisation of cycles.

On the other hand the spatial-wave pattern I document clearly indicates an important influence from local coupling between markets, and suggests the possibility at least, that a national cycle could have emerged out of the local interaction of local cycles.

I make a model based development of this novel coupled endogenous cycles hypothesis in the second, theoretical phase of my work:

I model 49 identical housing markets with autonomous cyclical dynamics (each characterised by the same quasi-periodic endogenous speculative cycles in a simple agent based endogenous expectations formation setting (Dieci & Westerhoff, 2012b)) but coupled according to the empirical spatial adjacency network for the 49 spatially contiguous U.S. states (such that not only own-market but also neighbouring markets have some influence on price expectations – the weight given to neighbouring markets controlled by a coupling parameter).

I show that for sufficiently weak coupling the national market (understood as the average price and aggregate quantities over all markets) is stable; but if coupling is increased a bifurcation occurs and markets: (i) synchronise over time (developing a collective or national cycle); and perhaps most interestingly (ii) east-west coast-to-center spatial-waves develop, *very* closely resembling those I document in the empirical part of this thesis (Essay 3/Section 4). This suggests the interesting possibility that not only the existence of spatial waves *per se*, but also the particular wave pattern observed may be driven by geography, in a purely topological sense (rather than important heterogeneities across different markets).

Overall this work thus leads to a novel simple and unified explanation for the striking set of phenomena I empirically document – phenomena very hard to explain within standard random shock or bubble frameworks. The sufficiency and parsimony of this minimal framework does not of course mean we should discard or discount other explanations and factors. It does seem to suggest however, that locally coupled locally unstable housing market dynamics may offer a valuable new framework, the relevance of which deserves further exploration.

Taken together, the empirical and theoretical elements of this thesis lead to a view of U.S. housing market cyclicality that combines familiar elements: (i) spatial dependence between adjacent markets (consistent with an important strand of thought in the real estate literature that argues housing markets may be best represented as a series of interconnected regional and local markets (Meen, 1996)); and (ii) intrinsic cyclicality (which, though not widely studied, arises in behavioural house price models). The combination of these familiar elements, leads to a new paradigm framework able to generate and account for rich spatio-temporal phenomena.

This re-conceptualizes the local vs. national character of housing market dynamics: we can neither consider housing in terms of a national aggregate, nor in terms of entirely local markets, and the sources of national instability may be found in local phenomena.

The empirical relevance of this framework suggested by the ready explanation it provides for key historical facts, raises for example the question whether we should expect intensified national housing instability on an on-going basis. It also has distinct policy implications. The synchronisation of local cycles might imply on the one hand increased spillovers from autonomous housing dynamics to wider economy as well potentially as increased transmission and/or amplification by housing of policy and other shocks;

meanwhile it might also make housing more amenable to countercyclical policies and sharpen housing based channels for national policy transmission.

8.2 Future Research Opportunities

The work I present in this thesis clears the path for a number of new research programs in housing economics, macro-financial questions and beyond.

One obvious extension of considerable interest would simply be to extend the temporal span of the analysis. This is currently restricted by data availability, however historical time series already existing or currently under construction might form the basis for similar analysis covering some 100 years of data. Meanwhile there is an important project deserving resourcing to build more comprehensive historical data on house prices, transactions and finance building on the trail blazed by Rose (2020).

Another obvious direction for further research would be to revisit data for other housing markets, such as the U.K. (where the "ripple effect" literature originated) with the methodological tools I deploy here in my study of U.S. housing.

The empirical work I present suggests an important role for endogenous dynamics in sub-national house price cycles. However the serious investigation of the dynamic process *generating* these cycles, or even identification of other relevant state variables in the cycle process, is left to future work.

Meanwhile, although I specify a cycle model for my theoretical modeling exercise, the key results I obtain here are very unlikely to be specific to the particular local cycle process I employ here, but rather are likely to hold for a general class of models consistent with the more general framework I set out, of locally interacting markets characterised by intrinsic cycle dynamics. Indeed the qualitative character of cycle dynamics is more crucial in this context.

Since both my empirical and theoretical results are thus agnostic with respect to the dynamic process generating sub-national price cycles, the work presented in this thesis motivates further work on developing, and empirically discriminating between and testing theories of endogenous local housing market cyclicality.

This project should be informed and supported by further research to explore other housing, financial and real variables at a spatially disaggregated level (e.g. fluctuations in housing market churn, house building, mortgage default rates, employment) both using the same methodological strategies employed here, and using cross-wavelet based approach to understand the relationships between different variables in a scale specific way over space and time.

This work could help to begin to identify relevant state variables in cycle dynamics; and unpick the housing-finance-real economy nexus within a spatially disaggregated framework that accommodates time-evolving relationships.

Moreover further empirical and theoretical work to qualify the dynamics in the data, and explore alternative possibilities – e.g. limit-cycle vs. noise driven oscillations – in a model-based setting is also called for.

Given a relevant model - probably a richer model integrating housing supply side and potentially also housing finance - another direction for further modelling work would be to attempt to empirically estimate model parameters and explore whether, with proper parameterisation to reflect relevant spatial heterogeneities, this sort of model can reproduce other key spatio-temporal features of the house price data – e.g. where I have already shown that the local coupling of cycles can explain the travelling-wave pattern in the data, one hypothesis might be that once the model accounts for the real supply elasticity in different markets, it could simultaneously account for the pattern of cycle amplitudes across different markets.

Related to this, the empirical instantaneous-phase series might be further exploited in order to recover local couplings between markets in a data driven way, as well as to make a more detailed study of how synchronisation developed and the role of shocks and policy events vs. endogenous synchronisation dynamics. Under the hypothesis that individual markets are characterised by limit-cycle dynamics we must employ methods suitable for identifying (possibly time-varying) weak couplings between cycles (Cadieu & Koepsell, 2010; Casadiego, Nitzan, Hallerberg, & Timme, 2017; A. Pikovsky & Mrowka, 2007; M. G. Rosenblum & Pikovsky, 2001; Stankovski, Duggento, McClintock, & Stefanovska, 2012; Tirabassi, Sevilla-escoboza, Buldú, & Masoller, 2015). In particular methods for studying perturbations of the phase-series could help to reveal interdependencies between the cycles in different markets and, hypothetically, other participating variables - i.e. couplings may show up in deviations from a deterministic trend or common stochastic trend in the phase-series for each market cycle thus be amenable application of more conventional econometric methods to the multivariate phase series (Østergaard, Ditlevsen, & Rahbek, 2017; Tirabassi et al., 2015).

Alternatively they might be used to study the impact (if any) of local policy events such as the series of bilateral/multi-lateral reciprocal interstate banking agreements prior to 1995 studied by Landier (2017) and others.

Given the substantial element of predictability implied by regular spatio-temporal dynamics documented, it would also be interesting to explore how this can be exploited for forecasting purposes.

My project here has been motivated by empirical evidence of housing cycles and aimed at explaining these, however the framework I develop could have theoretical implications beyond housing since these results raise the question whether coupled endogenous dynamics paradigm could be relevant for understanding the dynamics of other economic systems. For example the "trade-comovement puzzle" and international business cycle comovement (R. C. Johnson, 2014; Kose & Yi, 2006)? Or the role of sectoral comovement in aggregate business cycles (Foerster et al., 2011; Garin, 2018; Lehn, Winberry, & Booth, 2020; Thomas, 2018).

Note also that it would be a mistake to see the relevance of empirical methods I employ in this thesis as restricted only to periodic time series/dynamics. This is not the case, and for example instantaneous phase-based methods whilst perhaps more intuitive in the context of periodic dynamics, may also be usefully employed to identify and study dependencies for other types of non-stationary time-series processes.

9 References

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10 Methods appendix

10.1 Wavelets methods

10.1.1 Morlet wavelet: relationship between scale and frequency

For the Morlet wavelet, the relation between frequencies, f, and wavelet scales, a, is particularly simple and is given by

$$\left(\frac{1}{f}\right) = \frac{4\pi a}{(\omega_0 + \sqrt{2 + \omega_0^2})}$$

when $\omega_0 \approx 2\pi$, the wavelet scale a is inversely related to the frequency so that

$$f \approx \frac{1}{a}$$

This greatly simplifies/aids the interpretation of wavelet analysis since for all equations the wavelet scale a may be substituted for the far more intuitive $\frac{1}{f}$ (that is the cycle period).

10.1.2 Cone of influence

Applied to finite length time-series, the continuous wavelet transform inevitably suffers from "edge effects" or distortions. Wavelet spectrum values are incorrectly computed at the beginning and end of a finite time-series due to missing data. It is standard to pad the ends of the series with zeros (and this is the strategy I employ for the analysis presented in this thesis). Since the "effective support" of the wavelet at a given scale is proportional to the scale, these "edge effects" increase with scale. The region of the transform that is impacted by this problem is referred to as the "cone of influence" or COI. Results that fall within this region should be interpreted with care. For further details see Soares & Aguiar-Conraria (2011) or other introduction to the continuous wavelet transform.

10.1.3 Relationship between phase-difference and time-lag

The instantaneous phase-difference $\theta_{x,y}(a,\tau)$ can be easily converted into an instantaneous time-difference by the relationship

$$\Delta T_{x,y}(a,\tau) = \frac{\theta_{x,y}(a,\tau)}{\omega(a)} \qquad (31)$$

where $\omega(a)$ is the angular frequency corresponding to the scale a.

10.1.4 Confidence intervals on mean-phase (difference)

Following Zar (1999) (equations 26.23-26.26) and Matlab implementation by Berens (2009) in CircStat, the confidence Intervals for the mean angle (of the phase difference) is computed as the $(1-\delta)$%-confidence intervals for the population mean. See Berens (2009, p. 11) for details to be reproduced/explained here.

10.2 PSY methodology

To identify and date the onset dates for bubble and collapse episodes, I employ the procedure proposed by Phillips, Shi and Yu (2015a, 2015b) (PSY) based on the augmented Dickey-Fuller (ADF) model specification and a recursive evolving algorithm (Section 10.2.1), combined with the bootstrapping procedure proposed in Phillips and Shi (2018b)[157] (Section 10.2.2) designed to mitigate the potential impact of heteroskedasticity and to effect family-wise size control in recursive testing algorithms. This procedure provides a framework for detecting both explosive bubble and collapse/crisis episodes,[158] and a consistent date-stamping strategy for the origination and termination of multiple episodes (Phillips & Shi, 2017, 2018a; Phillips et al., 2015b).[159]

10.2.1 The Augmented Dickey-Fuller test and recursive evolving algorithm

The hypothesis of a mildly explosive process is tested against the null of a ‘martingale’ process with asymptotic drift

$$H_0: p_t = dT^{-\eta} + p_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim NID(0, \sigma^2) \tag{32}$$

$$H_1: p_t = \delta_T p_{t-1} + \varepsilon_t \tag{33}$$

The term $dT^{-\eta}$ captures any mild drift that may be present in prices but which is of smaller order than the martingale component and is therefore asymptotically negligible (Phillips & Shi, 2018b, p. 5), where d is a constant, T sample size, and the localizing coefficient η is greater than $\frac{1}{2}$. $\delta_T = 1 + cT^{-\theta}$ with $c > 0$ and $\theta \in (0,1)$.. The ADF test statistic is the t-statistic on the least squares estimate of the coefficient of p_{t-1} in the regression model chosen for the PSY procedure

$$\Delta p_t = \alpha + \beta p_{t-1} + \sum_{k=1}^{K} \gamma_k \Delta p_{t-k} + \varepsilon_t \tag{34}$$

157 This procedure was introduced in order to simultaneously addresses both heteroskedasticity (Harvey et al., 2016) and multiplicity issues in testing.

158 The method is a generalized version of the sup augmented Dickey–Fuller (ADF) test of Phillips et al. (2011).

159 These procedures are implemented using Matlab code made available by Shuping Shi. This can be found at https://sites.google.com/site/shupingshi

which includes the intercept α but no time trend and nests the null hypothesis as a special case with $\alpha = dT^{-\eta}$ and $\beta = 0$. The K lag terms are included to account for serial correlation.

The PSY procedure calculates the ADF statistic recursively from a backward expanding sample sequence. If t_{start} and t_{end} are the start and end points of the regression sample, the ADF statistic calculated from this sample is denoted $ADF_{t_{end}}^{t_{start}}$. The starting point of the sample varies from the first observation t_0 to $t^{\dagger} - w_0 + 1$ where $t^{\dagger}$ is the observation of interest and w_0 is the minimum number of observations required in order to estimate Eq.34. The resulting ADF sequence is shown as

$$\{ADF_{t_{end}}^{t_{start}}\}_{t_{end}=t^{\dagger}}^{t_{start}\in[t_0,t^{\dagger}-w_0+1]} \qquad (35)$$

and inference regarding the explosiveness of observation $\Delta p_{t^{\dagger}}$ is based on the PSY statistic defined as the maximum value of the entire ADF sequence[160]

$$PSY_{t^{\dagger}}(w_0) = \sup \quad \{ADF_{t_{end}}^{t_{start}}\}_{t_{end}=t^{\dagger}}^{t_{start}\in[t_0,t^{\dagger}-w_0+1]} \qquad (36)$$

The supremum enables the selection of the 'optimal' starting point of the regression in the sense of providing the largest ADF statistic. This procedure can be repeated for each individual observation of interest ranging from w_0 to t_{end} generating the PSY statistic sequence $\{PSY_{t^{\dagger}}(w_0)\}_{t^{\dagger}\in[w_0,t_{end}]}$. In Figure 38 I reproduce a visual representation of the recursive evolving algorithm provided by Phillips and Shi (2018b)).

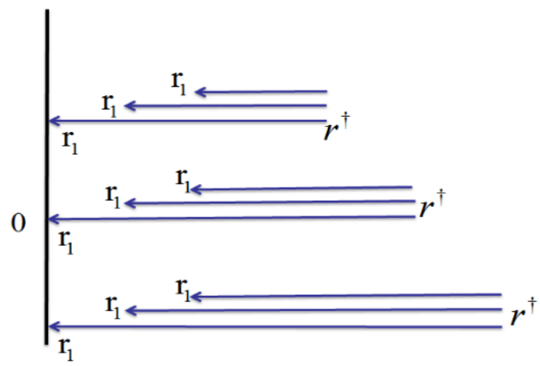


Figure 38: This figure reproduces illustration of PSY recursive evolving algorithm as presented in Phillips and Shi (2018b).

160 The backward supremum ADF.

10.2.2 Composite bootstrap procedure

I employ the bootstrap procedure suggested by Phillips & Shi (2018b) designed to mitigate the potential influence of unconditional heteroskedasticity and to address the multiplicity issue in recursive testing.

The composite bootstrap procedure ass set out by Phillips and Shi (2018b, p. 13) is:

Let w_0 and t_b be the number of observations in the window over which size is to be controlled.

Step 1: Using the full sample period, estimate the regression model Eq.34 under the imposition of the null hypothesis of $\beta = 0$ and obtain the estimated residuals e_t.

Step 2: For a sample size of $w_0 + t_b - 1$, generate bootstrap sample given by

$$\Delta p_t^b = \sum_{k=1}^{K} \hat{\gamma}_k \, \Delta p_{t-k}^b + e_t^b \tag{37}$$

with initial values $p_t^b = y_i$ with $i = 1, .., j+1$, and where $\hat{\gamma}_k$ are the OLS estimates obtained in the fitted regression from Step 1. The residuals $e_t^b = w_t e_l$ where w_t is randomly drawn from the standard normal distribution and e_l is randomly drawn with replacement from the estimated residuals e_t.

Step 3: Using the bootsrapped series, compute the PSY test statistic sequence $\{PSY_t^b\}_{t=w_0}^{w_0+t_b-1}$ and the maximum value of this test statistic sequence, giving

$$\boldsymbol{\mathcal{M}_t^b} = max \left(PSY_t^b\right)$$
$$t \in [w_0, w_0 + t_b - 1]$$

Step 4: Repeat Steps 2-3 for $B = 999$ times.

Step 5: The critical value of the PSY procedure is not give by the 95% percentiles of the sequence.

Step 2 of this iteration implements a wild bootstrap to address heteroskedasticity; and Steps 3-5 of the iteration replicate the PSY recursive test sequence and create critical values that account for multiplicity in the test sequence recursion.

11 Data appendix

11.1 House price data

Throughout this thesis I employ seasonally adjusted monthly Freddie Mac House Price Index data (FMHPI).

The FMHPI is a repeat-sales method index, where repeat transactions are defined as two first-lien mortgages that originate on different dates for the same house location. This includes loans originated for sales transactions, but also appraisal values for refinance transactions (at least one of the two mortgages is for a sales transaction i.e. refinance-to-refinance data pairs are excluded). The sample data only covers single-family and town home properties that are financed by conventional and conforming loans.[161]

The inclusion of appraisal values and limitation to mortgages sold to Fannie Mae or Freddie Mac may represent limitations to the data. However the availability of monthly frequency data represents an advantage since it improves temporal but also spectral resolution in the data. The widely used state level transaction based index provided by the Federal Housing Finance Agency (FHFA) is only available on a quarterly frequency (this data is employed for example by Davidoff (2013), Favara & Imbs (2015), Flor & Klarl (2017)).

Using other standard price indices (I look at FMHPI state level data, and also S&P/Case-Shiller metropolitan market data) yields very much the same results.

Some (slightly arbitrary) examples of other studies employing the FMHPI include: Mayer & Sinai (2007), Huang et al. (2017), Bailey et al. (2016).

The Freddie Mac House Price Index (FMHPI) data employed in analysis presented here can be found at the following link:
http://www.freddiemac.com/research/indices/house-price-index.page

Federal Housing Finance Agency (FHFA) house price index data can be found at:
https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index-Datasets.aspx#mpo

[161] A "conforming" mortgage meets the funding criteria of Fannie Mae and Freddie Mac—principally, a dollar limit on the size of the loan.

12 Data analysis appendix

12.1 Wavelet power spectra for all U.S. states

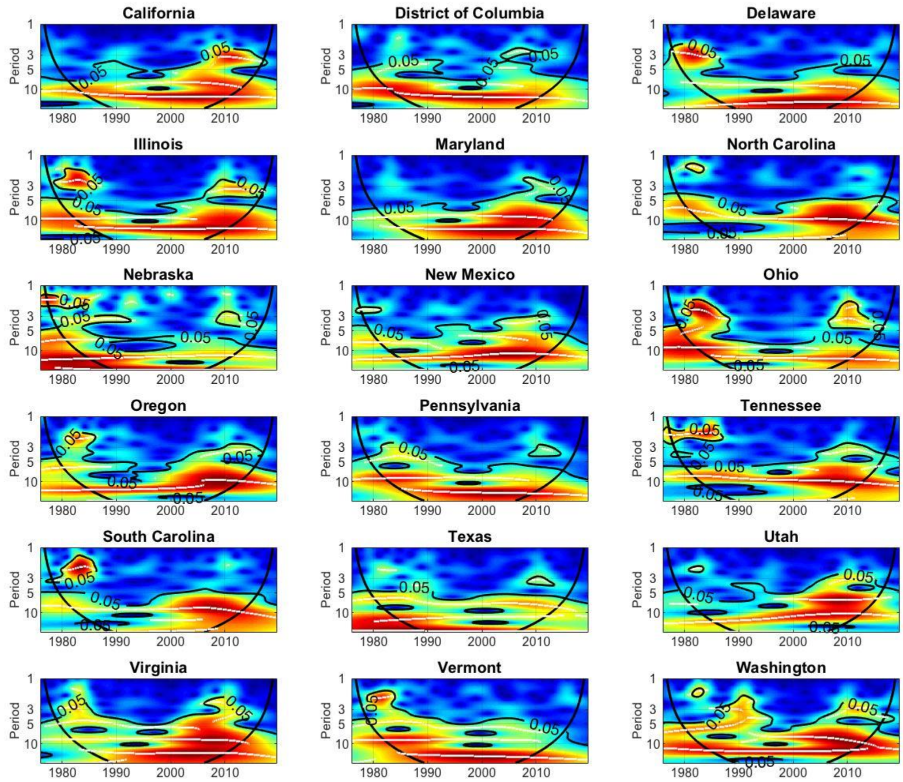
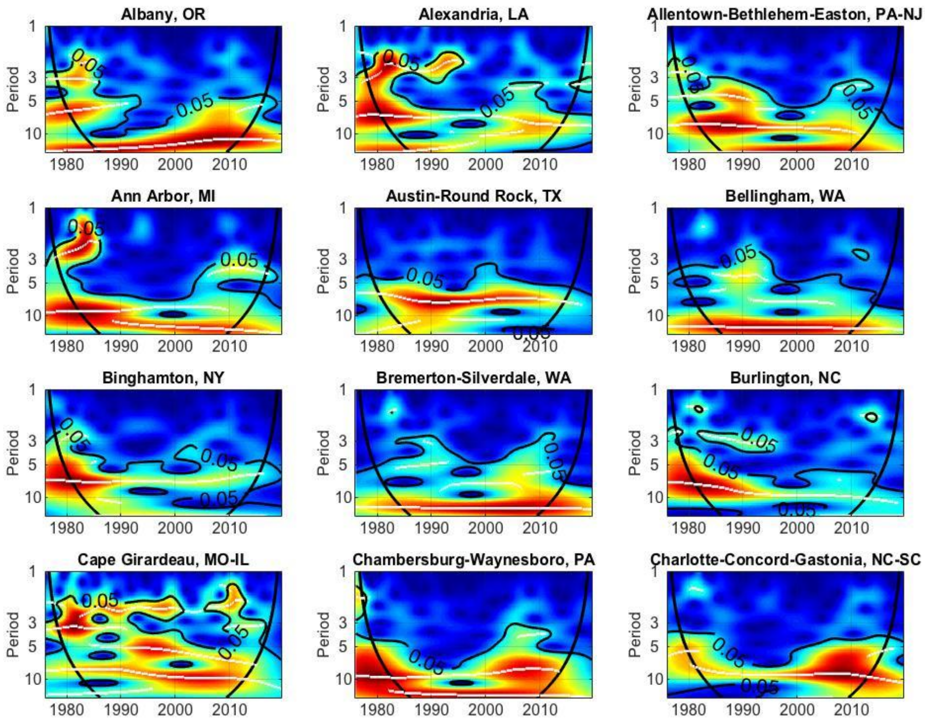
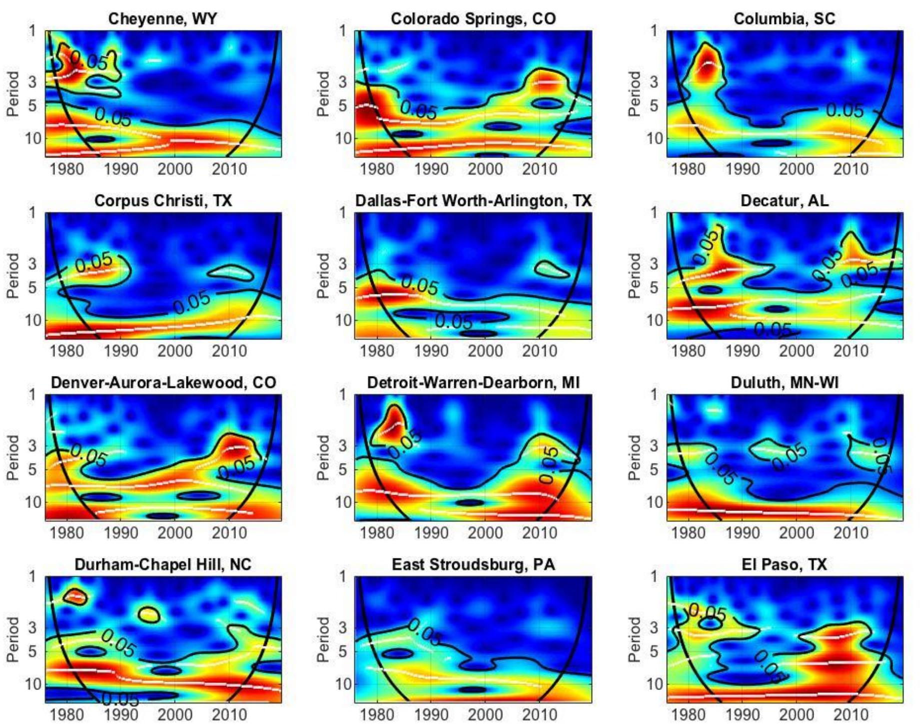


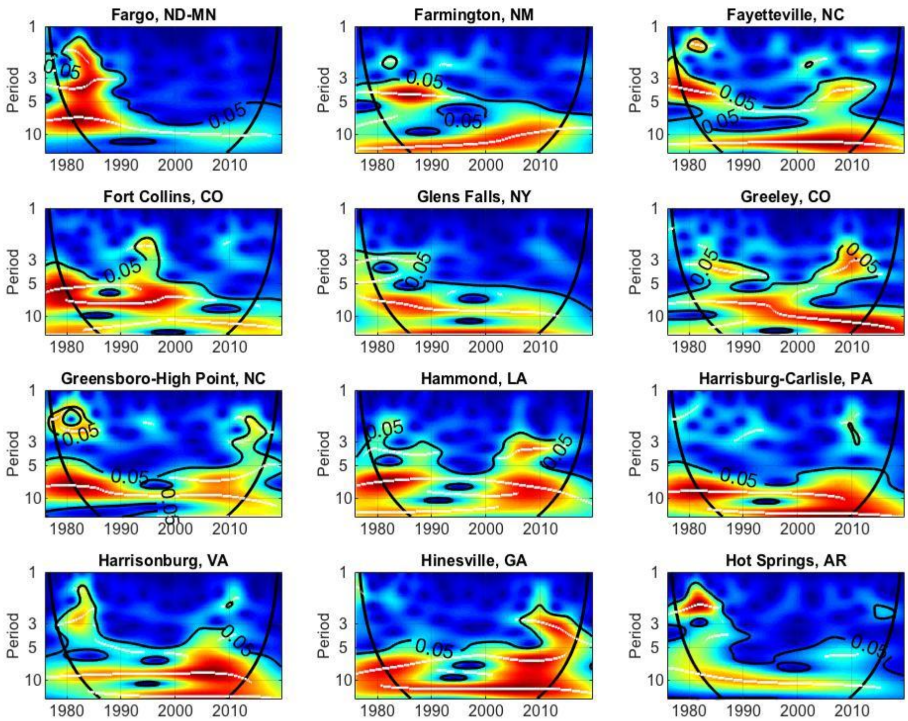
Figure 39: Example wavelet power spectra for state level house price series (transform obtained for seasonal log differences of monthly data).[162] Significance test against null of AR(1) process.

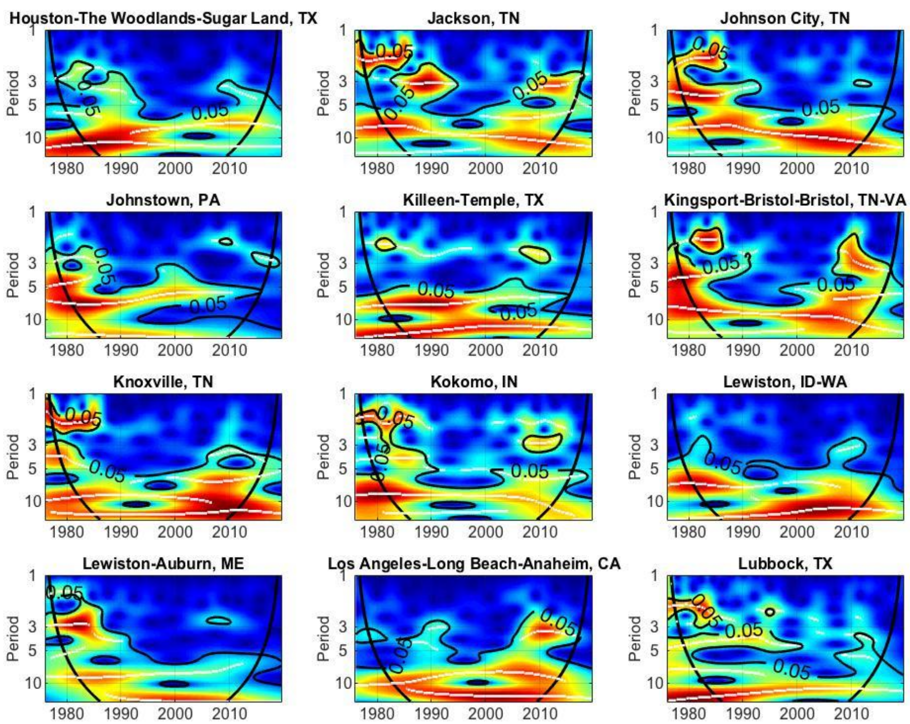
[162] I use seasonally adjusted monthly Freddie Mac House Price Index data. The availability of monthly data improves temporal but also spectral resolution. I take seasonal log-differences of the data before obtaining wavelet transform and power spectrum. The data can be found at the following link: http://www.freddiemac.com/research/indices/house-price-index.page

12.2 Wavelet power spectra for MSA level series






Fargo, ND-MN
Farmington, NM
Fayetteville, NC
Fort Collins, CO
Glens Falls, NY
Greeley, CO
Greensboro-High Point, NC
Hammond, LA
Harrisburg-Carlisle, PA
Harrisonburg, VA
Hinesville, GA
Hot Springs, AR
Period
1
3
5
10
1980
1990
2000
2010
0.05


Houston-The Woodlands-Sugar Land, TX
Jackson, TN
Johnson City, TN
Johnstown, PA
Killeen-Temple, TX
Kingsport-Bristol-Bristol, TN-VA
Knoxville, TN
Kokomo, IN
Lewiston, ID-WA
Lewiston-Auburn, ME
Los Angeles-Long Beach-Anaheim, CA
Lubbock, TX
Period
1
3
5
10
1980
1990
2000
2010
0.05