DAILY INTERBANK RATE DETERMINATION AND VOLATILITY IN A BANKING CRISIS

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Abstract

The paper studies daily interbank rate determination and volatility in the Dominican Republic during a major banking crisis. The investigation uses a novel, automatic, general-to-specific technology (PcGets) to reduce a baseline (mean) specification linking interbank rates and aggregate banking system excess reserves. This specification is subsequently embedded in a GARCH model. Recursive coefficient analysis reveals that in times of financial stability positive or negative shocks have similar effects. In contrast, during banking crisis negative impacts (e.g. a decrease in excess reserves) generate larger volatility of interbank rates than positive ones.

JEL classification numbers: E43; G21; C51.

Keywords: interbank interest rate; aggregate excess reserves; banking crisis; PcGets; GARCH; Dominican Republic.

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Interbank interest rate determination and volatility are of key importance in the day-to-day monitoring of monetary policy. In fact, many economies target the short-end of the yield curve as a policy strategy (e.g., Australia, Canada, and New Zealand), therefore enhancing the role of interbank rates (See Prati, Bartolini, and Bertola, 2003). In less developed systems -were monetary institutions are generally weak- a key step in developing an effective monetary policy strategy is the construction of a mechanism to affect short-term interest rates. Henceforth understanding interbank interest rate determination becomes of paramount importance.

In this context, the Dominican Republic –a country in which the banking system operates under a fractional reserves system- is of interest as a case study, particularly in the light of the severe banking crisis that affected the economy during 2002-2003. Remarkably, the total bailout package for the troubled banks amounted to almost 20% of GDP in 2003, with one bank (BANINTER) accounting for 15% of the total –likely to be amongst the most significant costs generated by a single financial institution. (See *The New York Times* editorial article "Dominican Republic in crisis", December 29th, 2003.) Clearly, it is important to better understand the impact that these events have on the interbank market, and particularly on its volatility[1].

The paper's contribution is to explore the link between interbank rates and excess reserves using a novel econometric technology, namely PcGets, the automatic model selection approach put forward by Hendry and Krolzig (2001, 2003), alongside more conventional volatility techniques (e.g. Bollerslev, 1986). To achieve this end the

[1] And (implicitly) on the rest of the term structure and the potential effectiveness of monetary policy

investigation employs daily data on aggregate excess reserves (in millions of Dominican Pesos- DoP), and interbank rates (in percentage points) for the period ranging from January 1999 to November 2003 –a total of 1,210 observations for each variable. The data source is the Central Bank of the Dominican Republic.

As a preliminary evaluation, Figure 1 displays excess reserves and the interbank rate. The graph clearly shows the expected negative relationship between these variables under a fractional reserves banking system. In order to investigate this relationship formally, the paper follows a two stage strategy.

Firstly, it models interbank interest rates as a function of excess reserves using a dynamic time series model since, as noted before, the DR operates a fractional reserves system. This model is computed using a general-to-specific (GETS) automatic technique -PcGets. The method in question makes operational the ideas developed by Hoover and Perez (1999) -which advanced an algorithm to reproduce the GETS methodology- alongside Hendry's approach to empirical econometric modeling (e.g. Hendry, 1995). The automated GETS approach starts the specification search from a general unrestricted model (GUM) that is assumed to represent the data generating process (DGP). On the reliability of the approach, Monte Carlo experiments by Hendry and Krolzig (2001) show that estimates obtained with the computer programme PcGets are close to those recovered from the actual DGP.

Secondly, and in the light of the high frequency data at hand, the inquiry proceeds to use the automatically selected model as the baseline specification for the *mean* equation in an asymmetric generalized autoregressive conditional heterocedasticy (GARCH) framework (Bollerslev, 1986; Hentschel, 1995).

The baseline specification for the first step is given by

$$r = \delta + \phi RES \,. \tag{1}$$

In (1) r is the interbank rate, while RES are the aggregate excess reserves of the banking system. δ is a constant term, while ϕ is a parameter to be determined empirically. The specification search process starts from a GUM that can be written as

$$r_t = \delta + \sum_{i=1}^{20} \lambda_i r_{t-i} + \sum_{j=0}^{20} \phi_j RES_{t-j} + u_t \,. \tag{2}$$

(2) is an autoregressive distributed lag (ADL) model of order 20 (See Hendry, Pagan, and Sargan, 1984), intended to capture the information contained in the previous month. Given that r and RES are integrated of order zero, equation (2) is modeled as a stationary system[2]. The final, automatically selected model, is

$$r_t = \underset{0.11}{0.63} + \underset{0.02}{0.39} r_{t-1} + \underset{0.02}{0.19} r_{t-2} + \underset{0.02}{0.15} r_{t-3} + \underset{0.02}{0.08} r_{t-5} + \underset{0.01}{0.09} r_{t-9} + \underset{0.01}{0.04} r_{t-14} - \underset{0.00001}{0.00009} RES_{t-3} . \tag{3}$$

Equation (3) has coefficients that are of a sensible magnitude (standard errors inside parentheses), with the ones affecting r displaying a decaying lag profile, as expected, and the one corresponding to RES being negative; all coefficients are significant at the 1% level. Note that the long run solution for the coefficient affecting RES is -0.0029.

[2] The augmented Dickey-Fuller test statistic for RES is -4.271, significant at the 1% level. The Dickey-Fuller test statistic for r is -4.351, also significant at the 1% level.

Now that a reasonable specification has been obtained to explain r, the study proceeds to estimate a GARCH model using this preferred solution. Specifically, the research strategy is to model the mean equation (3) alongside a general GARCH volatility equation (Bollerslev, 1986). Thus the econometric model can be written as

$$r_t = \alpha + \lambda_1 r_{t-1} + \lambda_2 r_{t-2} + \lambda_3 r_{t-3} + \lambda_5 r_{t-5} + \lambda_9 r_{t-9} + \lambda_{14} r_{t-14} + \phi RES_{t-3} + \omega h_t + u_t, \tag{4a}$$

$$h_t = \alpha_0 + \alpha_1 (u_{t-1} + \vartheta)^2 + \psi D_{t-1}(u_{t-1} + \vartheta)^2 + \beta_1 h_{t-1}. \tag{4b}$$

Note that this specification is quite flexible, by allowing for asymmetric (ϑ) and threshold (ψ), and in-mean-effects (ω) in the variance (4b) and mean (4a) equations, respectively, i.e. an ATGARCH-M (1, 1). In this framework $D_{t-1} = 1$ if $u_{t-1} \prec \vartheta$, and zero otherwise. Notably, this specification encompasses several members of the GARCH family (See Hentschel, 1995). The model is estimated using the maximum likelihood technique, and robust standard errors are computed (displayed inside parentheses). The exercise yields the following results

$$r_t = \underset{0.23}{0.43} + \underset{0.06}{0.38}\, r_{t-1} + \underset{0.06}{0.26}\, r_{t-2} + \underset{0.04}{0.18}\, r_{t-3} + \underset{0.03}{0.06}\, r_{t-5} + \underset{0.02}{0.07}\, r_{t-9} - \underset{0.00003}{0.00006}\, RES_{t-3} - \underset{0.02}{0.08}\, h_t, \tag{5a}$$

$$h_t = \underset{0.02}{0.09} + \underset{0.16}{0.56}(u_{t-1} - \underset{0.09}{0.18})^2 + \underset{0.07}{0.46}\, h_{t-1}. \tag{5b}$$

$$T = 1{,}174\,; Port.m\left\langle \chi^2(95) \right\rangle = 104.92[0.2285]; ARCH(1,2) - F(2,1158) = 0.2229[0.8002].$$

Note that in this final model r_{14} and ψ (intended to capture the threshold effect) are not present, since they were not statistically significant. The reader should also note that several calendar and institutional effects were tested (in the mean and variance equations) but did not add to the model's fit, at least above the rest of the indicators retained, and therefore do not appear in the final results. Most of the coefficients reported in (5a) and (5b) are significant at the 1% level -and at least at the 5%. Additionally, autocorrelation (*Port.m*) and ARCH tests are passed by the final model, and are reported at the bottom of equations (5a) and (5b)[3].

A crucial coefficient reported in (5a) and (5b) is ϑ, the one capturing asymmetric effects. It shows that, on average, positive shocks on interbank interest rate volatility have a smaller impact than negative ones. Additionally, the in-mean-effect ϖ is significant. Note, however, that the traditional risk-return trade-off interpretation of ϖ does not apply in this case. In fact the coefficient is negative, implying that a positive shock to volatility (e.g. an increase in excess reserves) reduces the interbank interest rate.

In order to further evaluate these findings, the recursively estimated GARCH coefficients' t-ratios are exhibited in Figure 2. A salient feature of these graphs is the increased significance of all the volatility indicators roughly from August 2002 (marked with ellipses). Remarkably, at this point in time the monetary authorities began to provide liquidity assistance to the main troubled bank –BANINTER (See Figure 1). It is worth noting that the GARCH asymmetric coefficient's t-ratio actually becomes increasingly significant *only after* the unset of the crisis. So apparently in times of financial stability positive or negative shocks have similar effects. In contrast, during banking crisis negative impacts generate larger volatility of interbank rates.

These finding have important implications for monetary policy design and implementation. If monetary authorities use interbank rates to send signals to the rest of

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[3] See Hendry and Krolzig (2003) for further details on these tests.

the term structure of interest rates, it is of great importance to monitor excess reserves and interbank rates so that any surge in volatility arising from shocks to these variables - such as reserves deficiencies generated by troubled banks- can be curtail, and henceforth safeguard monetary policy effectiveness. The study shows that asymmetric volatility indicators could prove valuable as early warning indicators in the day-to-day monitoring of the interbank market.

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Figure 1
Daily interbank rate (%) and aggregate excess reserves, 1999.01-2003.11

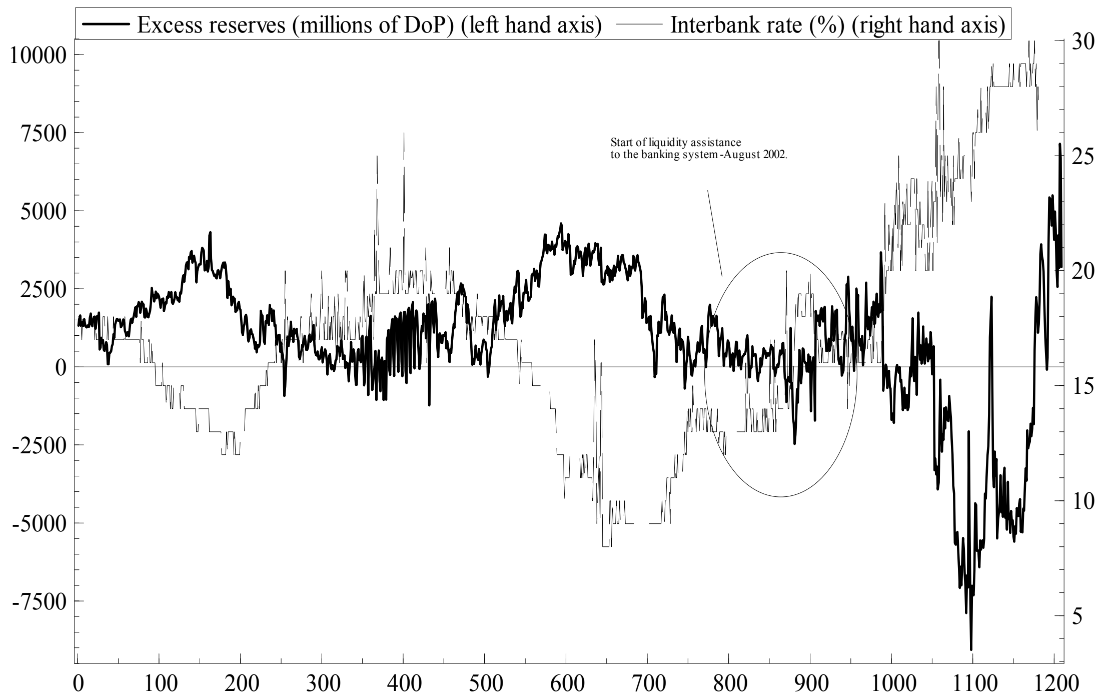

Figure 2
AGARCH-M recursive t-ratios