

Non-linearity in Monetary Policy Transmission: Roles of Liquidity and SFIs in Bank Lending Channel

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Abstract

This paper examines a plausible non-linear relationship in the bank lending channel of monetary policy transmission, which cannot be captured by conventional linear models. We identify *aggregate* liquidity in the commercial bank system as an important factor that influences bank lending, whereby banks may respond differently to changes in monetary instruments when liquidity is plenty, from when it is scarce. We apply threshold-type models to data from Thailand between January 2007 and March 2013 ($T = 75$), and find statistically significant evidence that the impact on bank loans of changes in the policy rate is stronger amid tighter liquidity. We then investigate the impact of Specialized Financial Institutions (SFIs) which also compete with commercial banks for deposits, although their loans can be quite different in nature from those of the latter. In light of our findings, SFIs should improve the effectiveness of the bank lending channel, vis-à-vis the interest rate channel, as they share the same pool of the economy's liquidity as commercial banks. Our empirical analysis suggests that SFIs' actions seem to help improve the efficacy of this particular transmission channel; nevertheless, the evidence is at best mixed whether the incremental "contribution" of SFIs is higher than that of the commercial banks' liquidity level *per se*.

Keywords: Monetary policy transmission; Bank lending channel; Regime switching; Threshold model; Specialized Financial Institutions

JEL Classification: C22, G21, E51, E52

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การส่งผ่านนโยบายการเงินแบบไม่ใช่เชิงเส้น: บทบาทของสภาพคล่องและสถาบันการเงินเฉพาะกิจในช่องทางการปล่อยสินเชื่อของธนาคารพาณิชย์

บทคัดย่อ

งานวิจัยนี้มีวัตถุประสงค์ที่จะทำการศึกษากลไกการส่งผ่านนโยบายการเงินแบบไม่ใช่เชิงเส้น โดยมุ่งเน้นไปที่ช่องทางการปล่อยสินเชื่อของธนาคารพาณิชย์ (Bank lending channel) ซึ่งไม่สามารถตรวจพบได้โดยแบบจำลองเชิงเส้นทั่วไป ผู้ศึกษาได้ตั้งสมมติฐานว่า สภาพคล่องของระบบธนาคารพาณิชย์ เป็นตัวแปรสำคัญที่ส่งผลกระทบต่อช่องทางการส่งผ่านนโยบายการเงินข้างต้น กล่าวคือ ธนาคารพาณิชย์อาจตอบสนองต่อการเปลี่ยนแปลงนโยบายการเงินในขณะที่สภาพคล่องของระบบตึงตัว ต่างออกไปจากกรณีที่สภาพคล่องไม่ตึงตัว ผู้ศึกษาจึงได้เลือกใช้แบบจำลองที่มีการเปลี่ยนแปลงค่าตามขีดแบ่ง (Threshold model) เพื่อทดสอบสมมติฐานกับข้อมูลของระบบธนาคารพาณิชย์ไทย ในช่วง มกราคม 2550 ถึง มีนาคม 2556 (รวมทั้งสิ้น 75 เดือน) ผลการประมาณชี้ว่ากลไกการส่งผ่านนโยบายการเงินในช่องทางการปล่อยสินเชื่อของธนาคารพาณิชย์มีประสิทธิภาพมากขึ้นเมื่อสภาพคล่องของระบบธนาคารพาณิชย์ “ตึงตัว” เป็นไปตามสมมติฐานหลัก จากนั้นผู้ศึกษาจึงได้เริ่มพิจารณาบทบาทของสถาบันการเงินเฉพาะกิจซึ่งแข่งขันกับธนาคารพาณิชย์เพื่อดึงดูดเงินฝาก และได้ตั้งสมมติฐานอิงกับผลเชิงประจักษ์ข้างต้นว่า สถาบันการเงินเฉพาะกิจน่าจะช่วยเสริมความมีประสิทธิภาพของการส่งผ่านนโยบายการเงินได้ (ในช่องทางการปล่อยสินเชื่อ ไม่ใช่ช่องทางอัตราดอกเบี้ย) ซึ่งผลการประมาณเป็นไปในทิศทางเดียวกับที่คาด อย่างไรก็ตาม ผู้วิจัยยังไม่ได้ข้อสรุปที่ชัดเจนว่าการแข่งขันกับสถาบันการเงินเฉพาะกิจ มีผลต่อการส่งผ่านนโยบายการเงินมากกว่า การตึงตัวของสภาพคล่องในระบบธนาคารพาณิชย์เองหรือไม่ อย่างไร

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Non-linearity in Monetary Policy Transmission: Roles of Liquidity and SFIs in Bank Lending Channel

1. Introduction

Bank lending is the important transmission channel of monetary policy. Tenet of the literature on bank-lending channel led by Bernanke and Blinder (1988) hinges on liquidity as the conduit that links monetary policy to aggregate loan supply. The central bank influences liquidity in the banking system, i.e. 'reserves', so as to control the policy rate. To banks, these induced changes in liquidity directly impact deposit volume and hence loanable funds, provided that banks face frictions in raising other liabilities to replace deposit. Kashyap and Stein (2000) provide empirical evidence supporting the bank-lending channel. Based on the U.S. commercial bank data, their study finds that degrees of transmission of monetary policy to bank lending vary across banks, depending on their liquidity positions. Effectiveness of monetary policy is more pronounced for banks with less liquid balance sheet.

While numerous empirical works have been done in several countries, there are only few papers that probe into the existence of the bank-lending channel in Thailand. Disyatat and Vongsinsirikul (2002), IMF (2002), and Charoensaeng and Manakit (2007) are among the present few. These papers share a close resemblance in empirical strategy based on the standard vector-autoregressive model on aggregate time-series data. Impulse responses of commercial bank loans to the policy rate are then used as the sole evidence of the bank-lending channel. Their results point to limited presence of this transmission channel. Provided that there are no formal statistical tests performed, existing evidence in favor of the bank-lending channel remains thus far inconclusive.

However, the insight drawn from Kashyap and Stein (2000) highlights the nonlinearity between monetary policy and bank lending induced by different 'states' of liquidity. The instance of this state-dependent relationship can be observed in the current context whereby the Bank of Thailand's policy rate decisions appear to render muted responses from commercial banks. Typical explanations to this phenomenon have pointed to banks' competition for liquidity. To this, Specialized Financial Institutions or SFIs are deemed as the main culprit that crowds out liquidity in the Thai deposit market. Existing literature are largely focused on establishing a linear reduced-form linkage from the policy rate to lending activity of Thai commercial banks. In effect, bypassing impact and implication that SFIs' competition and liquidity environment have on the banking system could potentially bias those results. This paper aims to fill this void by providing empirical evidence on monetary policy transmission via bank-lending channel with systematic incorporation of SFIs and liquidity regimes.

This paper first examines a plausible non-linear relationship in the bank lending channel of monetary policy transmission, which cannot be captured by conventional linear models. We identify aggregate liquidity in the commercial bank system as an important factor that influences bank lending, whereby banks may respond differently to changes in monetary instruments when liquidity is plenty, from when it is scarce. We apply threshold-type models to data from Thailand between January 2007 and March 2013 ($n = 75$), and find statistically significant evidence that transmission mechanism “works better” amid tighter liquidity.

By using threshold models which involve cross-regimes, we then investigate the impact of Specialized Financial Institutions (SFIs) which also compete with commercial banks for deposits, although their loans can be quite different in nature from those of the latter. In light of our findings, SFIs should improve the effectiveness of monetary policy transmission as they share the same pool of the economy’s liquidity as commercial banks. Our empirical analysis suggests that SFIs’ actions seem to help improve the efficacy of the bank lending channel; nevertheless, the evidence is at best mixed whether the incremental contribution of SFIs is higher than that of the commercial banks’ liquidity level *per se*.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature where the main focus will be placed on balance sheet effects of monetary policy changes. Section 3 presents stylised facts of the Thai banking system in order to motivate the dataset in hands. Then in Section 4 we explain our research methodology, covering our econometric models, data, and estimation method in detail. Section 5 presents and discusses the main empirical results. Finally, Section 6 concludes and suggests further work.

2. Literature Review *[Sketchy & very brief]*

2.1 Bank lending channel as one of the transmission mechanisms

Mishkin (1996) provides an overview of the transmission mechanisms of monetary policy, i.e. the mechanisms through which monetary policy affects the economy. As Mishkin puts it, expansionary monetary policy, which increases bank reserves and deposits, increases the quantity of bank loans available; this increase in loans will cause investment spending (and probably consumption spending too) to rise.

Boivin et al. (2010) categorises the bank lending channel as one of the ‘non-neoclassical channels.’ These channels arise because of market imperfections, for example, asymmetric information that lead to barriers to efficient financial market functioning.

2.2 Balance sheet effects

Bernanke and Blinder (1988) developed models of aggregate demand (IS/LM-typed models) which allow roles for both money and ‘credit’ (bank loans). They assume that both borrowers and lenders choose between bonds and loans according to the interest rates on the two credit instruments; otherwise, they are viewed as perfect substitutions.

Kashyap and Stein (2000) use a US data set that includes quarterly observations of every insured US commercial bank from 1976 to 1993, a total of 961,530 bank-quarters. By using a two-step regression procedure, they found evidence that the impact of monetary policy on lending is stronger for banks with less liquid balance sheets.

2.3 Prior research on Thailand

To examine the co-movements in the stance of monetary policy, bank loans, and economic activity (as measured by private investment and core inflation rate), Charoenseang and Manakit (2007) use a vector-autoregressive or VAR model to produce the impulse-responses of a shock in the 14-day repurchase rate (then the policy rate). They found that an increase in the 14-day repurchase rate “significantly” reduce commercial banks credit to private sector for about 4 months. They thus conclude that the credit channel through commercial bank lending is still a valid monetary transmission mechanism in Thailand. Nevertheless, no statistical tests were conducted in order to support this conclusion, not to mention that the relationship is reversed (i.e. a positive shock in the policy rate leads to an increase in bank loans) from the tenth month onwards.

An earlier study by the International Monetary Fund (IMF) in 2002 similarly addresses the issue of the transmission of monetary policy by using vector-autoregressions. The main findings of the paper are that changes in monetary policy are associated with changes in real output, and that the main channel for transmission is *not* bank

lending but asset prices. The paper recommends an acceleration of then ongoing reforms in the financial sector, following the 1997 Asian crisis, that would allow the bank-lending channel to become more operative.

Disyatat and Vongsinsirikul (2002) use VAR models for logs of GDP, price level, RP14, and loans, and generate impulse responses of monetary policy tightening to examine the role of bank loans in the transmission mechanism. They found that loans *eventually* fall following a monetary shock with the maximum response occurring after 7 quarters. Disyatat and Vongsinsirikul explain that this is ‘what one would expect’ since loans are quasi-contractual commitments, and thus may be inert to change.

Overall, the existing evidence in favor of the bank lending channel remains inconclusive.

2.4 Non-linear models and regimes

While we postpone the detailed description of econometric models to the next section, we provide a general discussion of our modelling rationale here.

The main problem associated with intrinsically linear econometric models is that they may produce inconsistent estimates – provided that the true data generating process is non-linear in nature. All studies above concerning Thai data sets involve the application of linear-type models: AR, ARX, VAR, VARX.

In Thailand, we do not have the luxury of such an extensive commercial bank data set, and our time-series data are shorter going back. To sum up, neither our n , nor T , is adequately large to follow the methodology of Kashyap and Stein’s (2000). We compensate by using more complicated models and techniques.

Threshold models, unlike the impulse responses, are compatible with standard statistical tests of significance. When interpreting IRF, one usually simply looks at the “ ± 2 s.d.” or sometimes known as “Bollinger” band, and make inferences accordingly. Such ‘visual inspection’ methods may be too crude.

3. Stylised facts of the Thai Banking System [To be completed]

4. Methodology

This section firstly discusses the econometric models used in our study, then describes the dataset, and finally explains the overview of our estimation procedure. Some details are postponed to be discussed in conjunction with the empirical results in the next section, when appropriate.

4.1 Econometric Specification

Our base specification is an autoregressive distributed lag (ARDL) model that explains commercial banks' loan growth by its history (lagged endogenous variable), as well as changes in the Bank of Thailand's policy rate (exogenous variable). That is, we estimate:

$$\Delta \log(L_t) = \eta + \sum_{i=1}^{12} \alpha_i \Delta \log(L_{t-i}) + \sum_{j=0}^{12} \beta_j \Delta \log(RP_{t-j}) + \varepsilon_t, \quad (1)$$

where L_t denotes commercial banks' loans (in baht term) at time t , RP_t the one-day repurchase rate, and ε_t the residual term which is assumed to be well-behaved. Such a dynamic specification allows for delays in monetary transmission. The lagged values of the endogenous variable serve as control variables; this explains the absence of other economic indicators in our specification.

We will pay most attention to the impact of the monetary policy stance on loans, i.e. the coefficient β_j 's. The key parameter of our interest is defined as:

$$\mathbf{B} = \sum_{j=0}^{12} \beta_j,$$

which may be thought of as the long-run multiplier of monetary policy in the bank lending channel. Given the estimate $\hat{\mathbf{B}}$, we can then conduct a straightforward Wald test to examine whether there is a statistically significant "long-run" relationship between changes in monetary policy stance and commercial banks' lending. In particular, the null hypothesis is whether $\mathbf{B} < \mathbf{0}$. It is worth noting beforehand that due to high correlations among the explanatory variables, a statistical test on individual coefficients, such as a t -test, will be invalid.

Equation (1) is a useful starting point to examine the bank lending channel, but it does not take into account the existing level of liquidity in the banking system. As discussed earlier, there is prior information that liquidity should influence decision of banks in one way or another. We thus allow the responses of loan growth to changes in policy rate to vary across 'liquidity regimes' as follows.

$$\Delta \log(L_t) = \begin{cases} \eta + \sum_{i=1}^{12} \alpha_i \Delta \log(L_{t-i}) + \sum_{j=0}^{12} \beta_j^{(h)} \Delta \log(RP_{t-j}) + \varepsilon_t, & \text{if } z_t > c; \\ \eta + \sum_{i=1}^{12} \alpha_i \Delta \log(L_{t-i}) + \sum_{j=0}^{12} \beta_j^{(l)} \Delta \log(RP_{t-j}) + \varepsilon_t, & \text{if } z_t \leq c. \end{cases}$$

This is a threshold-type specification that splits our sample in two with respect to the relevant value of the variable z_t , and the threshold c which can be either treated as fixed and known, or estimated empirically. We call z_t a regime indicator, and it is assumed to be exogenous to the system. In this study, z_t corresponds to a measure of the commercial banking system's liquidity such as the loan-to-deposit ratio (LD) or the loan-to-deposit-and-bill ratio (LDB). Except for the β 's, all parameters, including the residual terms, are regime-independent.

The introduction of regimes via thresholds, as Tong (1990) puts it, provides the local approximation over the possible states.¹ Doing so thus allows the analysis of a complex stochastic system by decomposing it into simpler subsystems. Moreover, unlike the hidden Markov model (Hamilton 1989, 1994), threshold-type models give a regime classification that is discrete, i.e. it is not described by transition probabilities, but is conditionally known. This makes interpretation of results easier, and it proves practical when switching is relatively infrequent. In addition, threshold models are very popular tools in modelling returns on many asset classes, including stocks (Li and Lam, 1995), exchange rates (Alba and Park 2005), real estate (Lizieri *et al.*, 2012), and venture capital (McKenzie *et al.*, 2012), to name but a few.

The above regime-switching specification can be written more succinctly by introducing a dummy variable I_t in an incremental setting as follows.

$$\Delta \log(L_t) = \eta + \sum_{i=1}^{12} \alpha_i \Delta \log(L_{t-i}) + \sum_{j=0}^{12} \beta_j \Delta \log(RP_{t-j}) + \sum_{j=0}^{12} \gamma_j \Delta \log(RP_{t-j}) \times I_t + \varepsilon_t, \quad (2)$$

where $I_t = \mathbf{1}(z_t > c)$ indicates the "high" regime, i.e. when LD is high, for instance. We then shift our focus from the quantity \mathbf{B} to the (nonlinear) contribution of the liquidity factor:

$$\Gamma = \sum_{j=0}^{12} \gamma_j.$$

Our main hypothesis is that $\Gamma < \mathbf{0}$, i.e. tighter liquidity helps with monetary policy transmission. Again, a Wald test may be conducted on the estimate $\hat{\Gamma}$.

¹ Tong (1990) provides an excellent textbook treatment on this subject, as well as on other non-linear time series models. Readers might also want to consult Tong (1978), his earlier original manuscript.

Not only does Equation (2) makes better use of data as it incorporates extraneous information regarding regimes, it also improves upon (1) which muddles up the regime-dependent parameters, provided that such regimes do exist. It can be shown that

$$\mathbf{B}^{(1)} = (1 - \pi) \mathbf{B}^{(2)} + \pi(\mathbf{B}^{(2)} + \Gamma) = \mathbf{B}^{(2)} + \pi\Gamma, \quad (3)$$

where $\mathbf{B}^{(i)}$ is \mathbf{B} under specification i , and the state probability $\pi = \Pr(I_t = 1) = \Pr(z > c)$. As a result, $\mathbf{B}^{(1)}$ will not be the best measure to convey the bank lending channel, especially from a policy making perspective. We provide a general discussion of this result in Appendix A.

Finally, we test a hypothesis that Specialized Financial Institutions (SFIs) – by competing with commercial banks for liquidity – play a significant role in the bank lending channel or not. A natural approach to take Equation (2) forward is to introduce another dummy variable which captures actions of these institutions. The previous specification is thus expanded into:

$$\begin{aligned} \Delta \log(L_t) = & \eta + \sum_{i=1}^{12} \alpha_i \Delta \log(L_{t-i}) + \sum_{j=0}^{12} \beta_j \Delta \log(RP_{t-j}) + \sum_{j=0}^{12} \gamma_j \Delta \log(RP_{t-j}) \times I_{1t} \\ & + \sum_{j=0}^{12} \lambda_j \Delta \log(RP_{t-j}) \times I_{2t} + \varepsilon_t. \end{aligned} \quad (4)$$

We now denote the liquidity indicator by $I_{1t} = \mathbf{1}(z_{1t} > c_1)$ as defined previously. The additional terms, on the other hand, correspond to the indicator $I_{2t} = \mathbf{1}(z_{2t} > c_2)$ which describes the SFIs' degree of aggressiveness in fund raising. Similarly, we define $\Lambda = \sum_{j=0}^{12} \lambda_j$.

As will be described shortly, we measure z_{2t} by either SFIs' deposit growth, or loan growth. When the rate of growth surpasses a certain threshold, SFIs' actions are deemed to be in an 'aggressive' state. Note that we abstain from including any interaction terms between I_{1t} and I_{2t} in this specification as doing so would not only consume the degree of freedom very quickly, but also likely to bring about multicollinearity problems, exact or otherwise.

In effect, Equation (4) generates four scenarios, depending on the values of the two indicators, namely (i) 'tight liquidity' and 'aggressive SFIs actions'; (ii) 'tight liquidity' and 'nonaggressive SFIs actions'; (iii) 'loose liquidity' and 'aggressive SFIs actions'; and finally (iv) "loose liquidity' and 'nonaggressive SFIs actions'. We posit that monetary policy transmission works best in scenario (i), and worst in (iv).

4.2 Data

We obtain all data from the Bank of Thailand (BOT). They are monthly data from January 2007 to March 2013 ($T = 75$). The choice of the starting period was based mainly on data availability.² The BOT follows the Monetary and Financial Statistics Manual (MFSM2000) in compiling these data. All monetary values are in domestic currency (baht) terms.

Our endogenous variable is loosely termed ‘commercial bank loans’. Commercial banks (CBs) comprise (i) Domestically registered commercial banks, and (ii) Foreign bank branches including Bangkok International Banking Facility or BIBF. Loans comprise overdrafts, borrowings, non-negotiable bills, including accrued interests. Unless stated, loans are net of interbank lending, i.e. excluding credits due from other financial institutions and money market. We use various classifications to define the endogenous variable, including by loan types, by maturities, and by bank sizes. These specifics will be described later on in the text.

The main explanatory variable is the monetary policy stance. This is measured by the one-day repurchase rate, and we use the month-end figures in our study. In Thailand, the policy rate is set by the Monetary Policy Committee (MPC) which meets approximately every six weeks.³ Since May 2000, the BOT has operated under the inflation targeting framework with the main objective of maintaining price stability, which is defined as ‘low and stable inflation’. In practice, the MPC agrees with the Minister of Finance on the (core) inflation target range that is appropriate for economic stability and sustainable economic growth. The policy rate is by all measures the key monetary policy instrument that helps keep the price level in check.

We use two closely linked, though subtly different, measures of liquidity. The first one is Loan-to-Deposit (LD) ratio of the CBs’ system. LD refers to the proportion of deposit used in granting credit of the banking system. The BOT calculates this ratio from balance sheet data submitted by CBs. Higher LD means a larger proportion of deposit is used in issuing loans, thereby signaling liquidity tightening. LD includes interbank transactions, and hence is supposed to be a good measure of how much liquidity is available. Our second measure of liquidity is Loan-to-Deposit-and-B/E (LDB) ratio. B/E stands for Bill of Exchange, issued by CBs to mobilize fund from customers and other financial institutions. LDB does not include interbank, and may seem inferior to LD, but B/E used to be a popular way for CBs to raise funds. It started to become an important funding instrument in late 2006. LD does not capture this movement.

² All bank balance sheet data that we consider, except for the amount of Bill of Exchange (B/E), actually go back to prior 2007. B/E data, on the other hand, are available from 2007 onwards. Since B/E is used in the calculation of the LDB ratio, which is instrumental to our study, we begin our sample in January 2007 accordingly. This decision is also partly due to the change in the Bank of Thailand’s policy rate as explained in the footnote below.

³ The 14-day repurchase rate was used as the policy interest rate up until 16 January 2007, after which the policy interest rate was switched to the one-day repurchase rate.

Finally, we consider data for Specialized Financial Institutions (SFIs) to examine how they “interact” with CBs. SFIs are government-sponsored depository corporations, but are under the BOT’s supervision. Currently, there are six SFIs in Thailand, namely Government Savings Bank, Government Housing Bank, Bank for Agriculture and Agricultural Cooperatives, Export-Import Bank of Thailand, Islamic Bank of Thailand, and Small and Medium Enterprise Development Bank of Thailand. The BOT also reports collective balance sheet data of SFIs, although they are probably dominated by the Government Savings Bank.

We measure SFIs’ aggressiveness in fund raising by calculating year-over-year (y-o-y) percentage changes of their deposits. Higher growth suggests stronger competition in their quest for liquidity. We also use y-o-y growth in SFIs’ loans as an alternative, seemingly less direct, indication of SFIs’ actions. The total amount of SFI loans, similar to the classification of commercial banks’ loans, comprises loans to other non-financial corporations, loans to other residential sectors, and other loans.

4.3 Estimation Procedure

The non-regime specification as in Equation (1) can be estimated straightforwardly by the method of ordinary least squares (OLS), but less so for the regime-switching specifications. This is because Equation (2) involves the selection of the threshold c , while (4) involves two thresholds c_1 and c_2 . Rather than assuming certain threshold values, we choose them empirically by maximizing the regression’s goodness of fit, according to the procedure below.

In order to find \hat{c} , we search over all possible values of $c \in \{z_t\}_1^T$ in order to minimize the regression’s sum of squared residuals, conditional on the value c . Such a “grid-search” problem involves the search domain of order $O(T)$ – where T denotes the number of observations. This procedure, suggested by Hansen (2000), boils down to running OLS for T times; it can thus be easily handled for low-frequency data (e.g. monthly like ours). For the cross-regime specification, which requires the pair (\hat{c}_1, \hat{c}_2) , a similar procedure is applicable except that the problem is now of order $O(T^2)$, and hence it requires more computational time, as well as longer time to achieve convergence.

We note though that this is a local optimisation procedure, and as with nonlinear problems in general, it may not guarantee a global minimum. Moreover, our experience suggests that certain values of $c \in \{z_t\}_1^T$, especially those at both tails of the distribution, will result in exact or near multicollinearity problems. When this happens, we drop such values from the list of threshold candidates.

5. Main Results

While we experimented with a wide array of data, a certain number of recurring themes arise across specifications. In other words, our models seem to be robust in terms of economic identification. We will discuss these main findings at length in this section, and summarize them at the closing where we will also propose some policy implication.

5.1 The Impact of Liquidity in the Bank Lending Channel

Table 1 below shows estimation results of models for (i) Thai commercial banks' total loans, including interbank lending; and (ii) business and retail loans only. The latter might thus better represent loans to private real sectors.

<Table 1 about here>

Under the base specification (1) – which does not distinguish between the impact in different regimes – the estimated long run multiplier \hat{B} has an unexpected positive sign, although it is not always statistically significant, depending on the endogenous variable at play. This could be a consequence of a weak relationship or a delayed transmission in the bank lending channel or both. Nevertheless, from a model selection perspective, such findings do not immediately suggest that the base specification is useless. We still deem it statistically adequate as the regression residuals do not seem to show any evidence of autocorrelation as judged by the Ljung-Box Q -statistics.

On the other hand, the threshold models – which decompose the multiplier with respect to the liquidity regime – yield the estimates that are more in line with our prior belief. Looking at the models for total loans, for example, the 'base' multiplier remains positive, but increases in size (from 0.053 to 0.137) and statistical significance (p -value drops from 0.179 to 0.006). This is the case when LD is less than 98.24%, which occupies about two-thirds of our sample (the state probability for 'tight' liquidity is about a third). Figure 1 gives an illustration of the estimated threshold, and hence the liquidity regimes.

<Figure 1 about here>

More interesting is the incremental effect of monetary policy changes in the tight liquidity regime, or $\hat{\Gamma}$. It has a pre-supposed negative value, of -0.196, but is only weakly significant (at 10% level). This piece of evidence provides some support to our hypothesis that the bank lending channel of monetary policy transmission functions better in the tighter liquidity regime. When we add $\hat{\Gamma}$ to \hat{B} , we arrive with the long-run multiplier in the tight

liquidity regime of -0.06 , although the estimate is no longer significant. In addition, models which use LDB as an indicator yields qualitatively similar results to those which use LD, suggesting a satisfactory degree of robustness.

The relationship between estimated parameters in the base model and those in the threshold models also conform to Equation (3) presented previously. Again, when we look at the models for total loans with LD as an indicator, the multiplier estimate of 0.053 has the same order of magnitude as the combination: $0.137 + (-0.196 \times 0.333) = 0.071$, allowing for some margin due to sampling.

The threshold models, nevertheless, noticeably improve upon the base specification in terms of their goodness of fit. While *R-squared* will naturally increase due to the inclusion of more explanatory variables, we see higher *Adjusted R-squared*, as well as lower Akaike and Bayesian Information Criteria (not reported here), in case of the threshold models, regardless of the indicator z used. In essence, the threshold models “got more” out of the data, than their non-regime counterpart did. In this aspect, LD appears to be a better indicator of liquidity regimes than LDB in general though. This provides the basis for our further analyses.

Finally, we note that our models seem to fit data of ‘business and retail loans only’ better than those of total commercial banks’ loans. Not only do regressions on the former yield larger *Adjusted R-squared*, but their estimated parameters also attain higher level of significance. The incremental effect of tight liquidity $\hat{\Gamma}$, for instance, is now significant at less than 1% level for the specification with LD, and at 5% with LDB. Yet, the resulting $\hat{B} + \hat{\Gamma}$ has positive values (of 0.017 and 0.061 respectively), which contradict the results for total loans.

5.2 Results by Bank Size & Loan Maturity

Now we consider additional dimensions of our sample where we classify commercial banks according to their sizes. We follow the Bank of Thailand’s convention, and group banks according to their total assets into: Large, Medium, and Small. Our hypothesis is that larger banks should be *less* sensitive to a policy change in the tight liquidity regime, as they tend to have more stable deposit’s base, and more access to “outside” funding. The estimation results in Table 2, however, show otherwise.

<Table 2 about here>

The contribution of tighter liquidity, as measured by $\hat{\Gamma}$, is negative across bank sizes, re-emphasizing that the bank lending channel works better amid tight liquidity. However, those of Large and Small’s do not differ much from zero in size; in fact, none of them is significantly different from zero. This is a stark contrast to our hypothesis which posits that size does matter. We note, however, that the selected threshold for small-sized banks (at LD of 101%) is markedly higher than that of the other two groups (at about 94%). This might be due to the nature of small

banks which rely relatively less on deposits, and more on borrowings and other instruments. Our proposition is confirmed when we look at the threshold for LDB of smaller banks' which seems to be more comparable with those of the other two sizes; it is actually very close to that of the medium-sized banks.

The transmission of monetary policy via the bank lending channel seems to be more/most prevalent among medium-sized banks. We found that, in the tight liquidity regime, a one-off 1% increase (as opposed to a 1 percentage point increase) in the policy rate will result in a 0.032% fall in growth of total loans (excluding interbank items). Currently when the repurchase rate is below 3% per annum, a 25 basis-point cut translate to roughly an 8% fall – and hence loan growth should drop by 0.24%. This impact appears to be very marginal, despite tighter liquidity, and it is confirmed by a Wald test result which yields high *p-value*.

On the contrary, when we replace LD by LDB, the impact of interest rate changes in the tight liquidity regime becomes much more rigorous for medium-sized banks, suggesting a fall of 2.7% over a course of a year (since the multiplier is now equal to -0.895). This sounds like a more reasonable magnitude of policy impact, thereby highlighting the importance of the choice of the regime indicator. The switch from LD to LDB does not change results for the other two groups, whose regressions also show better fit than those of medium-sized banks according to the *Adjusted R-squared*. In terms of economic interpretation, however, these results imply that medium-sized banks might find it relatively more difficult to substitute deposits by other modes of funding (other than B/E) – and hence they might be more vulnerable to liquidity squeezes. This finding seems to have a direct policy implication.

Next, we try a different way of conditioning our dataset: By separating commercial banks' loans into Long and Short maturities. Here, we use the sum of Bills (Domestic, Export, Import, Trust receipts and other bills) and Overdrafts as a proxy of 'short-term' loan, while all term loans are labeled 'long-term'. We hypothesize that loans with longer maturities should be *more* sensitive to a policy change in the tight liquidity regime. This is inspired by the concept of *duration* in finance literature.⁴ Duration measures the sensitivity of percentage changes in the bond's price to changes in its yield. This measure generally grows with maturity of the underlying bond, and hence assets with longer maturity are more prone to interest rate changes. We therefore expect monetary transmission to be stronger on long-term loans. The estimation results are reported in Table 3 below. Here we only focus on models with LD as an indicator as it usually "works better" than LDB.

<Table 3 about here>

As expected, our threshold models explain growth of long-term loans better than they do short-term loans, according to the *Adjusted R-squared*. The results also differ with respect to the parameter estimates, where the

⁴ See standard finance or risk-management textbooks e.g. Hull (2010) or Hull (2011) for detailed descriptions and properties of duration.

model for long-term loans yields not only negative and significant $\hat{\Gamma}$ (-0.427 with virtually zero *p-value*), but negative and significant $\hat{B} + \hat{\Gamma}$ too (-0.276, again, with virtually zero *p-value*). This suggests that the bank lending channel *does* exist in case of long-term loans, when liquidity is tight. The models for short-term loans do not share the same remark. The threshold values for both maturities, nevertheless, are virtually identical at LD of 101%.

5.3 The Impact of Specialized Financial Institutions

Our last question concerns the roles of Specialized Financial Institutions (SFIs) in the bank lending channel. The underlying assumption is that by competing with commercial banks for liquidity in the financial institution system, SFIs should improve the efficacy of the bank lending channel. Consequently, we introduce the concept of ‘SFI regime’ as distinguished by how aggressive their actions are, i.e. whether they grow a lot of loans or deposits in a certain period. Doing so will result in threshold models with cross-regimes.

As introduced in Equation (4), the relevant regressions require the identification of two conditioning variables. We use LD as the liquidity indicator, as we did previously, while we measure SFIs’ aggressiveness either by their loan growth or their deposit growth.⁵ As will be shown shortly, the choice of the indicator of SFI regimes, or z_2 , becomes a critical issue as it can have widely different implications. We note in passing that the specification of two different indicators leads to four distinct scenarios, as laid out in the methodology section. It is also possible that our estimation results will yield an ‘impossible’ regime, i.e. one whose state probability is naught.

<Table 4 about here>

Table 4 compares the results using year-over-year growth of SFIs’ deposits as the second regime indicator, with those using growth of SFIs’ loans. The present results seem to be less stable than the previous ones, due to a large number of parameters specified in each model. The regression for the total amount of commercial banks’ loan, where z_2 is SFIs’ deposit growth, implies explosive behaviour where the estimated parameters are greater than a unit in absolute value, e.g. the incremental effect of liquidity $\hat{\Gamma}$ is estimated to be 6.597. Admittedly, such large swings in parameter values may yield subsequent statistical tests less reliable, yet our main conclusions still appear to be robust across various specifications; this is quite reassuring.

In Table 4, most $\hat{\Gamma}$ ’s are negative, as we would expect – this is the previously-seen impact of tighter liquidity. The impact of SFIs’ aggressiveness as measured by $\hat{\Lambda}$, on the other hand, varies with the choice of the SFI regime indicator, where the results using SFIs’ deposits are more broadly in line with our expectation. This might be

⁵ Our empirical results are robust to the choice of the liquidity indicator, although LD generally yields better goodness of fit than LDB.

partly because deposits are a more direct measure of liquidity as, roughly speaking, a dollar (baht) gained by SFIs is a dollar lost by commercial banks. Another possible explanation is that SFI loans could be quite different in nature from those of commercial banks; in particular, they are guided more by the government’s policies, and less by market forces.

Let us now focus on the case for ‘business and retail loans only’ with SFIs’ deposit growth as the second indicator. When LD is above 96.38% and SFIs’ deposit grow faster than 7.86% year-on-year – which represents about a third of our sample – we find strong evidence of the bank lending channel. That is, the sum $\hat{B} + \hat{\Gamma} + \hat{\Lambda}$ is equal to -0.102, and it is highly significant. This scenario is consistent with when liquidity is probably tightest. This finding is simply another “manifestation” of the gist of our paper – the bank lending channel “works better” amid tighter liquidity.

When liquidity of commercial banks is tight but SFIs’ actions are nonaggressive, the transmission seems to be impaired as $\hat{B} + \hat{\Gamma}$ is $1.602 > 0$. Likewise, when liquidity is not tight but SFIs grow deposits relatively quickly – which is a predominant scenario as it accounts for almost half of our sample – the transmission seems to be impaired as $\hat{B} + \hat{\Lambda}$ is $0.195 > 0$ too. Nevertheless, the incremental contribution to the bank lending channel due to SFIs seems to be larger than that of the liquidity level *per se* as $\hat{\Lambda}$ is much smaller than $\hat{\Gamma}$. However, if we look at the regression whose z_2 is SFIs’ loan growth, the relationship is reversed ($0.373 = \hat{\Lambda}$ is much larger than $\hat{\Gamma} = -0.470$).

Therefore, the evidence is at best mixed on which “contributor” has higher impact on the efficacy of the bank lending channel. Both indicators are comparable in terms of the resulting regressions’ goodness of fit. But closer inspection suggest that using SFIs’s deposit growth as an aggressiveness indicator tends to tilt the results more towards SFIs effects, while using SFIs’ loan growth gives more weight to liquidity effects.

The above feature is carried forward when we classify loans data by bank size, and by their maturity. Table 5 below reports estimation results of threshold models which use LD and SFIs’ deposit growth as the first and second regime indicator respectively.

<Table 5 about here>

All $\hat{\Lambda}$ ’s, except that the regression for Small-bank loans, are negative and smaller than $\hat{\Gamma}$ – as we would for the models with SFIs’ deposit growth. Besides, many of the main findings obtained from our simpler two-regime models are also present here. Medium-sized banks tend to be most sensitive to liquidity tightening as, unlike their peers, both their $\hat{\Lambda}$ and $\hat{\Gamma}$ are negative and highly significant. We also found that the bank lending channel is

probably most effective for long-term loans, as it is the only specification whose sum $\hat{\mathbf{B}} + \hat{\mathbf{\Gamma}} + \hat{\mathbf{\Lambda}}$ is negative and highly statistically significant.

5.4 Overall Discussion of the Results & Policy Implications [To be completed]

Consistent across all our empirical results is the evidence of stronger responses to changes in monetary policy stance of commercial bank lending when liquidity is relatively scarce. More specifically, we see some evidence of positive multiplier in the loose regime, and find significant evidence of negative multiplier specifically for the tight regime, resulting in the possibility of the mild impact overall.

Most of the time it does not matter whether to use LD or LDB. But we have seen a few exceptions. The search for optimal regime indicators is an empirical question, and hence our paper opens up the frontier of possibilities to connect monetary policy transmission to alternative regimes or regime indicators.

6. Conclusion

In this study, we try to answer age-old question of monetary transmission through the bank lending channel. In particular, we focus our study on the case of Thailand due to lack of consensus of the results on the transmission and its uniqueness in facing the direct funding competition from the government's Specialized Financial Institutions (SFIs).

Although well-established elsewhere, the empirical evidence on Thai banking variables remains at best inconclusive on how effective are the changes in the stance of monetary policy in influence the *aggregate* bank lending volume. Using insights from previous literature, in particular from Kashyap and Stein (2000), we study how this inconclusiveness may be due to a changing liquidity environment underlying different periods of study.

To this end, we examine the plausible non-linear relation in the bank lending channel of monetary transmission by employing threshold models to elicit regime-specific responsiveness of bank lending to changes in the monetary policy stance. Our results show that aggregate liquidity in the commercial bank system is indeed an important indicator of how well the pass through in the bank lending channel would be. In line with previous works, tighter liquidity environment leads to more effective transmission of monetary policy. Since Thai commercial bank system switches overtime between tight and lax liquidity, and consequently between "effective" and "ineffective" region, our results explain the inconclusive nature of previous literature, which based mostly linear models and linear relationships.

We investigate further the effect of liquidity regime by introducing a catalyst of liquidity tightening with bank competition with SFIs. We have found that competition with the SFIs help improve the effectiveness of monetary policy transmission, especially during the time of deposit competition as reflected in high deposit growth rates of the SFIs. The results strongly support the view that competition enhances the transmission mechanism, particularly from the *price impulses* to *aggregate quantity* transmission.

However, our results may still be insufficient for a definite conclusion some dimensions which require future works to address. One important dimension is the interest rate channel, which focuses more on *price to price* transmission. Evidence elsewhere has also show that imperfect competition in banking system can potentially lead to an incomplete pass-through of interest rates.⁶ This channel is not explored within the context of our current work, but

⁶ See for example, Mier-y-Teran (2012) and Sathapholdeja and Suwankiri (2012) [available upon request].

imperative for understanding the full impact of competition and liquidity on the monetary policy transmission mechanism.

Second, our work here has shown that the degree of non-linearity may influence the effectiveness of policy transmission. To further deepen the analysis, future works may also want focus on asymmetry of transmission (upward versus downward policy rate adjustments) for different liquidity regimes. We suspect that the transmission mechanism will play out differently across liquidity and competition regimes.

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Appendix A: Relationship between switching and non-switching parameters

Suppose, without loss of generality, that the endogenous variable y_t follows the data generating process below.

$$y_t = \begin{cases} w_t' \alpha + x_t' \beta_1 + \varepsilon_t, & \text{if } z_t > c; \\ w_t' \alpha + x_t' \beta_2 + \varepsilon_t & \text{if } z_t \leq c. \end{cases}$$

The parameters are divided into two groups: the regime-independent α which corresponds to the vector of explanatory variables w_t , and the regime-dependent β which corresponds to x_t . The distribution of the regime indicator z_t is described by the state probability $\pi = \Pr(z_t > c)$. The residual term ε_t is assumed to be well-behaved; in particular, it has zero conditional expectation with respect to w_t and x_t .

By using the law of iterated expectation, it can be shown that

$$\begin{aligned} E[y_t | w_t', x_t'] &= EE[y_t | w_t', x_t', z_t] = \pi \times (w_t' \alpha + x_t' \beta_1) + (1 - \pi) \times (w_t' \alpha + x_t' \beta_2) \\ &= w_t' \alpha + x_t' (\pi \beta_1 + (1 - \pi) \beta_2) \\ &= w_t' \alpha + x_t' \beta. \end{aligned}$$

As a result, for a model that ignores regimes, β in the corresponding mean equation is the weighted average of the regime-specific β 's where the weight is given by π , the state probability.

Provided that there exists a consistent estimator of β , it follows directly from the result above that

$$\hat{\beta} \xrightarrow{p} \beta = \pi \beta_1 + (1 - \pi) \beta_2, \quad (\text{A.1})$$

i.e. the non-regime estimate will confound the effects in the two regimes. Consequently, certain information is lost.

Now, by following the same line of reasoning as when deriving (A.1), we can show that

$$\mathbf{B}^{(1)} = (1 - \pi) \mathbf{B}^{(2)} + \pi (\mathbf{B}^{(2)} + \Gamma) = \mathbf{B}^{(2)} + \pi \Gamma,$$

as shown in the paper. Recall that \mathbf{B} is the sum of the coefficients of percentage changes in policy rate. The non-regime $\mathbf{B}^{(1)}$ thus masks the impact on the bank lending channel of liquidity which affects the relationship in a non-linear manner.

Tables & Figures

Table 1: The bank lending channel in different liquidity regimes

Endogenous variable	Total CB Loans incl. Interbank			CB Business + Retail Loans		
	(1)	(2) $z = LD$	(2) $z = LDB$	(1)	(2) $z = LD$	(2) $z = LDB$
$\hat{\mathbf{B}}$	0.053	0.137	0.104	0.066	0.136	0.167
<i>(p-value)</i>	<i>(0.179)</i>	<i>(0.006)</i>	<i>(0.032)</i>	<i>(0.015)</i>	<i>(0.000)</i>	<i>(0.006)</i>
$\hat{\Gamma}$		-0.196	-0.163		-0.119	-0.106
<i>(p-value)</i>		<i>(0.095)</i>	<i>(0.230)</i>		<i>(0.005)</i>	<i>(0.049)</i>
$\hat{\mathbf{B}} + \hat{\Gamma}$		-0.059	-0.059		0.017	0.061
<i>(p-value)</i>		<i>(0.503)</i>	<i>(0.599)</i>		<i>(0.451)</i>	<i>(0.033)</i>
\hat{c}		98.24%	87.12%		94.75%	85.18%
$\hat{\pi}$		33.33%	46.67%		57.33%	76.00%
<i>R-squared</i>	0.446	0.685	0.659	0.670	0.805	0.796
<i>Adj. R-squared</i>	0.157	0.342	0.288	0.498	0.593	0.575
<i>Q(24)</i>	<i>0.938</i>	<i>0.992</i>	<i>0.955</i>	<i>0.995</i>	<i>0.820</i>	<i>0.864</i>

This table presents the estimation results of our base specification (1) compared with those of the threshold models (2). The parameter \mathbf{B} is the sum of β 's, the effects of changes in the policy rate on loan growth. Below each estimate is the *p-value* from a corresponding Wald test under the null that the true parameter is equal to zero. For the threshold models, \mathbf{B} represents the long-run multiplier of monetary policy when liquidity is relatively 'loose' which occurs when the indicator z is smaller than the threshold c in value. The chosen threshold value should be interpreted in conjunction with the estimate of the state probability $\pi = \Pr(z > c)$. The parameter Γ is the incremental effect of policy rate changes when LD (or LDB) is above its threshold, and hence the sum $\mathbf{B} + \Gamma$ represents the long-run multiplier when liquidity is 'tight'. We also report two goodness-of-fit measures, namely R-squared and Adjusted R-squared, along with the *p-value* of the Ljung-Box Q-statistic with 24 lags. The Q-statistic detects autocorrelation in the regression's residuals – the null hypothesis is that there is no autocorrelation up to a certain lag number – and thus provides evidence for model adequacy.

Table 2: Estimation results by bank size

Endogenous variable	Large			Medium			Small		
	(1)	(2) $z = LD$		(1)	(2) $z = LD$	(2) $z = LDB$	(1)	(2) $z = LD$	
\hat{B}	0.081	0.066	0.054	0.031	0.192	0.049	0.023	0.039	0.132
(p-value)	(0.094)	(0.257)	(0.482)	(0.352)	(0.032)	(0.114)	(0.513)	(0.462)	(0.108)
$\hat{\Gamma}$		-0.037	-0.016		-0.224	-0.943		-0.021	0.390
(p-value)		(0.506)	(0.820)		(0.030)	(0.012)		(0.835)	(0.631)
$\hat{B} + \hat{\Gamma}$		0.029	0.037		-0.032	-0.895		0.017	0.522
(p-value)		(0.464)	(0.491)		(0.495)	(0.014)		(0.824)	(0.520)
\hat{c}		94.60%	85.832		94.37%	90.14%		101.10%	90.65%
$\hat{\pi}$		58.67%	64.00%		62.67%	20.00%		20.00%	17.33%
R-squared	0.560	0.791	0.701	0.463	0.663	0.652	0.635	0.769	0.797
Adj. R-squared	0.331	0.563	0.376	0.184	0.296	0.274	0.444	0.517	0.576
$Q(24)$	1.000	0.976	0.999	0.999	0.790	0.443	1.000	0.997	0.979

See notes under Table 1.

Table 3: Estimation results by loan maturity

Endogenous variable	Long-term		Short-term	
	(1)	(2) $z = LD$	(1)	(2) $z = LD$
\hat{B}	0.017	0.151	0.142	0.099
(p-value)	(0.778)	(0.007)	(0.073)	(0.224)
$\hat{\Gamma}$		-0.427		0.662
(p-value)		(0.000)		(0.000)
$\hat{B} + \hat{\Gamma}$		-0.276		0.761
(p-value)		(0.001)		(0.000)
\hat{c}		100.99%		101.48%
$\hat{\pi}$		21.33%		17.33%
R-squared	0.459	0.729	0.457	0.689
Adj. R-squared	0.177	0.435	0.175	0.352
Q(24)	0.981	0.993	1.000	1.000

See notes under Table 1.

Table 4: The roles of SFIs in the bank lending channel under different liquidity regimes

Specification	(3) $z_1 = \text{LD}$ $z_2 = \text{SFIs' Deposit growth}$		(3) $z_1 = \text{LD}$ $z_2 = \text{SFIs' Loan growth}$	
	Total CB Loans <i>incl.</i> Interbank	CB Business + Retail Loans	Total CB Loans <i>incl.</i> Interbank	CB Business + Retail Loans
$\hat{\mathbf{B}}$	0.066	1.899	0.036	0.128
<i>(p-value)</i>	<i>(0.398)</i>	<i>(0.003)</i>	<i>(0.667)</i>	<i>(0.002)</i>
$\hat{\mathbf{\Gamma}}$	6.597	-0.297	-0.575	-0.470
<i>(p-value)</i>	<i>(0.002)</i>	<i>(0.000)</i>	<i>(0.099)</i>	<i>(0.000)</i>
$\hat{\mathbf{B}} + \hat{\mathbf{\Gamma}}$	6.663	1.602	-0.539	-0.342
<i>(p-value)</i>	<i>(0.001)</i>	<i>(0.007)</i>	<i>(0.057)</i>	<i>(0.008)</i>
$\hat{\mathbf{\Lambda}}$	-6.961	-1.704	0.293	0.373
<i>(p-value)</i>	<i>(0.001)</i>	<i>(0.006)</i>	<i>(0.122)</i>	<i>(0.004)</i>
$\hat{\mathbf{B}} + \hat{\mathbf{\Lambda}}$	-6.895	0.195	0.329	0.501
<i>(p-value)</i>	<i>(0.001)</i>	<i>(0.000)</i>	<i>(0.186)</i>	<i>(0.000)</i>
$\hat{\mathbf{B}} + \hat{\mathbf{\Gamma}} + \hat{\mathbf{\Lambda}}$	-0.298	-0.102	-0.247	0.031
<i>(p-value)</i>	<i>(0.000)</i>	<i>(0.010)</i>	<i>(0.200)</i>	<i>(0.123)</i>
\hat{c}_1	98.48%	96.38%	98.24%	94.37%
\hat{c}_2	20.72%	7.86%	18.06%	9.44%
$\hat{\pi}_{HH}$	17.33%	34.67%	14.67%	54.67%
$\hat{\pi}_{HL}$	12.00%	9.33%	18.67%	8.00%
$\hat{\pi}_{LH}$	10.67%	46.67%	5.33%	21.33%
$\hat{\pi}_{LL}$	60.00%	9.33%	61.33%	16.00%
<i>R-squared</i>	0.867	0.912	0.873	0.915
<i>Adj. R-squared</i>	0.559	0.707	0.580	0.716
<i>Q(24)</i>	0.374	0.946	0.999	0.996

This table presents the estimation results of our threshold models which involve cross-regimes between commercial banks' liquidity (z_1) and aggressiveness of Specialized Financial Institutions' (SFIs) action (z_2). For basic descriptions, see notes under Table 1. The parameter $\mathbf{\Lambda}$ is the incremental effect due to SFIs' aggressive deposit raising, i.e. when

the year-over-year deposit growth is above c_2 . The state probabilities are defined as:

$$\pi_{HH} = \Pr(z_1 > c_1 \cap z_2 > c_2), \pi_{HL} = \Pr(z_1 > c_1 \cap z_2 \leq c_2), \pi_{LH} = \Pr(z_1 \leq c_1 \cap z_2 > c_2), \text{ and}$$

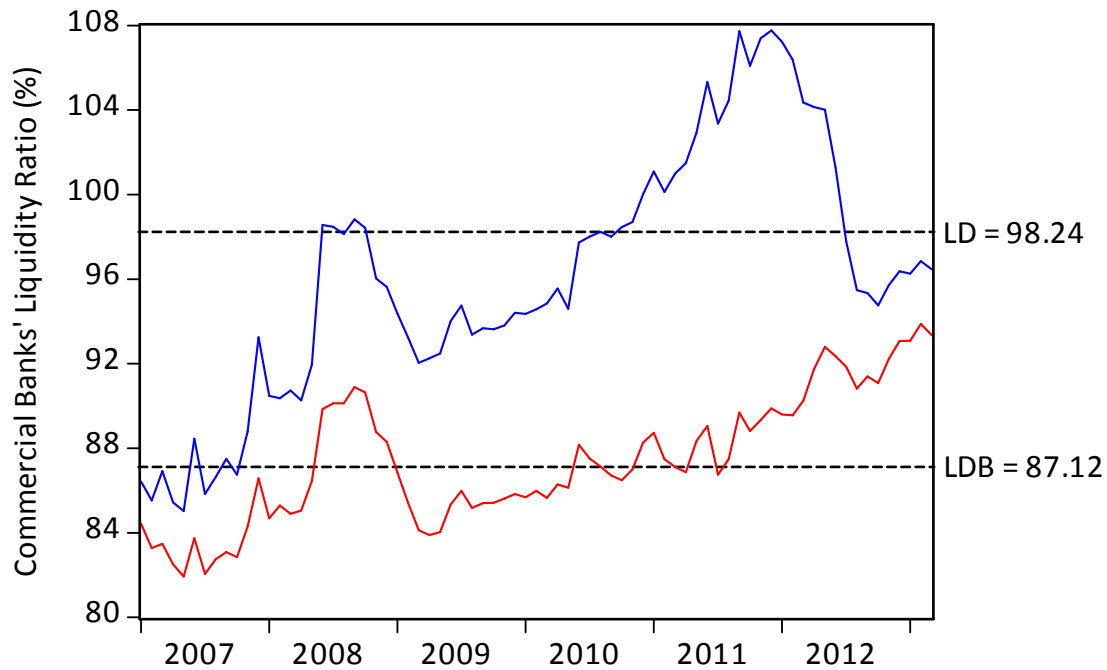
$$\pi_{LL} = \Pr(z_1 \leq c_1 \cap z_2 \leq c_2)$$

Table 5: The roles of SFIs in the bank lending channel under different liquidity regimes

Specification	(3) $z_1 = \text{LD}$ $z_2 = \text{SFI's Deposit growth}$				
Classification	By bank size			By maturity	
Endogenous variable	Large	Medium	Small	Long-term	Short-term
$\hat{\mathbf{B}}$	0.076	0.642	0.179	1.276	0.170
(<i>p-value</i>)	(0.288)	(0.000)	(0.263)	(0.439)	(0.087)
$\hat{\mathbf{\Gamma}}$	-0.011	-0.217	-1.249	-0.514	0.025
(<i>p-value</i>)	(0.912)	(0.005)	(0.000)	(0.002)	(0.862)
$\hat{\mathbf{B}} + \hat{\mathbf{\Gamma}}$	0.065	0.424	-1.070	0.762	0.194
(<i>p-value</i>)	(0.314)	(0.006)	(0.000)	(0.640)	(0.067)
$\hat{\mathbf{\Lambda}}$	-0.130	-0.504	1.067	-1.124	-0.330
(<i>p-value</i>)	(0.154)	(0.001)	(0.000)	(0.489)	(0.003)
$\hat{\mathbf{B}} + \hat{\mathbf{\Lambda}}$	-0.054	0.138	1.247	0.152	-0.161
(<i>p-value</i>)	(0.688)	(0.006)	(0.000)	(0.028)	(0.205)
$\hat{\mathbf{B}} + \hat{\mathbf{\Gamma}} + \hat{\mathbf{\Lambda}}$	-0.065	-0.079	-0.003	-0.361	-0.136
(<i>p-value</i>)	(0.212)	(0.106)	(0.963)	(0.013)	(0.144)
\hat{c}_1	94.60%	94.77%	95.34%	100.99%	94.37%
\hat{c}_2	20.86%	10.93%	16.88%	9.25%	21.43%
$\hat{\pi}_{HH}$	24.00%	41.33%	30.67%	21.33%	25.33%
$\hat{\pi}_{HL}$	34.67%	14.67%	22.67%	0.00%	37.33%
$\hat{\pi}_{LH}$	2.67%	30.67%	9.33%	57.33%	0.00%
$\hat{\pi}_{LL}$	38.67%	13.33%	37.33%	21.33%	37.33%
<i>R-squared</i>	0.910	0.857	0.894	0.873	0.899
<i>Adj. R-squared</i>	0.701	0.525	0.647	0.580	0.664
<i>Q(24)</i>	0.816	0.135	0.692	0.763	0.811

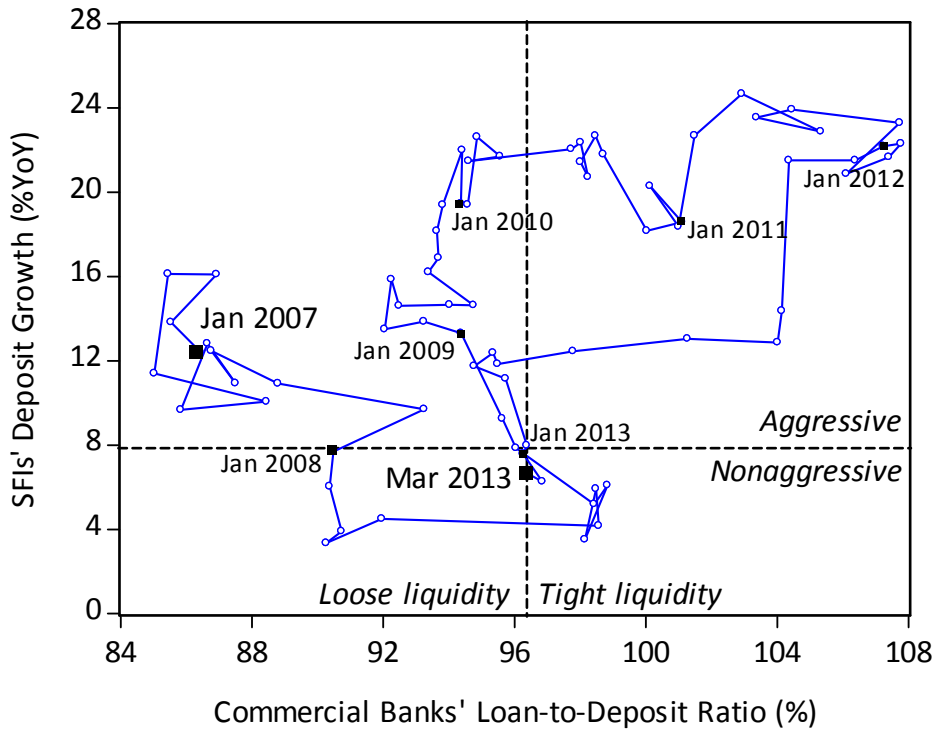
See notes under Table 4.

Figure 1: Liquidity regimes as implied by LD & LDB ratios



This figure shows liquidity regimes in the Thai commercial bank's system, with respect to the Loan-to-Deposit (LD) and the Loan-to-Deposit-and-Bill (LDB) ratios. Note that LD is always greater than LDB. As shown in Table 1, our model for the total amount of commercial banks' loans (including interbank lending) chose the threshold of 98.24% for LD – above which liquidity is considered 'tight', and 'loose' otherwise – while the threshold for LDB is 87.12%. We note that the classifications by the two liquidity indicators generally coincide, but they seem to have diverged markedly since the second half of 2012.

Figure 2: Cross-regimes of commercial banks' liquidity and SFI's aggressiveness



This figure shows the four scenarios implied by our threshold model for commercial banks' business and retail loans, which contain two indicators: the liquidity measure, and the aggressiveness of Specialized Financial Institutions. The solid line maps out evolution of the two indicators over time. The larger dots in the figure mark the first and last observations, whereas smaller prints suggest the beginning of each year. The two indicators appear to have moderate correlation, of just below 50% in size. Nevertheless, the evolution of the pair over time does seem to suggest the presence of a co-integrating relationship, as confirmed by both the Engle-Granger and the Johansen tests. According to our empirical results, liquidity in the commercial bank's system is said to be 'tight' when the loan-to-deposit ratio (LD) is greater than 96.38%; otherwise, it is 'loose'. On the other hand, we deem SFIs to be aggressive when their monthly deposit growth is greater than 7.86% year-over-year. The 'tight liquidity' – 'aggressive SFIs actions' scenario accounts for 34.67% of our sample, in which the bank lending channel is supposed be most proficient. The 'loose liquidity' – 'nonaggressive SFIs actions' scenario, on the other hand, accounts for a higher portion of 46.67%.