Interest rate pass-through in Thailand: New evidence from loan-level data

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June 2019

Work in progress – please do not cite without the authors' permission.

Abstract

We conduct extensive pass-through analyses using the Bank of Thailand's Loan Arrangement (LAR) database. This dataset provides information on all new loans, with outstanding of 20 million baht or higher, granted by commercial banks in Thailand on a monthly basis. Such high granularity allows us not only to observe heterogeneity across firms (borrowers) and banks (lenders), but also to gauge distributional impact of monetary policy transmission – neither of which is possible at the aggregate level. Our analyses are centered about the measure 'New Loan Rate' (NLR), which is calculated from interest payments of new business loans weighted by loan size. NLR, which is representative of contractual rates, shows significant deviations from Minimum Loan Rate (MLR), which is an average 'window' rate quoted for prime customers. A misspecification analysis shows that pass-through is much stronger on NLR than their window counterpart, yielding conclusions from conventional transmission analyses conducted on MLR invalid. Regressions on loan-level NLR show that firms with large total assets and multiple-bank relationships tend to be associated with stronger pass-through ("balance sheet channel") while banks with relatively liquid balance sheet and high profitability ratios tend to be correlated with weaker pass-through ("bank lending channel"). In terms of industry type, NLR on loans of agricultural firms are relatively insensitive to changes in monetary policy, while those in manufacturing are most susceptible to rate changes. The results are broadly in line with the literature, and robust to the specification of firm/bank fixed effects. Further, quantile regressions reveal that pass-through is significantly stronger in loans with NLR in the lower-percentiles compared with those in the higher-ones, highlighting a strong distributional effect on monetary policy transmission in Thailand.

Keywords: Interest rate pass-though; Loan-level data; New Loan Rate; Bank of Thailand

JEL classification: E52, E58, E43

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1. Introduction *(brief & sketchy)*

An analysis of interest rate pass-through has been a recurring theme in monetary policy research. Not only is the topic directly related to the efficacy of monetary policy transmission, which may fluctuate overtime, empirical literature has also documented variations with respect to other dimensions, such as the strength of financial institutions' balance sheet by which monetary policy is being transmitted. Recently, the use of micro-data enables researchers to gain further insights into this issue. Such high granularity allows pass-through heterogeneity across borrowers (firms) and lenders (banks) to be observed, as well as the gauge of distributional of monetary policy transmission – neither of which is possible at the aggregate level.

Monetary policy is conducted under the flexible inflation targeting framework in Thailand, where the one-day repurchase rate (RP1D) is the main policy instrument. In this paper, we conduct extensive pass-through analyses from RP1D to the measure 'New Loan Rate' (NLR) by using the Bank of Thailand's Loan Arrangement (LAR) database. This dataset provides information on all new loans, with outstanding of 20 million baht or higher, granted by commercial banks in Thailand loan on a monthly basis. NLR is calculated from interest payments of new business loans weighted by loan size, and is representative of contractual rates. Movements of this particular interest rate show significant departure from those of Minimum Loan Rate (MLR), which is an average 'window' rate quoted for prime customers. A misspecification analysis confirms this point, where pass-through is much stronger on NLR than their window counterpart, yielding conclusions from conventional transmission analyses conducted on MLR invalid. In addition, the finding reflects the practice of lending at 'MLR minus X%' by commercial banks, a well-known fact yet undocumented in academic literature.

By joining LAR with two other databases, we are able interest rate pass-through according to loan-firm-bank relationships. Regressions on loan-level NLR show that firms with large total assets and multiple-bank relationships tend to be associated with stronger pass-through ("balance sheet channel") while banks with relatively liquid balance sheet and high profitability ratios tend to be correlated with weaker pass-through ("bank lending channel"). In terms of industry type, NLR on loans of agricultural firms are relatively insensitive to changes in monetary policy, while those in manufacturing are most susceptible to rate changes. The results are broadly in line with the literature, and robust to the specification of firm/bank fixed effects.

Further, quantile regressions reveal that pass-through is significantly stronger in loans with NLR in the lower-percentiles compared with those in the higher-ones, highlighting a strong distributional effect on monetary policy transmission in Thailand. We believe this is a novel contribution to the literature both in terms of the data being used as well as the quantitative techniques employed. We also add to the literature with respect to the experience from an emerging economy.

The organization of the paper is as follows. Section 2 describes datasets, and presents key descriptive statistics and stylized facts. Sections 3-5 tackle misspecification analysis, pass-through heterogeneity and distributional effects respectively, accompanied by corresponding review of literature. Section 6 looks at a potential structural break around the Global Financial Crisis. The last section concludes and suggests future research.

2. Data and preliminary analysis

2.1 Data Sources

There are three primary data sources utilized in our study: (1) contract-level loan data from the Bank of Thailand's Loan Arrangement (LAR) database, (2) balance sheet and firm profile data from the Department of Business Development's Company Profile and Financial Statement (CPFS) database, and (3) detailed financial statements for lending institutions from the Bank of Thailand. We also leverage macroeconomic and yield curve data, including GDP growth, inflation, market volatility (VIX), and policy rate expectations (government yield slope), from the Bank of Thailand, Bloomberg and the Thai Bond Market Association.

The LAR database consists of contract-level data for loans issued by financial institutions. The financial institutions are obligated to report to the Bank of Thailand all loans where the total credit line or outstanding amount for the individual/firm exceed 20 million Baht. We have selected 42 financial institutions for this study, which includes all Thai commercial banks, foreign bank subsidiaries, and foreign bank branches. The data includes loan characteristics reported at the end of each month spanning from January 2004 to March 2018.

The LAR database represents approximately 75% of total credit in the banking system. We have sub-selected a portion of the database out by the following criteria to focus on Thai monetary policy transmission. We would like to focus on how the corporate loan rates change over time and how they respond to the policy rate. This could be cleanly accomplished by studying rates for new loans. Only THB denominated loans are used in the study. Foreign currency loans were excluded as they follow the yield curve of their currencies and are largely unaffected by Thai monetary policy. Credit card loans and loans made to financial intermediaries, government agencies, and non-residents were also excluded. It was observed that loan rates for these groups tend to cluster together away from other groups and do not generally obey regular monetary policy transmission mechanisms.

The most important variable in this paper is the new loan rate (NLR). NLR is the contract-level loan rate from the LAR database. The variables that will eventually be used in this study are factors that we believe influence NLR. The loan characteristics chosen are loan duration, loan types, and loan purposes. Loan duration is calculated by subtracting maturity date from the origination date. Loan types are dummy variables indicating whether the loan is considered to be term loans, domestic bills of exchange, international bills of exchange, overdrafts, or others. Loan purposes are also dummy variables categorizing the purpose of loans as consumption, investment, refinance, working capital, or others.

The CPFS database is maintained by the Department of Business Development (DBD) in the Ministry of Commerce. Firms doing business in Thailand are required to annually submit profit and loss statements and balance sheets to the DBD. In this study, we are mostly interested in the business type, bargaining power, asset size, and key financial ratios. Business type is defined by International Standard Industrial Classification of All Economic Activities (ISIC code). Firm bargaining power is represented by the number of bank relationships, defined to be the number of banks each firm has outstanding loans with at the end of each month. The database contains data for roughly 800,000 firms in the time span between 2004 and 2016. This database is not as up-to-date as other data sources as there is a lag time of approximately two years before it is published.

Financial institutions are required to send detailed financial statements to the Bank of Thailand each month. The time span for this dataset, as well as the type of financial institutions, were chosen to match those already mentioned in the LAR database.

The variables in the set of bank characteristics include capital, liquidity, funding structure, business model, operating cost, and risk appetite. The first bank variable is capital which is reflected by capital adequacy ratio (CAR). The second bank characteristic is loan over deposit and bill of exchange ratio (LDR), reflecting bank liquidity. Funding structure and business model are described by the ratio of deposits in current and saving accounts to total deposits (CASA ratio) and the ratio of interest income to total income (interest income ratio), respectively. The last bank variable is the net interest margin (NIM), representing the risk appetite.

The three databases are merged together. The data from the LAR database and the financial institutions dataset could be combined rather seamlessly. The frequency of the dataset is the same and the data from the financial institutions dataset is complete. The CPFS database is more problematic as the frequency is on an annual basis and there are some issues with missing data. We've made the following hierarchical choice to merge the dataset. We first try to merge loan data to the previous year's CPFS data. We are assuming that the banks have up-to-date (we assumed that the most up-to-date data is the previous year's) financial information before they make their loan decision (compared to the published version, which is available on a 2 year lag). If the previous year's data is not found in the CPFS database, we move back another year and use firm data from 2 years ago. If data from 2 years ago is also not available, we resort back to using the same year CPFS data (this is to done mainly to take into account the start of the two databases, both in 2004). After merging the three datasets, each record will then contain the variables associated with the loan characteristic, the variables associated with the issuing bank, and the variables associated with the borrowing firm.

The data is then cleaned and some obvious inconsistencies were removed. These inconsistencies include missing values and extreme values such as negative or zero contract amounts, contract rates, assets, liabilities, and equities. After filtering and data cleanup, we are left with approximately 2.2 million loan records.

2.2 Descriptive statistics

Table *1* shows a summary of the categorical variables. Firms are grouped into sectors based on ISIC codes. The two industries dominating the Thai loan landscape are commerce and industrials companies, which represent about 90% of all loans. The next three largest sectors are construction, services, and real estate. The Bank of Thailand categorized banks into 4 groups: large Thai banks, medium Thai banks, small Thai banks, and foreign banks. The large banks account for roughly 80% of all loan originations.

Table 1 categorical characteristics

ISIC Code	**100%**
Industrials	45%
Commerce	44%
Construction	5%
Services	3%
Real Estate	2%
Others	1%
Bank Type (BOT Classification)	**100%**
Large	79%
Medium	10%
Small	7%
Foreign	3%

Table *2* shows the key attributes for the 2.2 million loans. Firms and bank variables are based on loan records. Certain percentiles of each variable are tabulated. We noticed that the full range of each variable could be quite large. For example, NLR ranges from the minimum of 0.03% to a maximum of 50%. These extreme values suggest that we should study distributional effects in more detail.

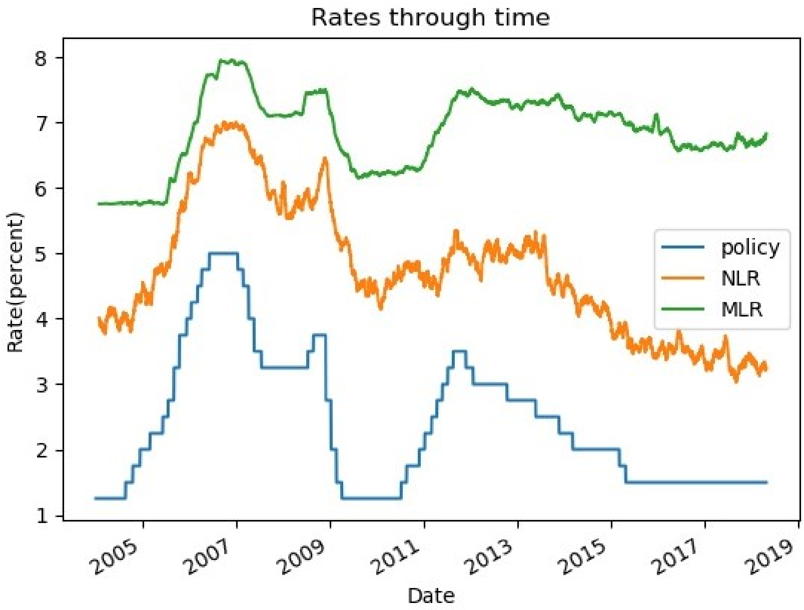
Table 2 Loan, firm, and bank characteristics (based on loan percentiles)

	10th pct	25th pct	50th pct	75th pct	90th pct
Loan Variables					
NLR (%)	3.15	4.52	6.15	7.50	9.30
Contract Amount (MM)	0.5	1.6	5.8	20	60
Firm Variables					
Bank Relationships	1	1	2	3	5
Firm Assets (MM)	49	99	255	777	2,171
ROE (%)	-9.5	1.5	6.5	14.4	24.5
Quick Ratio (%)	17	35	60	90	129
Debt/Equity Ratio	0.8	1.5	3.0	5.5	9.9
Debt Servicing Ratio	-0.9	1.1	1.9	4.0	10.5
Bank Variables					
BIS Ratio (%)	13.4	14.2	15.4	16.7	18.1
Loan to Deposit Ratio (%)	84	89	93	98	109
Current/Savings account to total deposit (%)	36	44	53	61	66
Interest Income to Total income (%)	69	74	79	84	88
Operating Costs (%)	0.37	0.42	0.51	0.56	0.62
NIM (%)	2.3	2.6	3.1	3.5	3.7

2.3 Stylized facts

The policy rates, NLR, and minimum loan rates (MLR) were plotted through time in **Figure *1*** The Bank of Thailand's benchmark policy rate is the 1-day bilateral repurchase rate. New loan rates are the rates of individual loans from the LAR database, weighted by the contract amount. The Bank of Thailand requires financial institutions to announce their individual benchmark rates charged to borrowers. One such rate is MLR, defined to be the rate at which the financial institution charges its high quality corporate customers. In **Figure *1***, the MLR of the individual banks are weighted based on new loan amounts in order to make them comparable to NLR. The NLR and MLR are volatile at the daily level and are shown as 20-day moving averages.

Figure 1 MLR vs NLR



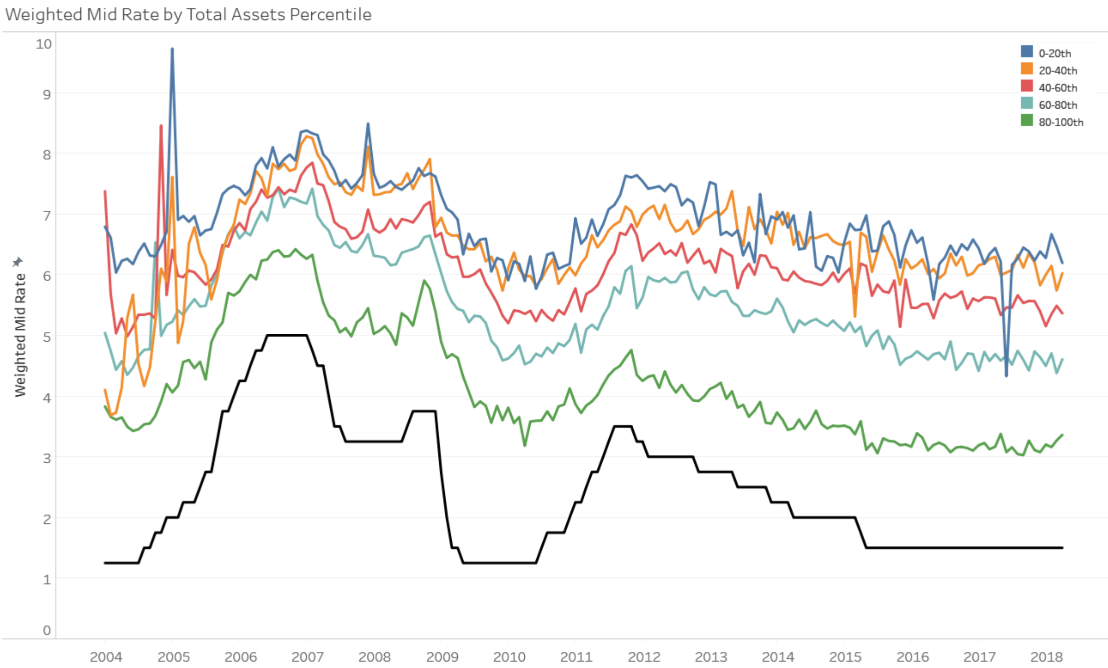
The weighted average NLR and MLR roughly tracks the policy rate. This can also be quantified by the correlation matrix in **Table *3*.** The correlation between the policy rate and NLR and MLR are 0.82 and 0.70, respectively. However, the correlation between MLR and NLR themselves are more modest at 0.48. Another thing to note is that the NLR is actually lower than the MLR throughout the sample period. Although the NLR is weighted by the contract amount and thus dominated by larger firms, we found that even the median new lending rate is lower than MLR (with a caveat that our sample starts off with firms on the higher end of the size spectrum).

Table 3 Correlation Matrix

Correlation Matrix	Policy Rate	NLR	MLR
Policy Rate	1.00	0.82	0.70
NLR	0.82	1.00	0.48
MLR	0.70	0.48	1.00

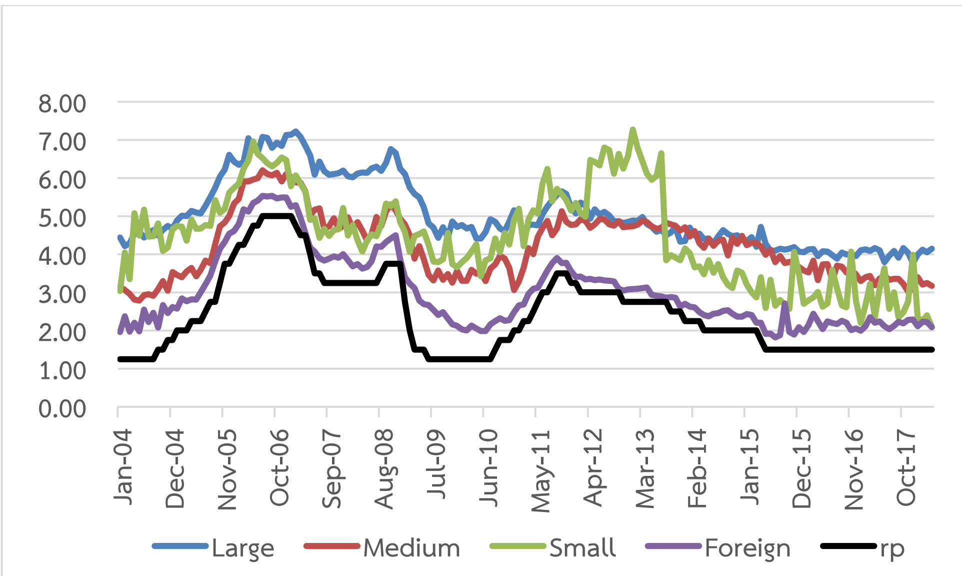
Loan rate differentiation through firm and bank characteristics can be observed visually. For example, the NLR for different percentiles of firm asset sizes are plotted over time in **Figure *2***. The plots clearly show a hierarchy where firms with the lowest assets receive the highest new loan rates and firms with the highest assets receive the lowest new loan rates. This is consistent with theory that banks price loans based on the credit-worthiness of the firms, as firms with more assets are more likely to have more buffer against bad outcomes and are less likely to default on their loans.

Figure 2 NLR by firm sizes



A similar differentiation of NLR could be observed when we group banks based on the Bank of Thailand's classification and are shown in **Figure 3**. Small Thai banks have NLR that are more volatile than other groups. Foreign banks have the lowest NLR, and large Thai banks have the highest rates over the whole timespan. We will want to find out whether this is caused by banks giving out different pricing for the same borrowers or caused by the borrowers being different in each group of banks.

Figure 3 NLR by bank groups



3. Misspecification analysis

In this section, we show the results of interest rate pass-through using two different measures of bank lending rates: MLR and NLR. MLR is a self-reported aggregated measure that is publicly available. NLR is more granular and proprietary; thus never seen used in previous literature on monetary transmission. If MLR is a good representation of the individual loan rates, then the information of overall pass-through should be the same as analyzing using NLR. It was already seen in the data section that the correlation coefficient between NLR and MLR is only modest at 0.48. Our hypothesis is, therefore, that the pass-through using the two different lending rates will be statistically different from each other.

First, we quantify the degree of pass-through in the long-run by estimating a simple interest rate model of the form:

Equation 1

$$Rate_{bt} = \alpha + \sum_{i=0}^{p} \beta_i RP_{t-i} + \varepsilon_{bt}$$

where $Rate_{bt}$ represents either NLR or MLR of bank b at time t, RP_{t-i} represents the Bank of Thailand policy rate at time $t-i$, ε_{bt} is the noise or disturbance term of bank b at time t. The term $\beta = \sum_{i=0}^{p} \beta_i$ is the total degree of interest rate pass-through, which is our key coefficient of interest.

Second, since banks' lending rate may not fully adjust to the changes in monetary policy in one period, we, then, estimate several simple interest rate pass-through models with different number of policy rate lags (varying p from 0 to 6). This enables us to gauge total degree of interest rate pass-through.

Table 4 The pass-through from policy rate to MLR and NLR

	No. of lags	0 lag	1 lag	2 lags	3 lags	4 lags	5 lags	6 lags
MLR	β	0.32***	0.33***	0.33***	0.34***	0.34***	0.35***	0.35***
	95% CI	0.24-0.40	0.24-0.41	0.25-0.42	0.26-0.42	0.26-0.43	0.27-0.43	0.27-0.43
	R-squared	0.19	0.22	0.22	0.23	0.23	0.23	0.23
NLR	β	0.69***	0.70***	0.70***	0.71***	0.71***	0.72***	0.72***
	95% CI	0.59-0.79	0.59-0.80	0.60-0.81	0.60-0.81	0.60-0.82	0.60-0.83	0.61-0.84
	R-squared	0.20	0.21	0.21	0.21	0.21	0.21	0.21
	Observations	45,491	45,491	45,491	45,491	45,491	45,491	45,491
	Banks	28	28	28	28	28	28	28

Note: 1) Data from January 2004 to March 2018 2) based on regression in Equation 1 3) *** denotes significance level of 1 percent

The total effect of changes in monetary policy on NLR and MLR are provided in **Table 4**. The estimated results for both measures show that there are statistically significant relationships between the policy rates and lending rates. The pass-through of MLR is between 32 and 35 percent. This value is in the same range as previous literature by Disyatat and Vongsinsirikul (2002) and by Charoenseang and Manakit (2006). In the case of NLR, the pass-through is around 69 to 72 percent, which is about twice as large as MLR. Moreover, those two 95 percent confidence intervals are not overlapping, which means that results of degree of pass-through given by NLR and MLR estimations are statistically different. This shows that monetary policy transmission may be understated using conventional analysis with the aggregated measure of lending rates in MLR. An inaccurate measure of the lending rates could yield inappropriate policy implications, hence policymakers should not overlook the importance of granular data. This paper, then, would investigate the interest rate pass-through using NLR, which is calculated from granular data, instead of MLR, together with CPFS database and financial institution dataset.

4. Pass-through heterogeneity

4.1 Related literature and empirical strategy

Interest rate pass-through from monetary policy to commercial bank rates has been a recurring theme for central banks. The simplest model of interest rate pass-through can be represented by regressing rates of interest on monetary policy rate. Gregor et al. (2009) described most of the empirical models of interest rate pass-through in the simple form of:

Equation 2

$$commercial\ bank\ rate_t = \alpha + \beta' reference\ rate_t + \varepsilon_t$$

where α represents a markup over the reference rate, and β shows the unconditional interest rate pass-through. Some studies, as well as our misspecification analysis in section 3, also applied this simpler model to study interest pass-through. However, the simple interest rate pass-through model can also modified by adding control variables (e.g. Horvath and Podpiera, 2012; Gambarcorta et al., 2015; Grigoli and Mota, 2017). The modified specification can be described as follows:

Equation 3

$$commercial\ bank\ rate_t = \alpha + \beta' reference\ rate_t + \gamma' control\ variables + \varepsilon_t$$

Control variables can be any variable that can influence the lending rates. These typically include macroeconomic factors and loan characteristics. The macroeconomic factors can include variables such as inflation (Holton and d'Acri, 2015), government bond yield (Holton and d'Acri, 2015; Cifarelli and Paladino, 2016; Gregor and Melecky, 2018), and the CBOE Volatility Index (VIX) (Grigoli and Mota, 2017). He and Wang (2013) included loan maturity and collateral into the interest rate pass-through model in order to capture loan characteristics that affected lending rates.

Therefore, our simple interest rate pass-through model formulated in section 3 can be improved by adding more variables to better evaluate interest rate pass-through. The bank lending rate depends not only on policy rate, but also on other variables such as interest rate risk, credit risk, liquidity premium, as well as banks' targeted profit. We had to expand the specification of our simple pass-through model in order to take into account control variables that affect new loan rates This expansion includes adding loan characteristics, bank characteristics, firm characteristics, and macroeconomic variables. Our paper is interested in the heterogeneity of the bank and firm characteristics and how they determine the level of interest rate and the magnitude of pass-through, therefore, the loan characteristics and macro variables serves only as control variables in the equation and their coefficients will not be displayed in the results. The baseline specification could then be written in the form of:

Equation 4

$$NLR_{lbkt} = \alpha + \textstyle\sum_{i=0}^{p} \beta_i RP_{t-i} + \boldsymbol{\gamma}' loan\ charateristics_{lt} + \boldsymbol{\delta}' bank\ charateristics_{bt} + \boldsymbol{\theta}' firm\ charateristics_{kt} + \boldsymbol{\varphi}' macro_t + \mu_b + \mu_k + \varepsilon_{lbkt}$$

where (1) NLR_{lbkt} represents new loan rate of each loan contract l that bank b gives to firm k at time t, (2) RP_{t-i} denotes Bank of Thailand policy rate at time $t-i$, (3) $loan\ charateristics_{lt}$ is the loan characteristics of loan contract l at time t, (4) $bank\ charateristics_{bt}$ represents bank characteristics of bank b at time t, (5) $firm\ charateristics_{kt}$ denotes firm characteristics of firm k at time t, and (6) $macro_t$ represent the macroeconomic variables at time t. Additionally, we also have added bank and firm fixed-effects in order to control for unobserved heterogeneity in each individual bank and each individual firm.

The bank characteristic variables are chosen because we think that they can affect NLR. Banks with higher CAR and lower LDR, reflecting higher capital and liquidity, should be able to set lower loan prices. In addition to these standard indicators, there are other characteristics that should affect loan rates. Banks with higher CASA ratio can set a lower loan rate as these types of deposits are the cheapest funding sources. As for business models, some banks have gradually altered their business strategies by shifting towards non-interest income in order to preserve profit during in the prolonged low interest rate environment. The banks' price setting behavior may or may not be affected by this. Next, banks with higher operating costs, which is normalized by total assets, should charge more expensive loan rates to cover these costs. The last variable to be included in the equation, the banks' risk appetite, determined by net interest margin (NIM), can directly influence banks' pricing setting behavior. The role of NIM in determining loan price is quite straightforward: the higher the targeted-NIM should translate to higher loan rates.

The firm characteristic variables were chosen in the same way as the bank variables. Firms with higher negotiation power and more bank relationships could use this leverage to obtain lower loan rates. A firm's asset size could mean that they have some buffer and are less likely to default on their obligations, which translates to a lower borrowing rate. The quick ratio, debts to equity (DE) ratio, and debts-service coverage ratio (DSCR) are a measure of firm's ability to repay its obligations with its most liquid assets, shareholder equity, and the cash flow respectively. Hence, firms with higher quick ratio, lower DE ratio, and higher DSCR tend to get lower loan rate. The ROE ratio is also related to the ability to generate cash flow and a higher ratio should mean a lower rate.

[To add references on rate setting behavior, especially those based on micro-dataset.]

Next, in order to observe heterogeneity of interest rate pass-through across bank and firm characteristics, the baseline specification should be expanded, where it can be written in the following form:

Equation 5

$$NLR_{lbkt} = \alpha + \sum_{i=0}^{p} \beta_i RP_{t-i} + \boldsymbol{\gamma}'loan\ charateristics_{lt} + \boldsymbol{\delta}'bank\ charateristics_{bt} + \boldsymbol{\theta}'firm\ charateristics_{kt} + \boldsymbol{\varphi}'macro_t + \mu_b + \mu_k + \boldsymbol{\omega}'\boldsymbol{interaction\ terms} + \varepsilon_{lbkt}$$

where $interaction\ terms$, which are added to the baseline specification, represent interaction terms between the policy interest rate and the observed characteristics of both banks and firms. These coefficients of interaction term allow us to examine how such characteristics influence the degree of pass-through.

It is known that information asymmetry and frictions in the credit markets allow banks to either amplify or dampen the impact of monetary policy through adjustments in credit supply (Bernanke and Blinder, 1988 and 1992), this is known as the credit channel. Bernanke and Gertler (1995) explained that the credit channel can be divided into two subgroups: the bank lending channel and the balance sheet channel. The mechanism behind the bank lending channel works through the lenders' or banks' balance sheet and the mechanism behind the balance sheet channel works through the borrowers' or firms' balance sheet. Afterwards, several studies attempt to test heterogeneity of monetary policy transmission across banks and firms (bank lending and balance sheet channels, respectively) using granular data (e.g. Gertler and Hubbard (1988), Gertler and Gilchrist (1994), Kashyap and Stein (2000), Khwaja and Mian (2008), and Jimenez et al (2012)). However, to the best of our knowledge, there has never been a study related to heterogeneity of interest rate pass-through using loan-level data in Thailand.

The development of our initial hypotheses of how bank and firm characteristics affect the pass-through of policy rates to bank lending rates are discussed here. We will start with bank characteristics, where Gambacorta (2008) found that banks maintaining higher level of capital have slower and weaker pass-through. However, for the case of Thailand, bank with different level of capital, CAR, might not generate a different response to policy rate. This is because Thai commercial banks have retained CAR almost twice as high as the requirement floor. This argument is supported by study of Ananchotikul and Seneviratne (2015), who used aggregate data and found weak evidence that different levels of bank capitalization create heterogeneous responses of bank lending volume to policy rates. Meanwhile, banks with higher LDR, reflecting tighter liquidity, respond to policy rate shocks stronger and faster (Kashyap and Stein, 2000). As for the less-standardized indicators, current and saving accounts are considered to be a source of stable funding for banks and, therefore, bank with a higher ratio of their funding in these accounts tend to be less sensitive to policy rate movements. With regards to business models, banks with more reliance on interest rate incomes should be more sensitive to policy rate changes. This is because those banks with less reliance on interest rate incomes can still generate a stable and predictable cash-flow following a change in policy rates through non-interest income.

Looking at the balance sheet channel, a number of studies have examined the effects of monetary policy on different types of firms. Gertler and Gilchrist (1994) pointed out that small and large firm respond to monetary policy at a different degree and speed. Theoretically, larger firms and firms that having more banks relationships, tend to get more stable loan supply; therefore, it was not surprising that, empirically, loan volume of those firms are less likely to be affected by monetary policy shock (Detragiache et al., 2000; Ananchotikul and Limjaroenrat, 2017). However, these results were based on loan quantities and the relationship between loan quantities and loan rates are still unclear and could well be different. We postulate that these firms could have a higher degree of the interest rate pass-through from policy rates as they receive low loan rates tracking closer to money market rates. This would mean firms with higher quick ratios, lower DE ratios, higher DSCR, and higher ROE are likely to be more responsive to policy rate shocks.

4.2 Results

4.2.1 Lag Selection

Before we start analyzing results, we have to choose the value of p, the number of policy-rates lag terms to use in the equation. We have selected three criteria for choosing the optimal number of lag terms for the baseline specification. For the first criterion, the chosen number should reflect total degree of pass-through from policy rate to lending rate. That is, when we add some more lag, $\sum_{i=0}^{p} \beta_i$, representing the total degree of pass-through, should be stable and statistically significant. Second, the goodness of fit of the model, which is reflected by overall adjusted R-squared, is also considered. For the last criterion, each β coefficient should be economically sensible. In other words, every β coefficient in front of the policy rate lags should be positive.

Table *5* shows the total pass-through from policy rate to NLR with different maximum lags of policy rates varying from zero to six, estimated from the baseline model Equation 4. These results show that the sum of policy rate coefficients gradually increases and plateaus as more lags are added. The 95 percent confidence intervals that overlap for models with more lags helps establish that the sums of the coefficients are not statistically different. The overall R-squared in the different models are almost indistinguishable. We have to resort to using the last criterion to make sure that all β_i coefficients of policy rate are positive and economically sensible. This is true when we include up to 2 lags of the policy rates. This implies that the effects of policy rate changes last for around 3 months and that the total interest rate pass-through from policy rate to NLR is about 60 percent.

Table 5 The total pass-through from policy rate to NLR estimated from the baseline model

No. of lags	0 lag	1 lag	2 lags	3 lags	4 lags	5 lags	6 lags
$\sum_{i=0}^{p}\boldsymbol{\beta_i}$	**0.57*** **	**0.59*** **	**0.60*** **	**0.61*** **	**0.62*** **	**0.62*** **	**0.62*** **
$\boldsymbol{\beta_0}$	0.57***	0.11***	0.19***	0.28***	0.31***	0.29***	0.26***
$\boldsymbol{\beta_1}$		0.48***	0.02	0.00	0.03**	0.07***	0.09***
$\boldsymbol{\beta_2}$			0.39***	-0.09***	-0.10***	-0.10***	-0.06***
$\boldsymbol{\beta_3}$				0.42***	0.09***	0.10***	0.12***
$\boldsymbol{\beta_4}$					0.29***	0.06***	0.04**
$\boldsymbol{\beta_5}$						0.20***	-0.05***
$\boldsymbol{\beta_6}$							0.22***
Constant	7.34***	6.76***	6.48***	6.36***	6.36***	6.32***	6.29***
95% CI of $\sum_{i=0}^{p}\boldsymbol{\beta_i}$	0.54-0.59	0.57-0.61	0.58-0.62	0.59-0.64	0.59-0.64	0.60-0.64	0.60-0.65
Overall R-squared	0.35	0.34	0.34	0.34	0.34	0.34	0.34

Notes: 1) Data from January 2004 to March 2018 2) ***, **, * denotes significant level of 1, 5, and 10 percent respectively 3) There are 2,154,064 observations, 28 banks, and 28,624 firms 6) The results include controls for loan characteristics and macro variables (loan types, loan maturity, loan purposes, GDP, headline inflation, VIX, and Thai government yield slope)

4.2.2 Loan rate setting – bank characteristics

According to the baseline model in ***Equation 4***, we use individual banks and firms fixed-effects to control for unobserved heterogeneity arising from those banks and firms. Nevertheless, bank and firm fixed-effects do not allow us to explore coefficients on bank size as classified by BOT's definition and business types represented by ISIC code as they are constant over time. Hence, we alter the baseline model by replacing firm and bank fixed-effects with higher-level clusters in order to be able to interpret meaningful results on the variables of interest.

Table *6* illustrates regression results from the baseline model (Equation 4) with different types of clusters. The first estimation is controlled with lower-level clusters (individual banks and firms), whereas the last one is controlled with higher-level clusters (bank size fixed-effects and business type fixed-effects). We found that the first three models similar results, that is, most of coefficients have the same signs and are of comparable size. Henceforth, we focus on model two and three in order to observe the influence of bank and firm characteristics on price setting behaviors and heterogeneities in the interest rate pass-through.

Table 6 The total pass-through from policy rate to NLR estimated from the baseline model

Variables of interest		(1)	(2)	(3)	(4)
Monetary policy	**RP**	0.6013***	0.6004***	0.5748***	0.5119***
Bank characteristics	**Medium bank**		-0.7801***		-1.0216***
	Small bank		0.0065		0.4073***
	Foreign bank		-0.2859***		-0.5450***
	CAR	0.0480***	0.0310***	0.0770***	0.0402***
	LDR	0.0046***	0.0024***	0.0018	-0.0041***
	CASA ratio	-0.0292***	-0.0225***	-0.0298**	-0.0292***
	Int. income ratio	-0.0003	-0.0007	-0.0003	-0.0007***
	Operating cost ratio	0.7260***	1.1855***	0.9219	1.6907***
	NIM	0.2581***	0.3065***	0.2881**	0.4395***
Firm characteristics	**Agriculture**			-0.4397***	-0.5596***
	Mining			0.1952	0.2626***
	Commerce			0.0422	0.0392***
	Construction			1.2161***	1.2094***
	Real estate			0.2703	0.2555***
	Utilities			-0.0318	-0.0431***
	Service			0.3626**	0.4280***
	Bank relationships	-0.1041***	-0.0985***	-0.1212***	-0.1119***
	Log(total assets)	-0.0450	-0.0449	-0.3399***	-0.3585***
	Quick ratio	-0.0043	-0.0032	-0.0083**	-0.0094***
	ROE ratio	-0.0005*	-0.0005*	-0.0001	0.0004***
	DE ratio	0.0038	0.0034	0.0079***	0.0094***
	DSCR	-0.0007**	-0.0007**	-0.0037***	-0.0040***
Overall R-squared		0.3388	0.3057	0.3364	0.3742
Firm fixed effect		yes	yes	no	no
Bank fixed effect		yes	no	yes	no
ISIC fixed effect		no	no	yes	yes
BOT's bank size classification fixed effect		no	yes	no	yes
Control variables		yes	yes	yes	yes

Notes: 1) Data from January 2004 to March 2018 2) ***, **, * denotes significant level of 1, 5, and 10 percent respectively 3) There are 2,154,064 observations, 28 banks, and 28,624 firms 6) The results include controls for loan characteristics and macro variables (loan types, loan maturity, loan purposes, GDP, headline inflation, VIX, and Thai government yield slope)

We can explore the price-setting behavior for banks using the estimation results shown in model 2 in **Table 6**. They suggest that banks with higher capital, tighter liquidity, less efficient operation, and higher risk appetite tend to set higher loan rates. Meanwhile, banks with more stable funding lend with lower rates and bank business models do not determine price setting. The baseline for bank size dummies is the group of large Thai banks. Both medium foreign banks set relatively lower lending rates than large Thai banks. The difference between small and large Thai banks are not statistically significant. This is likely because of competition as large banks do not need to fight for every loan and small banks may not have the economies of scale to offer lower rates. Other than the capital ratio, all the results are in line with expectations. Banks with high liquidity, more efficient operation, and more stable funding can afford to have lower lending rates. The relationship between NIM and higher lending rates are trivial as they have a circular relationship. Banks with a higher profitability and NIM targets will set higher rates and higher rates will lead to a higher NIM.

The results in **Table 6** show only how those characteristics determine NLR, and may be limited in showing how much each factor contribute to price setting differentiation in practice. We augment those results by finding the difference between the 75th and 25th percentile of each data variable and multiplying them by the coefficients. This will yield the interest rate differentiation between being in the 75th as oppose to being in the 25th percentile. We will call this number economically significant if it is greater than 5 basis points.

Equation 6

$$differentiation_X = \beta_x (X_{75} - X_{25})$$

where β_x is the coefficient of characteristic X; X_{75} and X_{25} are the 75th and 25th percentile of variable X.

The results are illustrated in **Table 7**. We do not show the results for bank size, as interquantile ranges for dummy variables are not meaningful. We find that funding structure, risk appetite, capital, and operational efficiency are the four main factors on the bank side that most affect differentiations in loan pricing. Bank heavily relying on CASA, which is reflected by being in the 75th percentile, seems to set lending rate lower than bank at the 25th percentile by almost 50 basis points. Meanwhile, the difference between maintaining a low or high LDR is unlikely to result in heterogeneity in bank pricing even though the variable (0.0046) is statistically significant because the total difference on the loan rate between the 75th percentile and 25th percentile is less than 5 basis points.

Table 7 Differentiation of loan pricing between bank at the 75th percentile and the 25th percentile of each determinant

Variables of interest		(β_x)	$(X_{75} - X_{25})$	Loan pricing differentiation
Bank characteristics	**CAR**	0.0480***	2.5	0.1200
	LDR	0.0046***	9	0.0414
	CASA ratio	-0.0292***	17	-0.4964
	Int. income ratio	-0.0003	10	-0.0030
	Operating cost ratio	0.7260***	0.14	0.1016
	NIM	0.2581***	0.9	0.2323
Firm characteristics	**Bank relationships**	-0.1041***	2	-0.2082
	Log(total assets)	-0.0450	6.52	-0.2934
	Quick ratio	-0.0043	55	-0.2365
	ROE ratio	-0.0005*	12.9	-0.0065
	DE ratio	0.0038	4	0.0152
	DSCR	-0.0007**	2.9	-0.0020

Notes: 1) Data from January 2004 to March 2018 2) ***, **, * denotes significant level of 1, 5, and 10 percent respectively 3) There are 2,154,064 observations, 28 banks, and 28,624 firms 6) The results include controls for loan characteristics and macro variables (loan types, loan maturity, loan purposes, GDP, headline inflation, VIX, and Thai government yield slope)

4.2.3 Loan rate setting – firm characteristics

The effect of firm characteristics on loan rate setting can be observed in **Table 6** using model 3. Firms with higher bargaining power, higher profitability and higher cash-flow-to-debt-costs receive lower loan rates. Better abilities to negotiate and bargain should lead to more favorable rates. Banks should price loans using the borrowers' risk profile and ROE and DSCR ratios is a good representation of the firms' ability to pay back debt. Meanwhile, firms in the services, real estate, and construction sectors are likely to obtain higher loan rates compared to the benchmark industrial sector. These sectors are more volatile and thus riskier in the long run than other sectors. On the other hand, agricultural firms tend to get lower loan rate. This could be a result of two factors. The first factor is that the food sector in general is not cyclical and the second factor is that there are many large agricultural conglomerates in Thailand and the simple balance sheet does not reflect relationships between firms.

Similar to the previous analysis on banks, we look at **Table 7** to analyze economic meaning of the coefficients by studying loan price differentiation. Bank relationships, ROE, and quick ratios are statistically significant and contribute to more differentiation of the loan rate than 20 basis points.

4.2.4 Pass-through – bank characteristics

Table *8* presents results for Equation 5 where we appended interaction terms between bank characteristics and policy rates to the baseline equation. The empirical results support that heterogeneity in bank characteristics do contribute to a difference in the degree of interest rate pass-through. We only include one type of interaction terms per regression for model parsimony and ease of interpretation, thus generating 7 different models. In model (1) where the interaction terms is between bank size and policy rates, we found that lending rates for small banks are least sensitive to changes in monetary policy, while foreign banks tend to pass monetary policy shocks through to their lending rates at a higher degree in comparison to other bank types. As predicted, we found in model (2) that the interest rate pass-through is weaker if the bank has higher capital. Meanwhile in model

(3), banks with relatively illiquid balance sheet are likely to be correlated with stronger pass-through. Other factors such as funding structure (4), efficiency (5), business model (6) and NIM (7) are also statistically significant in determining pass-through. Banks with more stable funding, less efficiency, and higher risk appetite have a tendency to be associated with weaker pass-through. On the other hand, there exists a stronger pass-through when the banks' business model substantially focus on interest rate income. However, in order to observe which factors economically contribute to heterogeneity of pass-through, the usage of differentiation between 75th percentile and the 25th percentile is considered again. We observe that higher operational efficiency, higher risk appetite, higher funding structure, and higher capital, generate an economic difference (>5 basis points) in the degree of pass-through between the 75th and the 25th percentiles.

4.2.5 Pass-through – firm characteristics

Heterogeneity in interest rate pass-through across firms is shown in **Table 9**. We again have 7 different models, each model include one type of interaction terms. Starting with business types (1), we found that every sector has a lower degree of pass-through compared to the baseline industrials sector. However, if we use statistical significance of 95 percent as the cut-off, only mining, construction, and service sectors have statistically lower pass-through.

Looking back to model 3 in **Table 6**, we observed a common trend that all these sectors receive higher rates than the baseline industrial sector. In general we found that firms that receive lower loan rates are likely to be strongly affected by changes in policy rate, and vice versa. Looking at statistical significance, such firms can be classified by high bargaining power, high assets, and low debt servicing costs. Our test for economic significance by pass-through differentiation showed that firm size seems to be the biggest source of heterogeneity of pass-through across firms. This is because larger firms at the 75th percentile tends to obtain higher pass-through, on average almost 30 basis points, compared to small firms at the 25th percentile. One other firm variable with both statistical significance and economical significance is bargaining power.

Table 8 Heterogeneity of interest rate pass-through across banks

Interaction terms between policy rate and bank characteristics ($\sum_{i=0}^{2} \omega_i$)	Model (1) Bank size	Model (2) capital	Model (3) liquidity	Model (4) Funding structure	Model (5) Business model	Model (6) Operational efficiency	Model (7) Risk appetite
Medium bank	0.0378						
Small bank	-0.1062***						
Foreign bank	0.1115***						
CAR		-0.0274***					
LD ratio			0.0015***				
CASA ratio				-0.0051***			
Int. income ratio					0.0034***		
Operating cost ratio						-0.8109***	
NIM							-0.1037***
75th percentile – 25th percentile		2.5	9	17	10	0.14	0.9
Loan pricing differentiation		-0.0685	0.0135	-0.0867	0.0340	-0.1135	-0.0933
Overall R-squared	0.3079	0.3134	0.3050	0.3081	0.3015	0.3156	0.3104
Firm fixed effect	yes	yes	yes	yes	yes	yes	yes
Bank fixed effect	no	no	no	no	no	no	no
ISIC dummy	no	no	no	no	no	no	no
BOT's bank size classification dummy	yes	yes	yes	yes	yes	yes	yes
Control variables	yes	yes	yes	yes	yes	yes	yes

Notes: 1) Data from January 2004 to March 2018 2) ***, **, * denotes significant level of 1, 5, and 10 percent respectively 3) There are 2,154,064 observations, 28 banks, and 28,624 firms 6) The results include controls for loan characteristics and macro variables (loan types, loan maturity, loan purposes, GDP, headline inflation, VIX, and Thai government yield slope)

Table 9 Heterogeneity of interest rate pass-through across firms

Interaction terms between policy rate and firm characteristics ($\sum_{i=0}^{2} \omega_i$)	Model (1) Business type	Model (2) Bargaining power	Model (3) size	Model (4) Liquidity	Model (5) Profitability	Model (6) Leverage	Model (7) Cash-flow generation to pay debt
Agriculture	-0.1983						
Mining	-0.1844**						
Commerce	-0.0427						
Construction	-0.1076**						
Real estate	-0.0650						
Utilities	-0.1029*						
Service	-0.1494**						
Bank relationships		0.0281**					
Log(total assets)			0.0443***				
Quick ratio				-0.0016			
ROE ratio					0.0000		
Debts to equity ratio						-0.0036	
DSCR							0.0007**
75^{th} percentile – 25^{th} percentile		2	6.52	55	12.9	4	2.9
Loan pricing differentiation		0.0562	0.2888	-0.0880	0.0004	-0.0144	0.0020
Overall R-squared	0.3371	0.3371	0.3375	0.3365	0.3364	0.3366	0.3365
Firm fixed effect	no	no	no	no	no	no	no
Bank fixed effect	yes	yes	yes	yes	yes	yes	yes
ISIC dummy	yes	yes	yes	yes	yes	yes	yes
BOT's bank size classification dummy	no	no	no	no	no	no	no
Control variables	yes	yes	yes	yes	yes	yes	yes

Notes: 1) Data from January 2004 to March 2018 2) ***, **, * denotes significant level of 1, 5, and 10 percent respectively 3) There are 2,154,064 observations, 28 banks, and 28,624 firms 6) The results include controls for loan characteristics and macro variables (loan types, loan maturity, loan purposes, GDP, headline inflation, VIX, and Thai government yield slope)

N

5. Distributional effects

Regression results for firm heterogeneity of pass-through to firms demonstrated that generally firms with characteristics that result in lower rates gets more pass-through than firms with characteristics that result in higher rates. In this section, we will use a different method to support the results from the previous regressions. We will answer the more generic question: controlling for other factors, do firms with lower borrowing rates receive more policy rate pass-through? This question can be answered using quantile regressions. Apart from the main question of interest, loan pricing factors for different quantiles can also be compared.

The method of quantile regression was first introduced by Koenker and Bassett (1978). An optimization problem to define quantiles given a set of data can be represented by the following equation.

Equation 7

$$\min_{\xi} \sum \rho_\tau(y_i - \xi)$$

where $\rho_\tau$is the tilted absolute value function and τ is the quantile of interest:

Equation 8

$$\rho_\tau(x) = \begin{cases} \tau x \quad if\ y_i > \xi \\ (\tau - 1)x \quad if\ \ y_i < \xi \end{cases}$$

In a typical linear regression, the coefficients can be found through the following ordinary least squares equation:

Equation 9

$$\min_{B} \sum (y_i - f(x_i, B))^2$$

In a similar manner, the coefficients of a quantile regression can be found by replacing the squared term by ρ_τ. The squares are not necessary since the ρ_τ function is defined to always be positive.

Equation 10

$$\min_{B} \sum \rho_\tau(y_i - \xi(x_i, B))$$

Literature on the distributional effects of monetary policy transmission is sparsely populated. Holton and d'Acri (2018) studied the distributional effects of bank characteristics on pass-through. However, their aim was slightly different as they were trying to split bank characteristic into quantiles and we are splitting loan rates into quantiles. They ran individual regressions to determine whether pass-through is different between the bank characteristic quantiles. The result showed that smaller banks and banks with higher NPL have higher pass-through than big banks and banks with lower NPL. De Santis and Surico (2013) studied the effects of monetary policy transmission using quantile regressions across multiple Eurozone countries but their dependent variable was loan growth, not lending rates like this paper.

There have been previous papers that covered the distributional effects of interest rates. Charles et al (2008) and Cheng et al (2015) used quantile regressions to study effects of race on vehicle and mortgage borrowing rates, respectively. These studies, however, did not look at policy rates and transmission mechanisms. We have not found literature that attempted to answer the same research question proposed in this section.

We use the base model from Equation 4 as a starting point for the quantile regressions. Given the more resource intensive task of finding numerical solutions via numerical methods, we decided to use the highest level clusters of bank size indicators and firm sector indicators as dummy variables. Three quantiles of interest were chosen: 50th, 25th, and 75th. The median regression will be used to further check the robustness of the results from section 4. The 25th and 75th percentiles will be used as proxies for firms receiving low borrowing rates and firms receiving high borrowing rates, respectively.

Equation 11

$$\begin{aligned} NLR_{lbkt}^{(q)} = \alpha^{(q)} + \textstyle\sum_{i=0}^{p} \beta_i^{(q)} RP_{t-i} + \boldsymbol{\gamma}^{(q)'} loan\ charateristics_{lt} + \\ \boldsymbol{\delta}^{(q)'} bank\ charateristics_{bt} + \boldsymbol{\theta}^{(q)'} firm\ charateristics_{kt} + \\ \boldsymbol{\varphi}^{(q)'} macro_t + \mu_b + \mu_k + \varepsilon_{lbkt}^{(q)} \end{aligned}$$

where $X^{(q)}$ is variable X in quantile q and $\beta^{(q)}$ represent the corresponding coefficients in quantile q.

The result for the median regression is shown in **Table 10**. The 25th and 75th quantile results, along with their differences, are also displayed. The result on pass-through is consistent with results from section 4.3 on firm heterogeneity. The loans in the 25th percentile receives approximately 0.20 more pass-through than loans in the 75th percentile. So the conclusion for the main question in this section is that monetary policy pass-through is higher for better firms with lower loan rates than those with higher loan rates.

The results of the distributional effects on bank characteristics are as follows. Loans in the 75th percentiles and originating from small, medium, and foreign banks receive lower rates than 25th percentiles compared to the baseline large banks. This may mean that the large banks place less value on riskier loans and is less competitive in that sector. The other coefficients of the bank characteristics are hard to interpret in this case since the quantiles are split using loan rates which more or less corresponds with creditworthiness of firms and not bank characteristics.

As for the distributional effects on firm characteristics, firms in real estate and services sectors have higher relative rates than industrial firms in the 75th percentile compared to the 25th percentile. Firms with more bank relationships and higher quick and debt-to-equity ratios get lower rates in the 75th percentile compared to the 25th percentile. While firms with higher assets, ROE ratio, and debt-servicing costs gets higher rates in the 75th percentile compared to 25th. The general result is similar to the base mean regression which is shown in the 4th column in **Table 6**. The overall pass-through for the median regression is 0.48 which is close to 0.51, the pass-through for the mean regression. The other coefficients have the same signs with one exception being the commerce firm type dummy. Although the commerce dummy coefficients in the two models are statistically different from zero, the economic interpretation may not be because the both coefficients are less than 5 basis points.

The 25^{th} and 75^{th} quantile results, along with their differences, are also displayed in **Table 10**. The result on pass-through is consistent with results from section 4.3 on firm heterogeneity. The loans in the 25^{th} percentile receives approximately 0.20 more pass-through than loans in the 75^{th} percentile. So the conclusion for the main question in this section is that monetary policy pass-through is higher for better firms with lower loan rates than those with higher loan rates.

The results of the distributional effects on bank characteristics are as follows. Loans in the 75^{th} percentiles and originating from small, medium, and foreign banks receive lower rates than 25^{th} percentiles compared to the baseline large banks. This may mean that the large banks place less value on riskier loans and is less competitive in that sector. The other coefficients of the bank characteristics are hard to interpret in this case since the quantiles are split using loan rates which more or less corresponds with creditworthiness of firms and not bank characteristics.

As for the distributional effects on firm characteristics, firms in real estate and services sectors have higher relative rates than industrial firms in the 75^{th} percentile compared to the 25^{th} percentile. Firms with more bank relationships and higher quick and debt-to-equity ratios get lower rates in the 75^{th} percentile compared to the 25^{th} percentile. While firms with higher assets, ROE ratio, and debt-servicing costs gets higher rates in the 75^{th} percentile compared to 25^{th}.

Table 10 Quantile regression results

Variables of interest		Median	25th	75th	75th-25th
Monetary policy	RP	0.4825***	0.6385***	0.4384***	-0.2001 ***
Bank characteristics	Medium bank	-0.8748***	-0.5252***	-1.1884***	-0.6631***
	Small bank	0.5330***	0.6026***	0.5251***	-0.0776***
	Foreign bank	-0.3411***	-0.2347***	-0.5437***	-0.3090***
	CAR	0.0272***	0.0283***	0.0149***	-0.0134***
	LDR	-0.0058***	-0.0010***	-0.0053***	-0.0042***
	CASA ratio	-0.0260***	-0.0166***	-0.0303***	-0.0137***
	Int. income ratio	-0.0004***	-0.0015***	0.0002***	0.0017***
	Oper cost ratio	1.4235***	1.2390***	2.9980***	1.759***
	NIM	0.3054***	0.2425***	0.5105***	0.2680***
Firm characteristics	Agriculture	-0.4886***	-0.3167***	-0.7433***	-0.4266***
	Mining	0.2766***	0.6080***	0.0297	-0.6377***
	Commerce	-0.0256***	0.0214***	-0.0160***	-0.0374***
	Construction	1.2224***	1.4818***	1.0842***	-0.3975***
	Real estate	0.6296***	0.3748***	0.4351***	0.0603***
	Utilities	-0.0259***	0.0850***	-0.1438***	-0.2288***
	Service	0.5848***	0.4752***	0.5795***	0.1044***
	Bank relationships	-0.1036***	-0.1143***	-0.1311***	-0.0168***
	Log(total assets)	-0.4135***	-0.3869***	-0.3354***	0.0515***
	Quick ratio	-0.0062***	-0.0062***	-0.0093***	-0.0094***
	ROE ratio	0.0009***	-0.0012***	0.0010***	0.0022***
	DE ratio	0.0095***	0.0109***	0.0038***	-0.0071***
	DSCR	-0.0037***	-0.0049***	-0.0032***	0.0018***
Overall R-squared		0.2654	0.2361	0.2139	
Firm fixed effect		No	No	No	
Bank fixed effect		No	No	No	
ISIC fixed effect		Yes	Yes	yes	
BOT's bank size fixed effect		Yes	Yes	Yes	
Control variables		Yes	Yes	Yes	

Note: (1) 75^{th} – 25^{th} column is the difference between the 75^{th} and 25^{th} percentiles
(2) significance in the last column is based on linear hypothesis testing
(3) *** denote significance level of 1 percent

6. Structural break – Global financial crisis (GFC)

Our dataset starts in 2004 and there has not been a crisis that specifically affected Thailand since that time. However, there have been multiple studies about how monetary transmission has changed since the global financial crisis in 2008/2009. Through studies of spreads in lending rates and policy rates, Illes and Lombardi (2013) demonstrated little change in transmission in the United States and Germany. Employing panel VAR models, Hristov (2014) found that interest rate pass-through in the Euro area has weakened since the global financial crisis. Havranek (2016) have confirmed similar results of weakening transmission using loans from the Czech Republic. We are then interested to see which of these two competing views apply to policy rate pass-through in Thailand.

The model used for this section will be slightly modified from the one used in section 4 in the first column of **Table 6**. The most granular model leveraging firm and bank fixed effects will be utilized here. We have added an after-GFC dummy variable (defined to be the date after January 31st, 2009) to the equation as follows:

Equation 12

$$NLR_{lbkt} = \alpha + \sum_{i=0}^{p} \beta_i RP_{t-i} + \sum_{i=0}^{p} \chi_i RP_{t-i} * GFCdummy + \boldsymbol{\eta} GFCdummy + \boldsymbol{\gamma}' loan\ charateristics_{lt} + \boldsymbol{\delta}' bank\ charateristics_{bt} + \boldsymbol{\theta}' firm\ charateristics_{kt} + \boldsymbol{\varphi}' macro_t + \mu_b + \mu_k + \varepsilon_{lbkt}$$

The results are shown in **Table 11**. **Figure 1** that showed MLR vs NLR over time would have given us a clue to the results for this section, most notably during the 2010-2011 hike cycle where the NLR was little changed compared to the policy rate. The overall transmission was markedly lowered after the global financial crisis, decreasing from 0.68 to 0.35. There appears to be a structural change after 2008/2009 even though Thai banks were not directly hit by the crisis. This decrease in transmission could in part be explained by an increase in liquidity. This excess liquidity in the Thai banking system could be explained by spillovers from other economies. Specifically, the unconventional policies taken by the Federal Reserve, Bank of England, and ECB, have increased the flow of funds into emerging market countries and provide excess liquidity. The implication here is that policy makers must take into account possible spillover effects from other countries into consideration

Table 11 Transmission after GFC

No. of lags	
$\sum_{i=0}^{2}(\beta_i)$	0.6847***
$\sum_{i=0}^{2}\chi_i$	-0.3393***
$\boldsymbol{\eta}$	0.8837
observations	2,154,064
Overall R-squared	0.3092

7. Conclusion

This paper make a significant contribution to the literature on the transmission of monetary policy by studying interest rate pass-through using loan-level data in Thailand. We show that aggregated measures such as MLR do not represent loan-level NLR and studies using aggregated measures may considerably understate the degree of pass-through in monetary policy.

We found that heterogeneity in bank characteristics leads to different degrees of monetary policy rate pass-through. The following characteristics economically affect pass-through: size, capital, funding structure, operational efficiency, and risk appetite. The pass-through is stronger for foreign banks and weaker for small banks. The reasoning behind this will require further research. The pass-through is weaker for banks with high capital, more cheap funding structure, high efficiency, and higher NIM. This tends to point out that banks with better balance sheets have less constraints and can choose to reduce the rate of pass-through.

The heterogeneity in firm characteristics also leads to different degrees of policy rate pass-through. The business sectors receiving higher rates, including mining, construction, and services, get less pass-through. Firms with higher bargaining power and higher size tend to receive more pass-through. The general theme is that firms with lower rates get statistically and economically higher pass-through, and vice versa. This was further confirmed using quantile regressions. The policy implication here is that policy rates have more of an effect on bigger and richer firms and less on the smaller, riskier ones.

The monetary policy rate pass-through was considerably weaker after the global financial crisis in 2008/2009. This is an interesting finding since the crisis did not directly affect the financial institutions in Thailand directly. This is likely caused by the excess liquidity in the financial system, an indirect effect of quantitative easing by central banks in the developed world.

There are several areas primed for further research. One such area is the policy rates' effect on loan quantities. It is known that monetary policy affects both the rate and the amount of corporate lending. This study dove into the details of the effects on the rate, thus the amount is left for further exploration. It would also be beneficial to further research the effects of monetary policy on loan demand and loan supply, but those research will require more granular data, such as loan applications and decisions to approve or decline them.

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