PIER

PUEY UNGPHAKORN INSTITUTE
FOR ECONOMIC RESEARCH

Bank Supply Shocks and Firm Investment: A Granular View from the Thai Credit Registry Data

by

Nasha Ananchotikul and Vorada Limjaroenrat

August 2017

Discussion Paper

No. 67

Bank Supply Shocks and Firm Investment:

A Granular View from the Thai Credit Registry Data

Nasha Ananchotikul

Vorada Limjaroenrat[1]

Draft: August 2017

Abstract

This paper attempts to link bank loan supply shocks to the real economic activity at the firm and aggregate level. We apply the methodology pioneered by Amiti and Weinstein (2017) to bank-firm credit registry dataset in Thailand for the period of 2004-2015. Loan growth dynamics of individual banks and individual firms are exactly decomposed into a time series of bank, firm, industry, and common shocks. We show that the bank and firm shocks obtained using this method are consistent with various measures of individual banks' and firms' balance sheet health, supporting the validity of the shock decomposition. Results from firm-level regressions indicate that bank supply shocks do matter for firm investment activity even after controlling for common, industry, firm-specific shocks and firm's leverage. We find that Thai firms are generally highly sensitive to bank lending shocks, particularly firms that borrow from only one bank and have low propensity to switch to another bank. The size and the dynamics of bank shocks appears to differ between heathy versus unhealthy, and small versus large firms, suggesting differential bank lending policy across different types of firms. At the aggregate level, we find that granular bank shock accounts for around 37 percent of aggregate lending growth and is the major source of financial shocks driving aggregate investment.

JEL classification: D22, E22, E44, G10, G21,

Keywords: Bank supply shocks, Credit cycle, Bank relationships, Bank concentration, Granular shocks, Firm investment, Credit registry data, Thailand

---

[1] Ananchotikul, Section Head: Monetary Policy Research, Puey Ungphakorn Institute for Economic Research, Bank of Thailand, nashaa@bot.or.th. Limjaroenrat, Senior Researcher, Puey Ungphakorn Institute for Economic Research, Bank of Thailand, voradal@bot.or.th. We would like to thank Piti Disyatat, Krislert Sampantharak, Naris Sathapholdeja, Phacharaphot Nuntramas, Wanchai Thanakornkitkul, and participants at PIER Research Workshop 2017 for comments and discussions. The views expressed here are those of the author and do not necessarily reflect those of the Puey Ungphakorn Institute for Economic Research and the Bank of Thailand.

1. INTRODUCTION

The real effect of credit supply shocks has long been an interest among researchers and policy makers. The academic literature emphasized the role of credit in amplifying the real business cycles (Bernanke et al., 1999; Kiyotaki and Moore, 1997, Peek and Rosengren, 2000). The global financial crisis of 2008 has brought this issue to the fore and underlined the need for policymakers to really understand the linkages between financial shocks and macroeconomic fluctuations. Particularly, interest has been in understanding how credit dynamics affect real variables. This paper aims to add to the existing literature in this area by investigating the impact of credit supply shocks on the firm-level as well as the aggregate-level outcome using Thailand as a case study.

Although it is by now generally accepted that there exists a link between bank supply shocks and the real economic activity, empirical studies on this issue remains relatively scarce. This is due to the difficulty of identifying credit supply from credit demand in the aggregate data since the observed credit growth is a result of changes in both credit demand and supply. Previous attempts to overcome such identification challenge rely on micro-level data and leverage on heterogeneity across banks and across firms in trying to isolate bank supply factors from firm demand factors. Khwaja and Mian (2008) pioneer in this area by using matched lender-borrower credit registry data. They exploit the cross-bank variation around an exogeneous shock to bank liquidity and estimate the differential loan growth rates made to the same borrower with multiple-bank relationships. Firm demand factors are absorbed using the time-varying firm fixed effects. However, the main drawback of this fixed-effect approach is that it relies on an appropriate instrument or an exogenous event in identifying bank shocks. In addition, the fix-effects structure tries to minimize the model's error when fitting a typical loan, but the behavior of a typical loan may not apply to the wide variety of other loans in the aggregate lending. Thus, the bank supply and firm demand shocks estimated under the fixed effects structure are unable to match the economy-wide credit growth variation, and hence cannot be used to study how idiosyncratic bank supply shocks matter for the aggregate economy.

In this paper, we apply a novel methodology proposed by Amiti and Weinstein (2017; AW henceforth) in decomposing loan growth into idiosyncratic bank supply and firm demand factors using the Thai account-level credit registry data spanning from 2004 to 2015. A key advantage of the AW method is that it takes into account the adding-up constraints so that bank supply shocks and firm demand shocks add up to match the aggregate-level lending and borrowing patterns. For each bank, the total loan growth will be exactly decomposed into a common shock, industry shock, firm borrowing shock, and idiosyncratic bank lending shock, without having to rely on either the fixed effects or instrumental variables.

Thailand makes an interesting case study on this topic given the exceptionally high concentration of the Thai credit market, both from the bank and the firm perspective. Lending by the top 5 banks account for as high as 60-70 percent of the economy-wide bank lending.

Similarly, the top 10 percent of borrowing firms hold as much as 70 percent of the total loan volume. The fact that the distribution of bank size by loan share is highly skewed implies that idiosyncratic bank loan supply shocks will not cancel out in aggregate and shocks generated by a large bank can have a non-trivial effect on the aggregate economy, according to the "granular hypothesis" of Gabaix (2011). Moreover, the fact that a large number of firms in Thailand are small firms which tend to have only one bank relationship makes it even more important to understand how negative idiosyncratic bank shocks affect these potentially more vulnerable firms.

Our paper contributes to the existing literature along the following dimensions. First, we are among the first to apply this new decomposition method of AW to an emerging market economy. AW and other studies employing the AW methodology analyze the effects of bank supply shock estimates in the context of advanced economies. The overall as well as the distributional effects of bank shocks may be vastly different in the case of emerging market economies given the lower level of financial development, less diversified bank and client base, and potentially weaker institutions. Moreover, our data coverage goes much beyond listed companies as used in AW. Our large dataset which includes various types of firms offers substantial heterogeneity and allows us to assess the differential impact of bank shocks on different firm types.

Second, our paper investigates bank-firm relationships extensively and asks whether firms with multiple bank relationships and firms with an ability to switch to a new bank are better able to protect their investment against bank supply shocks. We borrow the idea from the industrial organization literature in which it has been suggested both theoretically and empirically that lower customer switching costs could reduce welfare losses on the part of customers that are due to monopolistic rents exploited by the suppliers (e.g. Klemperer, 1995; Knittel, 1997). Applying this concept to our research question, we hypothesize that the ability to switch banks should also help reduce the negative effect of idiosyncratic bank shocks in the highly concentrated loan market environment.

Third, we also explore the asymmetric effects of bank shocks by allowing positive and negative bank shocks to have differential impact on firm investment for differential types of firms. And finally, while previous studies assume bank shocks at each point in time to be common across all clients, we postulate that this is a strong assumption by demonstrating that bank supply shocks for different types of clients (along the dimension of firms' health and size) can be greatly different in size and in their dynamics, and they can yield very different results in terms of the impact on firm investment.

A preview of our main findings is as follows. First, our results from the firm-level regressions indicate that bank supply shocks do matter for firm investment activity in the context of Thailand, particularly for smaller firms and firms that rely more on bank loans in their total financing. Second, in general firms with multiple bank relationships and firms that are able to switch to a new bank are less affected by bank shocks. This mitigating effect of having diversified bank relationships are especially important for small firms when faced with negative bank shocks. However, in the case of large firms, apparently multiple bank relationships are not helpful as we find that large firms with a single lending bank are actually better off in terms of observing less contraction in investment in the face of negative bank supply shocks. Third, banks seem to have differential lending policy towards different groups of customers. When we allow bank shocks to differ between healthy and unhealthy firms, and between small and large firms, we find that the shock estimates generated for different firm groups behave very differently. One highlight is that healthy firms appear to experience much more steady credit supply conditions, whereas bank supply shocks to unhealthy firms are much more volatile. Finally, at the aggregate level, we find strong evidence supporting the real effect of bank supply shocks on aggregate investment. Our results show that granular bank shock accounts for as much as 37 percent of aggregate credit growth, and it is the major source of financial shocks driving aggregate investment.

The paper is organized as follows. Section (2) provides description of our data and presents key stylized facts with a focus on loan share concentration and firm-bank relationships in the Thai credit market. Section (3) outlines loan growth decomposition methodology and the shock estimation. Section (4) tests the validity of the estimated shocks. Section (5) presents our regression analyses and discusses the results. Section (6) concludes.

2. DATA AND STYLIZED FACTS

2.1 The Data

Our matched bank-firm level loan dataset is derived from two main sources: (1) the Bank of Thailand's Loan Arrangement database, LAR (2) the Ministry of Commerce's Corporate Profile and Financial Statement, CPFS.

The first database, LAR, contains loan arrangements of individuals and corporate that has a total credit line or outstanding loan amount above 20 million Baht within a single bank. The data is reported on a monthly basis at the loan contract level since December 2003 by all financial institutions under the supervision of the Bank of Thailand. Although LAR contains both corporate and household loan arrangement that satisfy the minimum threshold above, in this paper we will consider only corporate sector loans and disregard loans made by households or individuals since our research focus is on the response of firms' investment to financial shocks.[2]

Financial institutions that report their loan data to the Bank of Thailand can be categorized into five groups: Thai commercial banks, foreign subsidiary banks, government's Specialized Financial Institutions (SFIs), finance companies, and credit fonciers, with the first two groups covering greater than 90 percent of the total reported loan amount. We exclude

[2] In addition, the household loan data contained in this LAR dataset is unlikely to be a representative of the country's overall household debt since the majority of household borrowers would not have high enough credit line or outstanding loan amount to meet the minimum reporting threshold.

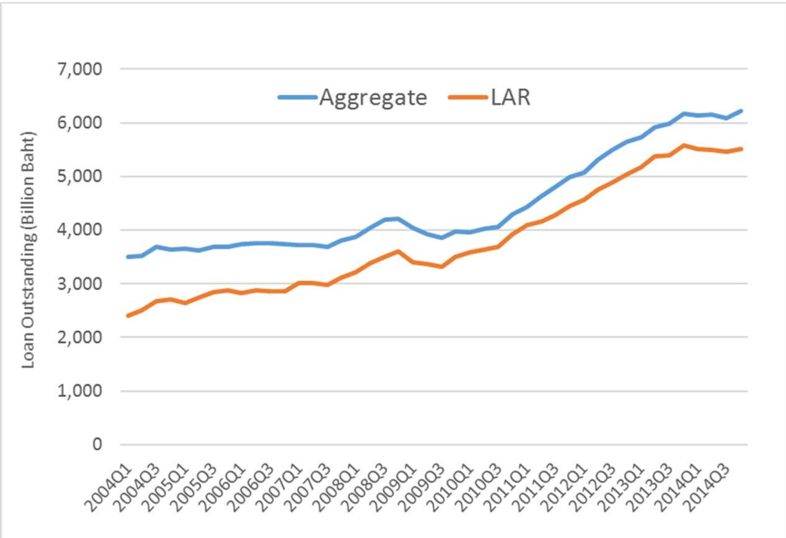
loan data reported by five government SFIs[3] from our dataset in order to isolate our results from the effect of government policies, so as to focus our analysis on the impact of bank supply shocks arising from private institutions.[4] Table 1 reports the number of reporting financial institutions in our dataset over the sample period.

Table 1: Number of banks (LAR database)

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
All financial institutions	55	47	43	41	41	38	38	41	40	41	40	44
Banks only	33	33	33	33	34	32	32	35	35	35	34	38

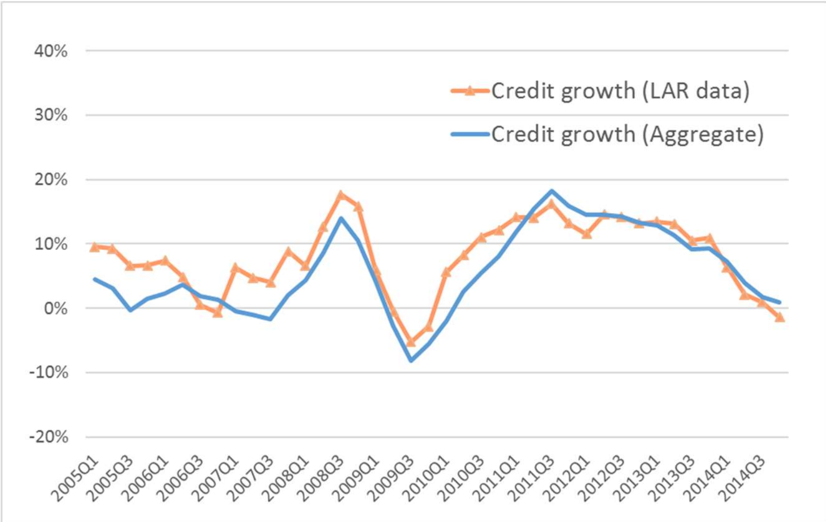
Although the LAR data has a rather high minimum reporting threshold as described above, making many firms with smaller loan arrangement missing from the dataset, we argue that the corporate loan data from the LAR database still represents the country's overall corporate sector loan fairly well. A total loan outstanding amount from the LAR dataset covers around 75-90 percent of the country's aggregate corporate lending (Figure 1), and the credit growth based on the LAR data closely traces the aggregate loan growth (Figure 2). And since our data contains *all* commercial banks in Thailand as major loan suppliers, it is thus suitable for studying idiosyncratic bank lending behaviors as well as the pattern of economy-wide corporate borrowing more generally.

Figure 1: Loan outstanding: Aggregate vs. LAR database



[3] The five SFIs excluded from our dataset are Bank for Agriculture and Agricultural Cooperatives, Government Saving Bank, Export-Import Bank of Thailand, Thai Credit Guarantee Corporation, and Islamic Bank of Thailand.
[4] Since government SFIs are more concentrated in household and small-sized loan segments, most loans in their portfolios are not included in the LAR database anyway. Thus, we do not lose much information by not including SFI loans.

Figure 2: Credit growth: Aggregate vs. LAR database



The second source of data, CPFS, provides financial information on the firm side. The database contains comprehensive registry and financial information of businesses registered in Thailand based on document officially submitted to the Ministry of Commerce and collected by the Bank of Thailand. The data is reported annually at the end of the year from 2001 onwards, covering approximately 300,000 firms per year.

We collapse year-end contract-level LAR dataset into bank-firm-year level. This dataset is then matched with the firm balance sheet data from CPFS. We track all cases of bank mergers and acquisitions (M&A), restructuring, and changes of name over the studying period and take care of these issues in the data to avoid misidentifying previously existing entities as newly established financial institutions. In constructing bank loan growth in the case of bank mergers, to avoid a jump in aggregate lending that was due purely to M&A, we re-base the total amount of lending in year *t-1* to be equal to the total amount of lending by the two banks that merged in year *t*. For example, if Bank A took over Bank B in year *t*, the base loan amount in year *t-1* for calculating loan growth in year *t* for Bank A would be set equal to sum of Bank A's and Bank B's loans in year *t-1*. In order to ensure sufficient observations for shock estimations, we drop financial institutions with fewer than ten borrowing firms for two consecutive years.

Initial CPFS data contains loan from 17 industries categorized by ISIC 1-digit codes.[5] In our sample, we drop firms from the finance and insurance industry to avoid interbank transactions, and also because the nature of investment by firms in this industry is very

[5] The 17 industries are (1) Manufacturing (2) Agricultural, forestry, fishing (3) Mining, quarrying (4) Electricity, gas, steam (5) Water supply (6) Construction (7) Wholesale, retail trade (8) Transport, storage (9) Accommodation, food service (10) Information, communication (11) Real estate (12) Professional, scientific and technical activities (13) Administrative, support activities (14) Education (15) Human health, social work activities (16) Arts, entertainment, recreation (17) Other service activities.

different from those in other industries.[6] The number of firms in our matched dataset is reported below in Table 2. We classify firms into small, medium, and large firms, based on firms' fixed asset size (see footnote of Table 2). Although the LAR dataset has a high reporting threshold—which renders the dataset underrepresenting the population of small borrowing firms in the economy, the final dataset still contains a significantly large number of small firms compared to the medium- and large-sized ones, which should be sufficient for making comparative analyses across firm sizes. The firm sample coverage here extends much beyond only stock-market listed firms that were used in the previous study of AW.[7] Our results would thus provide further insights into how smaller and non-listed firms that are arguably more financially constrained and more heavily reliant on bank loans would respond differently to bank supply shocks.[8]

Table 2: Number of firms (matched LAR-CPFS databases)

LAR-CPFS	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Small	10,340	11,210	11,152	11,805	12,407	11,841	12,252	13,130	14,037	15,371	16,931
Medium	3,864	4,199	4,303	4,568	4,968	4,942	5,143	5,210	5,465	5,922	6,449
Large	2,361	2,557	2,617	2,797	3,089	3,097	3,336	3,360	3,628	4,071	4,326
Total	**16,565**	**17,966**	**18,072**	**19,170**	**20,461**	**19,880**	**20,731**	**21,700**	**23,130**	**25,364**	**27,688**

Note: Firms' sizes are categorized into three size groups according to the Ministry of Industry's classification: (1) small firms (book value of fixed assets below 50 million baht), (2) medium firms (book value of fixed assets between 50 million baht and 200 million baht), and (3) large firms (book value of fixed assets greater than 200 million baht).

2.2 Key Stylized Facts

2.2.1 Loan market concentration

The main analysis of this study is to quantify the effect of "granular" shocks, from both the bank side and the firm side, on firms' real activities. The term "granular" is used to reflect the fact that individual firms and banks are not infinitesimally small relative to the size of the economy. This follows closely from Gabaix (2011) where he proposes that if banks (firms) are "granular" or not infinitesimally small in size, idiosyncratic shocks in one or more individual large banks (firms) will *not* cancel out in aggregate, as otherwise presumed by assuming a normal distribution of bank (firm) size and by the law of large number. Thus, these bank-level

[6] We construct firm-level investment as the change in fixed capital. This measure of investment could be biased for finance and insurance industry as the core business of firms in this industry involves less fixed capital assets than other industries.

[7] The number of listed firms in Thailand in both the Stock Exchange of Thailand (SET) and the Market for Alternative Investment (MAI) is currently registered at 733 as of July 2017.

[8] There are a few caveats associated with using fixed assets as a measure of firm size. This measure is likely to underestimate the size of some group of firms especially in the service sector. Also, disregarding the firm ownership structure may give rise to biases in some cases as some firms that appear small by fixed asset size may in fact be part of a large corporate conglomeration. We argue; however, that this classification is consistent with government policy that could differently affect different firm sizes.

(firm-level) shocks would be able to affect aggregate variables such as aggregate lending and aggregate investment.

To exhibit this "granularity" in our matched bank-firm data, we need to show that the size distributions of banks and firms are fat-tail or power-law distributed. To link the concept of granularity to our analysis of loan growth shocks, we look at the distributions of the loan size instead of the asset size of banks and firms. The fat-tail distribution of bank size can be reflected by high degree of concentration of loan share in a few large banks. Figure 3 shows the loan share of each bank in our dataset. It is clear that the Thai banking system is highly concentrated, with greater than 60 percent of overall loan outstanding belonging to only the five largest banks.

Figure 3: Bank Concentration

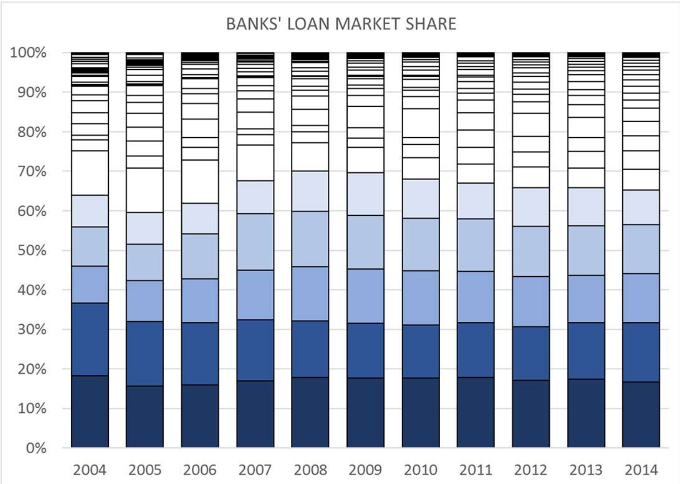
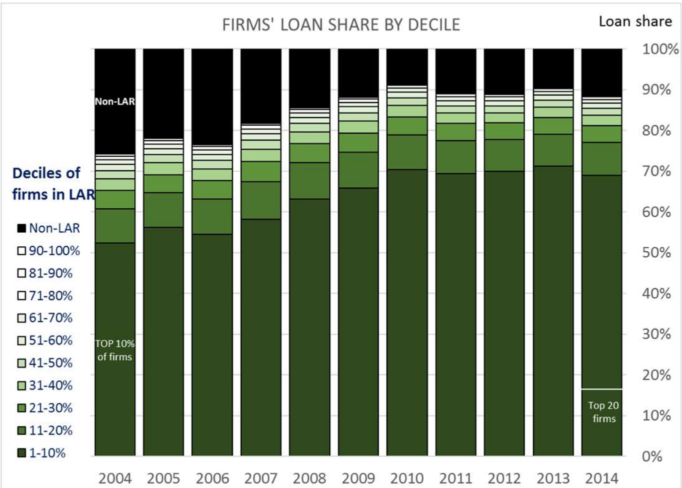


Figure 4: Firm Concentration



The picture is analogous for the firm concentration. Concentration of loan share on the firm side is shown in Figure 4 where firms are grouped in to ten deciles, ranked according to their loan share. To make sure that the loan share by each decile of firms is not biased due to the omission of smaller borrowing firms in our LAR dataset, we plug in the non-LAR loan outstanding figure to make the aggregate loan amount matched with the economy-wide lending. The chart confirms that loan distribution is also greatly concentrated. More than 60 percent of aggregate lending goes to the top 10 percent of firms in the entire economy.

The exceptionally high concentration of the Thai credit market, both from the bank and the firm perspective implies that the Thai aggregate economy may be particularly susceptible to negative idiosyncratic bank and firm shocks and thus makes Thailand an interesting testing ground of the granular hypothesis. It also stresses the importance of the microfoundation of bank and firm behaviors in gaining deeper understanding of aggregate fluctuations that affect the Thai real business cycles.

2.2.2 Firm-bank relationships

Firm-bank relationship is one aspect explored extensively in this study as we think it may matter for firms' access to finance and the ability of the firms to handle hard times. The main question we ask is whether the multiple bank relationships, as opposed to a single bank relationship, help mitigate the impact of idiosyncratic bank shocks on firms' investment. This section provides descriptive statistics on the firm-bank relationships of the Thai firms in our sample in order to establish stylized facts that will be useful for interpreting the results in our main analysis.

Figure 5 shows the distribution of firms by the number of borrowing relationships (number of lending banks per firm) and their loan share. The portion of firms that borrowed from a single bank at a time is strikingly high, at nearly 80 percent of the total observations. However, the amount of loans held by those with one bank relationship accounts for only about 30 percent, suggesting that firms with single bank relationship are mostly small borrowers. The fact that an unproportaionally large amount of loans belong to only a small number of well-connected large firms again confirms the power-law or the fat-tailed distribution of firms in our sample.

To investigate this relationship a bit more closely, Figure 6 provides a scattered plot of firms with the number of bank relationships (log scale) on the horizontal axis, and the size of the firms' total borrowing (log scale) on the vertical axis. To better illustrate the relationship between these two attributes, the plot shows only the 25th, 50th,75th percentile of the firm's loan size for each bank relationship bin, instead of plotting the whole loan size spectrum of firms for each bin. There is a clear positive relationship between firm's loan size and the number of bank relationships. On average, firms with more diverse bank relationships tend to be larger borrowers.

Table 3 shows that as many as 76 percent of the small firms (as classified by fixed-asset size) have only one borrowing relationship, as opposed to 39 percent in the case of the large

Figure 5: Distribution of the number of borrowing relationships

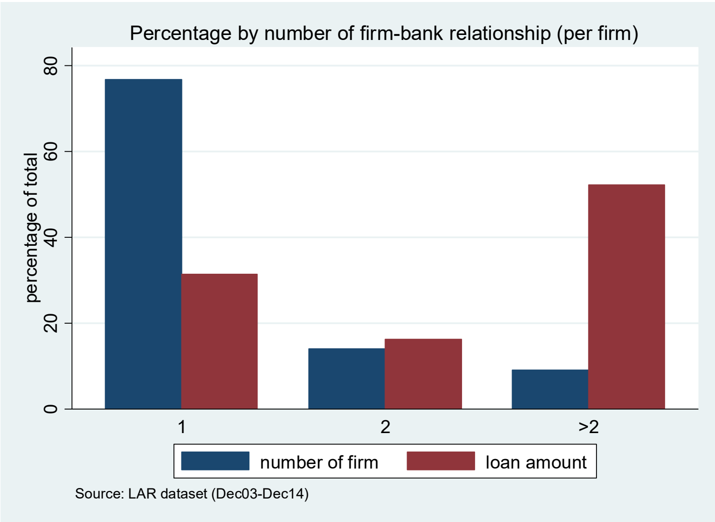
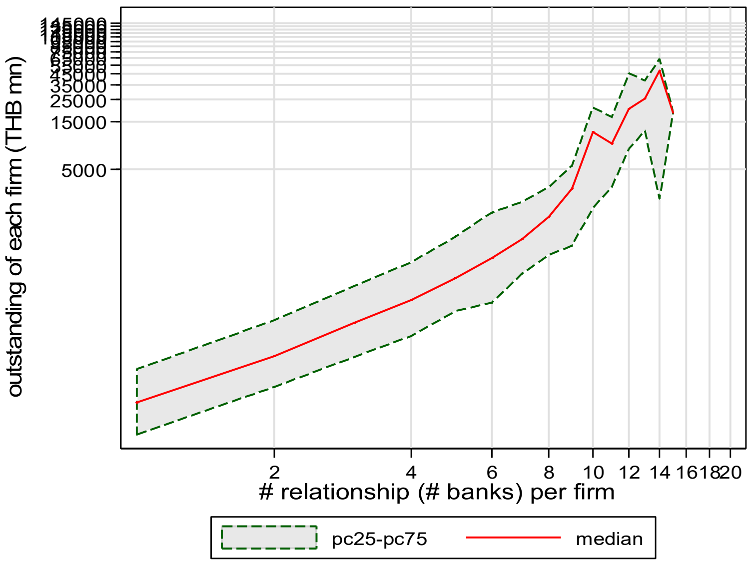


Figure 6: Distribution of the number of Borrowing Relationships (log-log plot)



firms. Overall, roughly two-thirds of the Thai sample firms have single-bank relationship in each year over the sample period. This is in sharp contrast with the data used by AW in which less than 2 percent of the listed Japanese firms borrowed from only one bank, though it is comparable to other studies such as Amador and Nagengast (2016), Degryse, et al. (2017) and Khwaja and Mian (2008) in which the share of single-bank-borrowing firms is as high as 50 percent in Portugal, 87 percent in Belgium, and 90 percent in Pakistan, respectively.

Table 3: Distribution of number of bank relationships by firm size, 2014

Number of bank relationships	Percentage share by firm size			
	Small	Medium	Large	*All firms*
1	75.5	62.6	38.7	*66.1*
2	17.4	22.5	24.0	*19.8*
3	4.6	8.5	14.8	*7.3*
4	1.5	3.5	8.5	*3.2*
5	0.6	1.6	4.9	*1.6*
>5	0.4	1.2	9.2	*2.1*
Total	100.0	100.0	100.0	*100.0*
Memo: Number of firms	*11,793*	*5,285*	*3,406*	*20,484*

Next, we explore the dynamics of the firm-bank relationship over time. This is another departure of our study from the past literature that focus exclusively on static borrowing relationships. We postulate that the ability for firms to switch or to reach out to a new bank when hit by negative shocks from the current lending banks, may help lessen the overall damaging effects on firm investment. Therefore, in assessing the importance of bank relationships in explaining the impact of bank shocks, we need to not only analyze from the current perspective, but also look at firms' future potential to initiate borrowing relationship with new banks as well.

Table 4: Probability of firms switching/expanding bank relationship in the next year

Number of bank relationships at year t	Number of observations (A)	... of which expanding to new bank relationships in year t+1 (B)	Likelihood of switching/expanding banks (B/A)
1	98,751	6,894	7%
2	26,727	3,334	12%
3	9,531	1,657	17%
4	4,142	950	23%
5	2,097	559	27%
6	1,210	363	30%
7	756	259	34%
8	457	165	36%
9	272	113	42%
10	157	66	42%
11	79	30	38%
12	54	24	44%
13	30	9	30%
14	21	12	57%
15	12	4	33%
16	11	3	27%
17	7	5	71%
18	1	0	0%
Total	**144,315**	**14,447**	**10%**

Table 4 reports the likelihood that firms switch to or expand bank relationships with a new bank, given the initial number of bank relationships. Note here that our definition of firms having a new bank relationship as reported in the third column of Table 4 covers both (1) firms borrowing from a new bank at time *t+1* while still keeping borrowing relationships with the existing banks from time *t*, and (2) firms switching to borrow from a new bank at time *t+1* and terminating borrowing relationship with the banks it used to borrow from at time *t*. The unit of observations reported here are firm-year observations.

Similar to the previously established stylized fact, we observe from Table 4 that the majority of firms borrowed from only one bank at a time. More interestingly, we can see from the fourth column of Table 4 that the likelihood of switching to or expanding relationships with a new bank in the next period increases almost monotonically with the number of bank relationships in the last period. If you pick one firm with one bank relationship in any period, there is as high as 93 percent chance that that particular firm will stick with only that one bank in the next year.

In fact, when we follow the firms over their life time (over our sample period spanning from 2005 to 2014), we find that 55 percent of the firms attached to only one bank throughout their life (Table 5). Again, the probability of having a new bank relationship increases with the number of bank relationship at the beginning of their lives in our sample period. Overall, the data reveal that approximately 60 percent of Thai firms never expanded their circle of borrowing relationships beyond the initial ones, even over the long span of time, arguably covering a complete business cycle.

Table 5: Probability of firms switch/expand relationship over life time

Share of firms out of total 35,265 firms								
Number of bank relationships in the first year	**Number of *new* bank relationships over life time**							
	0	**1**	**2**	**3**	**4**	**5**	**> 5**	**Total**
1	55.0%	19.9%	6.9%	2.5%	1.1%	0.5%	0.0%	**85.9%**
2	3.9%	2.3%	1.3%	0.6%	0.3%	0.2%	0.0%	**8.7%**
3	0.8%	0.6%	0.4%	0.2%	0.1%	0.1%	0.0%	**2.3%**
4	0.3%	0.2%	0.2%	0.2%	0.1%	0.1%	0.0%	**0.9%**
5	0.1%	0.1%	0.1%	0.1%	0.0%	0.1%	0.0%	**0.4%**
> 5	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.2%	**0.8%**
Total	**60.2%**	**23.2%**	**9.0%**	**3.7%**	**1.8%**	**1.0%**	**1.2%**	**100.0%**

These stylized facts on the firm-bank relationships in the Thai credit markets could be interpreted either as a reflection of: (I) *strong or loyal relationships* between firms and banks[9],

[9] For example, for small firms with good loan quality, the current bank will make sure to keep the relationship (eg. matching offers, discount on non-lending products) so as not to lose the customers to other banks. Thus, the

or (II) *financial frictions*—arising as a result of, for instance, no established credit record, lack of collateral—that prevent firms from flexibly borrowing from multiple loan suppliers. To better understand what the number of relationships implies for different types of firms, we will resort to econometric regressions that will follow in Section 5.

Putting together, the characteristics of the Thai credit market structure as described by high loan share concentration and bank relationship concentration underlines the potentially important role of granular bank shocks and their propagation in the Thai economy, which shall be unfolded in this study.

3. LOAN GROWTH DECOMPOSITION: Methodology

This section describes an econometric approach in decomposing loan supply shocks and loan demand shocks as proposed by AW (2017).

Consider a general class of empirical models where lending growth can be written as

$$\frac{\mathrm{L}_{fbt}-\mathrm{L}_{fbt-}}{\mathrm{L}_{fbt-}} = \alpha_{fbt} + \beta_{fbt} + \varepsilon_{fbt} \tag{1}$$

Equation (1) can be derived structurally where α_{fbt} captures the "firm-borrowing channel" or all factors affecting borrowing that are specific to the firm, e.g. firm-specific changes in productivity or investment opportunity. Similarly, β_{fbt} captures the "bank-borrowing channel" or bank-specific factors that result in decreases or increases in the lending of the particular bank. We also follow the literature and assume that the expectation of the error term is zero, $E[\varepsilon_{fbt}]$ =0.

Practically, Equation (1) can be estimated directly through time-varying bank- and firm-fixed effects, as in Khwaja and Mian (2008). However, using such methodology is arguably inefficient since it ignores the general equilibrium relations that underlie the observed outcome in the loan markets: that is, banks can lend out an additional loan only if at least one firm borrows more, and similarly, a firm can only obtain a new loan only if at least one bank is willing to lend more. AW calls this bank-lending and firm-borrowing linkages the "adding-up constraints" and argues that ignoring these constraints would result in biased estimates of shock decomposition that do not match with aggregate borrowing and lending patterns.

We follow AW's proposed methodology which takes into account these adding-up constraints. On the bank-side, banks' overall lending growth is expressed as bank-lending shock plus the weighted sum of firm-borrowing shocks as follows:

---

single-bank relationship for this type of firms may be by choice rather than due to financing frictions. Similarly, the multiple-bank relationships established by large firms may simply reflect banks' diversification motive as banks may desire to limit their portfolio exposure to a particular firm.

$$\mathrm{D}_{bt}{}^{B} = \frac{\sum_f \mathrm{L}_{fbt} - \sum_f \mathrm{L}_{fbt-1}}{\sum_f \mathrm{L}_{fbt-1}} = \beta_{bt} + \sum_f \phi_{fbt-1}\,\alpha_{ft} + \sum_f \phi_{fbt-1}\,\varepsilon_{fbt} \qquad (2)$$

where

$$\phi_{fbt-1} = \frac{\mathrm{L}_{fbt-1}}{\sum_f \mathrm{L}_{fbt-1}}$$

and $\mathrm{D}_{bt}{}^{B}$ is the growth rate of lending of bank *b* to all of its clients. Correspondingly, on the borrower side, firms' loan growth is expressed as the firm-borrowing shock plus the weighted sum of the bank-borrowing shocks as follow

$$\mathrm{D}_{ft}{}^{F} = \frac{\sum_b \mathrm{L}_{fbt} - \sum_b \mathrm{L}_{fbt-1}}{\sum_b \mathrm{L}_{fbt-1}} = \alpha_{ft} + \sum_b \theta_{fbt-1}\,\beta_{bt} + \sum_b \theta_{fbt-1}\,\varepsilon_{fbt} \qquad (3)$$

where

$$\theta_{fbt-1} = \frac{\mathrm{L}_{fbt-1}}{\sum_b \mathrm{L}_{fbt-1}}$$

and $\mathrm{D}_{ft}{}^{F}$ is the growth rate of total loans held by firm *f* across all of its banks. Given that both ϕ_{fbt-1} and θ_{fbt-1} are predetermined variables, this allows us to impose the following moment conditions on the data:

$$E\left[\sum_f \phi_{fbt-1}\,\varepsilon_{fbt-1}\right] = \sum_f \phi_{fbt-1} E\left[\varepsilon_{fbt-1}\right] = 0$$

and

$$E\left[\sum_f \theta_{fbt-1}\,\varepsilon_{fbt-1}\right] = \sum_f \theta_{fbt-1} E\left[\varepsilon_{fbt-1}\right] = 0$$

These conditions imply that we can choose our parameters such that the following equations hold in our data:

$$\mathrm{D}_{bt}{}^{B} = \beta_{bt} + \sum_f \phi_{fbt-1}\,\alpha_{ft} \qquad (4)$$

$$\mathrm{D}_{ft}{}^{F} = \alpha_{ft} + \sum_b \theta_{fbt-1}\,\beta_{bt} \qquad (5)$$

For each year, Equation (4) and (5) comprise a system of *F+B* linear equations and *F+B* unknowns, allowing us to solve for a unique vector of firm and banks shocks (up to a numeraire) in each time period. Consequently, each bank's aggregate lending can be exactly decomposed into the following four terms:

$$\mathbf{D}_{\boldsymbol{Bt}} = (\overline{A}_t + \overline{B}_t)\, \mathbf{1}_{\boldsymbol{B}} + \boldsymbol{\Phi}_{\boldsymbol{t-1}} \boldsymbol{N}_{\boldsymbol{t}} + \boldsymbol{\Phi}_{\boldsymbol{t-1}} \widetilde{\boldsymbol{A}}_{\boldsymbol{t}} + \widetilde{\boldsymbol{B}}_{\boldsymbol{t}} \tag{6}$$

where $\mathbf{D}_{\boldsymbol{Bt}}$ is a $B \times 1$ vector whose elements are each bank's total loan growth in year *t*; $(\overline{A}_t + \overline{B}_t)$ are the median firm and bank shocks in year *t*, i.e. the common shocks affecting all firm-bank relationships in year *t*; $\mathbf{1}_{\boldsymbol{B}}$ is a $B \times 1$ vector of 1's; $\boldsymbol{N}_{\boldsymbol{t}}$ is a vector containing the median firm shock in each firm's industry at time *t*; $\boldsymbol{\Phi}_{\boldsymbol{t-1}}$ is a $B \times F$ matrix that contains the weights of each firm in the lending portfolio of every bank:

$$\boldsymbol{\Phi}_{\boldsymbol{t}} \equiv \begin{pmatrix} \phi_{11t} & \cdots & \phi_{F1t} \\ \vdots & \ddots & \vdots \\ \phi_{1Bt} & \cdots & \phi_{FBt} \end{pmatrix}$$

The first term of equation (6) are "*__common shocks__*": changes in lending that are similar to all lending pairs in each time period, such as, the impact of monetary policy or changes in aggregate demand conditions. The second term is the "*__industry shock__*" which captures differences in the credit demand across industries or other industry-specific factors that affect similarly across all firms in the same industry. The third term is the "*__firm-borrowing shock__*" which captures changes in a bank's lending arising from idiosyncratic changes in firm demand or other firm-specific factors. Finally, the last term captures "*__bank-lending shock__*" which is a measure of bank-supply shocks independent of firm-specific, industry-specific, and economy-wide conditions.

One advantage of the method proposed by AW is that the loan supply shocks can be added up to match aggregate bank lending through appropriate weighting scheme. Let $\omega_{bt}{}^{B}$ be the average share of bank *b* in total lending in year *t*; $\omega_{ft}{}^{F}$ be the average share of firm *f* in total lending in year *t* and define $\mathbf{W}_{\boldsymbol{B,t}} \equiv [\, \omega_{1t}{}^{B}, \ldots\ \omega_{Bt}{}^{B}\ ]$. We can now rewrite Equation (6) to obtain

$$\mathbf{D}_{\boldsymbol{t}} = \mathbf{W}_{\boldsymbol{B,t-1}} \mathbf{D}_{\boldsymbol{Bt}} = (\overline{A}_t + \overline{B}_t) + \mathbf{W}_{\boldsymbol{B,t-1}} \boldsymbol{\Phi}_{\boldsymbol{t-1}} \boldsymbol{N}_{\boldsymbol{t}} + \mathbf{W}_{\boldsymbol{B,t-1}} \boldsymbol{\Phi}_{\boldsymbol{t-1}} \widetilde{\boldsymbol{A}}_{\boldsymbol{t}} + \mathbf{W}_{\boldsymbol{B,t-1}} \widetilde{\boldsymbol{B}}_{\boldsymbol{t}} \tag{7}$$

where $\mathbf{D}_{\boldsymbol{t}}$ is the aggregate loan growth and $\mathbf{D}_{\boldsymbol{Bt}}$ is the vector of loan growth of individual banks. Analogously to Equation (6), the first term captures common shocks on aggregate lending. The second term represents "granular industry shock" which is the weighted average industry shocks by industry size. The third term is the "granular firm shock", resulting from changes in firm-specific shocks that have non-negligible impact on aggregate lending. Finally, the fourth term is the "granular bank shock", the weighted average of the credit supply shocks of individual banks which will be particularly important if lending markets are concentrated.

AW's methodology used for shock decomposition may potentially be subject to estimation problems if the large number of firms in the sample have only one borrowing relationship, since the identification scheme relies on the variation of loan growth rates across different banks and different firms. However, we argue that the AW methodology still applies to our dataset regardless of the presence of many single-bank borrowers. This is because there is no bank that lends exclusively to a group of firms that do not borrow from other banks. In other words, all banks in our dataset have a diverse client base. Thus, the banks' supply shocks can be identified mainly using the variation of loan growth rates across their clients with multiple bank relationships. Moreover, the total loan volume of firms with a single bank relationship accounts for only a small portion of the total lending by all banks. Since by construction bank shocks are estimated using weights corresponding to the firms' share in the bank's lending portfolio, firms with small loan shares will have little influence on the bank shock estimation. Meanwhile, the moment conditions proposed by AW above also in principle allows for the estimation of firm shocks even for single-bank firms, unlike the fixed-effects approach such as in Khwaja and Mian (2008) in which the time-varying firm-specific factors would be absorbed totally by the firm fixed effects, thus cannot yield the estimates for firm-specific demand shocks for firms with only one bank relationship.[10]

4. RESULTS: ESTIMATED SHOCKS

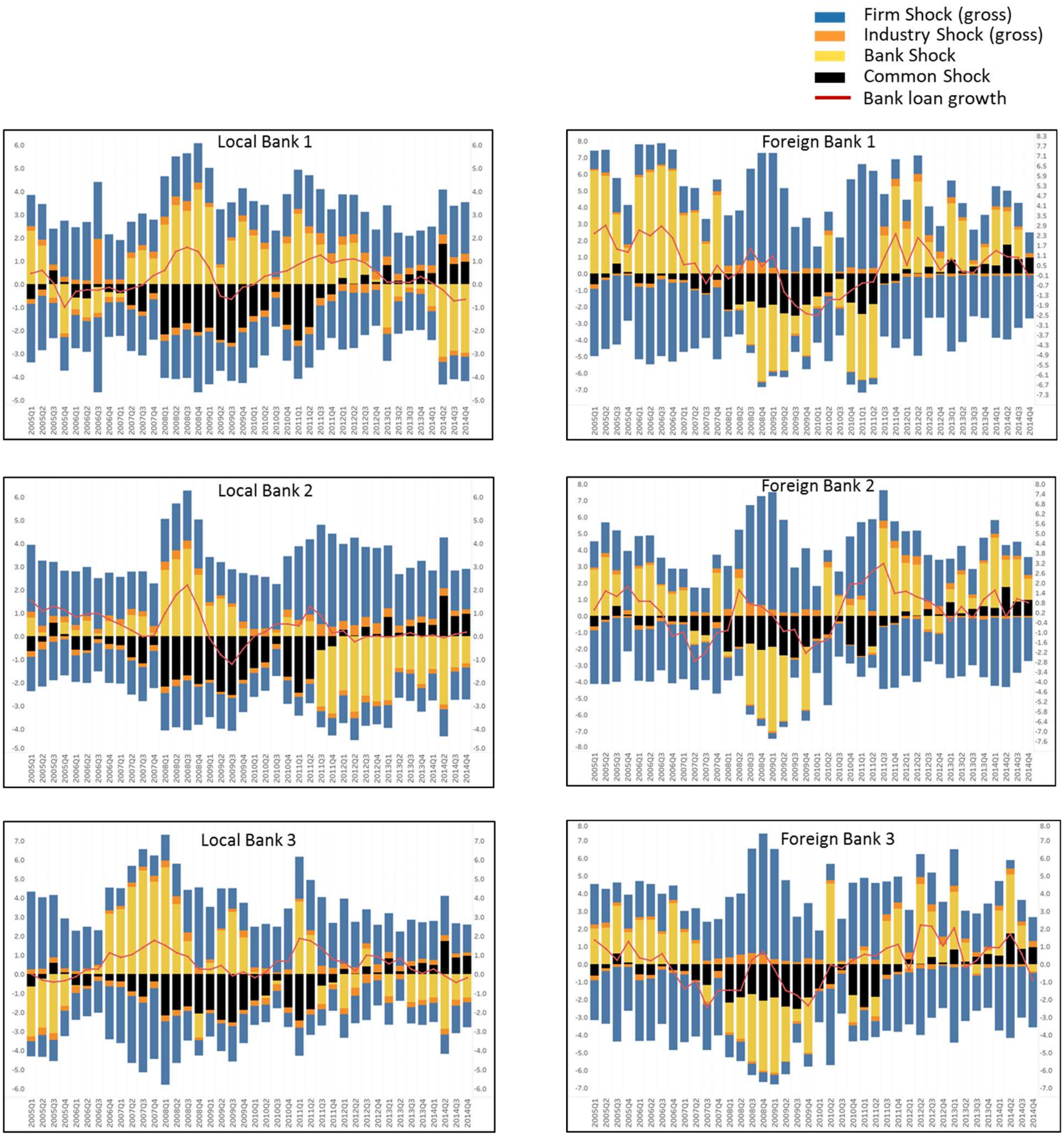
4.1 Bank-Level: Heterogeneity of Bank Shocks across Banks

One key advantage of this shock decomposition methodology is that it can be a potentially useful tool for the purpose of financial system monitoring for at least two reasons. First, as our credit registry database is available on a monthly basis and since the methodology is a period-on-period estimation, the shock decomposition using this method can thus be updated as frequently as the new monthly data becomes available. This would undoubtedly give an extra information for practitioners in identifying early where financing risks may be building up. Second, the methodology offers a convenient way to monitor *individual* bank's behavior regarding their loan supply dynamics at the granular level.

This section will discuss some interesting observations that shed light on the heterogeneous bank behavior by considering bank-by-bank loan growth decomposition. For illustration, Figure 8 shows the stacked bar charts of bank-level loan growth decomposition of three selected local Thai banks and three selected foreign subsidiary banks. We show examples of three banks from each group due to space considerations, but bank behaviors are similar among other local Thai banks and among other foreign banks.

[10] In any case, we have compared two estimates of bank supply shocks—one based on the full dataset, and other one based on a dataset that includes only multiple-bank borrowing firms. The two estimates yield very similar patterns of bank supply shocks, confirming sufficient identification even in the presence of a large number of single-bank firms.

Figure 7: Local VS Foreign Banks' loan growth decomposition



We can see clearly from Figure 7 that the patterns of bank shocks are distinct between the group of Thai local banks and the group of foreign banks. During the 2007-2009 Global Financial Crisis, positive bank shocks were still observed in several local banks while foreign banks had already cut their loan supply due to their idiosyncratic factors. We think this is intuitive given that Thai banks were less connected to the financial system in the advanced economies where the crisis originated and propagated, while foreign banks were more directly exposed to the crisis through the balance sheet linkages with their parent banks.

Given the fact that the idiosyncratic bank supply shock of each bank is estimated without any grouping of banks, the fact that local banks appear to have similar bank supply shock patterns which differ consistently from those of the foreign banks, points to the underlying factors (shared by local banks, but not foreign banks) that give rise to these shocks and could be captured by our decomposition method. We will further investigate the validity of these estimated shocks by comparing them with individual banks' characteristics and balance sheet positions in the next section.

4.2 Granular-Level: Evolution of Granular Shocks

Figure 8 plots four granular shocks calculated using the decomposition method as described in the previous section. The four shocks are (1) granular common shocks, (2) granular bank shocks, (3) granular firm shocks, and (4) granular industry shock.

The fact that we observe negative granular common shocks during 2007-2011, which coincides the turmoil period leading up to and in the aftermath of the Global Financial Crisis, helps confirm consistency of our decomposition methodology. Several other observations that help improve our understanding of the Thai loan growth dynamics are highlighted as follows.

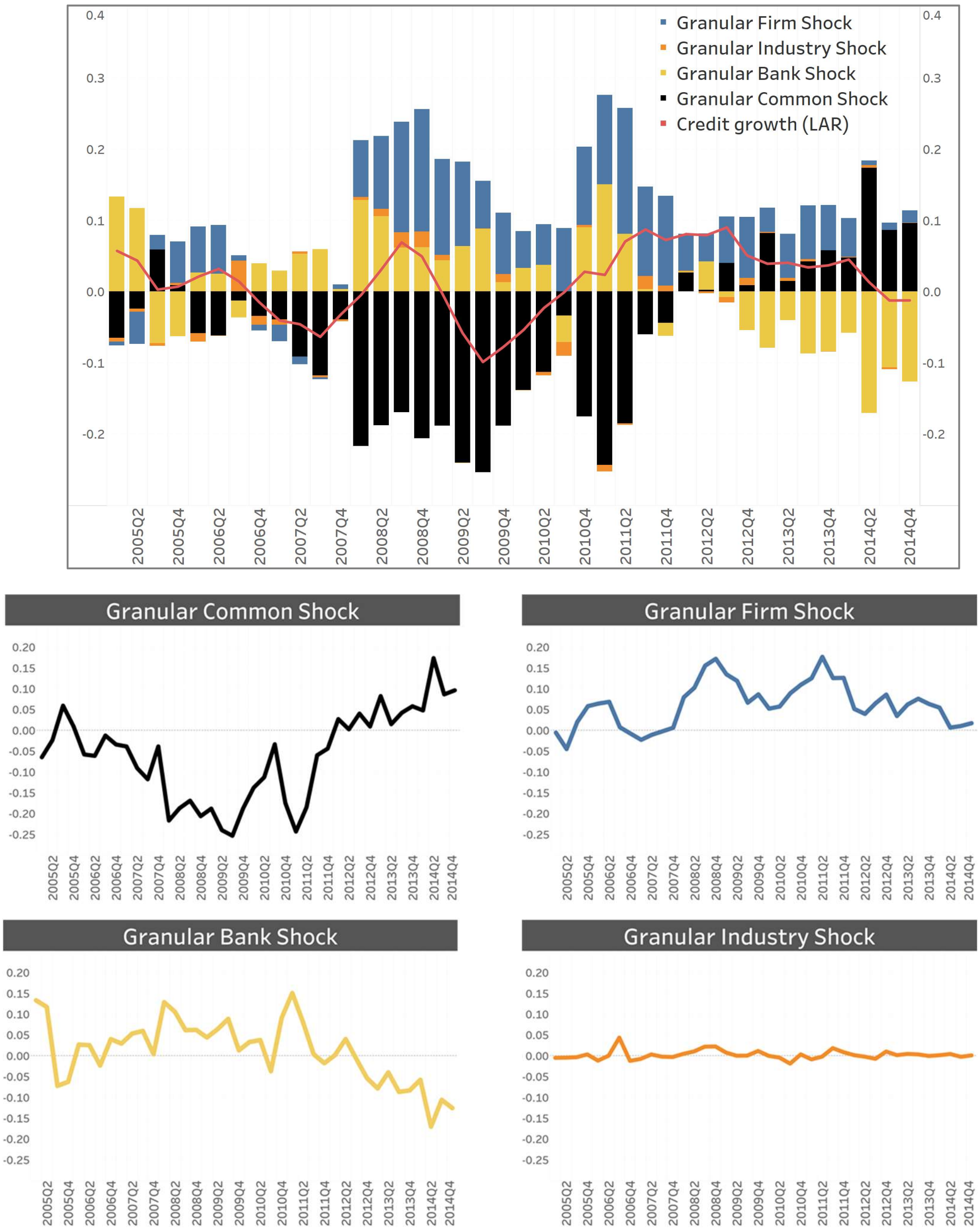
First, the aggregate loan growth alone (the red line in Figure 8) masks a lot of what is going on the granular level. While we observe a positive aggregate loan growth during 2008Q1-2009Q1 and 2010Q4-2011Q2, we can infer from the decomposition of the underlying shocks that this positive overall loan growth was driven by "big" players as reflected in the positive granular bank and firm shocks.[11] Meanwhile, the majority of firm-bank pairs were experiencing negative loan growth, as reflected by the large negative common shocks during those periods.

Second, from the firm's perspective, it also reveals that most of the time, big firms have experienced positive shocks, as reflected in the mostly positive granular firm shock. On the other hand, a large number of small players were more exposed to negative innovations, as implied by the negative common shock.

In sum, this loan growth decomposition exercise demonstrates that the aggregate-level loan growth rate conceals a great deal of the underlying dynamics of different granular components. In the next section, we will show that even the granular bank shock figure also masks significant heterogeneity at the bank level as well.

[11] Be reminded that these granular bank shocks and firm shocks are the weighted average of bank and firm shocks, respectively, using weights corresponding to the loan size of the banks and the firms, hence their dynamics are mainly driven by large banks and large firms.

Figure 8: Granular Shocks



5. FIRM-LEVEL REGRESSION ANALYSIS

We now turn to the main analysis of this study which is to examine the importance of bank loan supply shocks for the real economic activity, specifically, private sector investment. As discussed earlier, the advantage of the loan growth decomposition methodology developed by AW is that it exactly decomposes each firm's loan growth into time-varying firm shocks, bank shocks, industry shocks and common shocks, which can be added up to match the aggregate level of loan growth. Thus, we can assess the effects of bank shocks on investment both at the firm level as well as the aggregate level. We will examine each level of analysis in turns in the following subsections.

5.1 Idiosyncratic Bank Shocks and Firm-Level Investment

We will first examine the effect of idiosyncratic bank supply shocks on investment of individual firms. To measure the size of bank shocks for a firm in each time period, we calculate the weighted sum of bank shocks for each firm as:

$$BankShock_{ft} = \sum_{b} \theta_{fbt-1} \tilde{\beta}_{bt}$$

where the weights are the share of loans from individual banks in the total loan portfolio of firm *f* at time *t-1* and $\tilde{\beta}_{bt}$ is the bank shock of the corresponding bank *b* at time *t*. This aggregate bank shock at the firm level is our main variable of interest in the firm investment regression.[12] Firm-level investment rate is calculated as investment to capital ratio or $(K_t\text{-}K_{t-1})/K$. To control for firm balance sheet positions that may determine the level of firm investment, we employ a standard investment regression framework and include variables that proxy firms' cash flow and investment opportunities. Since cash flow variable is not available in our firm balance sheet data, we use net income to capital ratio and current asset to capital ratio as proxies for firms' cash flow. For investment opportunities, firm's profitability as measured by return-on-asset is used as a proxy. Firm fixed effects and time fixed effects are included in all regressions to control for unobserved firm characteristics and common factors affecting investment across all firms in each time period.

Table 6 presents our baseline results. All firm-level control variables are significant with expected signs, consistent with the standard investment regression. In Column 2, we add bank lending shock, firm borrowing shock, and industry borrowing shock that we obtain from the decomposition of firm's loan growth to the specification. We find positive and significant coefficients on all shock variables. It is not surprising that firm shock is strongly correlated with firm investment since it captures the change in bank loans arising from idiosyncratic changes in borrowing demand or borrowing capacity of the firms, which should be closely tied to firms' investment opportunities. The positive effect of the industry borrowing shock on firm-level investment implies that individual firms in the same industry also face with industry-wide shocks that vary from one industry to another. These might be due to demand shocks, technological shocks, global price shocks, or other factors that affect growth outlook, and hence bank lending and investment, of each industry.

[12] Ideally, using 'term loans' to calculate bank loan supply shocks should better reflect firm investment financing. However, due to data limitation, we are not able to distinguish term loans from other types of loans such as revolving or working capital loans.

Now turn to our key variable, the bank shock, which we find to have a positive and significant relationship with firm investment. Note that this result is in contrast with the result of AW which finds a negative impact of bank shocks on investment for Japanese firms. This discrepancy in the results could arise from the fact that the sample firms used in AW are very large firms listed on the Japanese stock exchange, while our sample of Thai firms also include small- and medium-sized companies. Only when we rerun the regression using a sample comprising exclusively of the largest Thai firms[13]—most of which should be stock market listed firms—the coefficient on bank shocks becomes statistically not different from zero, consistent with the finding by Amador and Nagengast (2016) using the Portuguese sample. **Overall, the results imply that Thai firms are generally highly sensitive to bank lending shocks**, potentially due to the heavily bank-based economic system, lack of alternative financing, and the exceptionally high degree of bank concentration in the loan market. **Only a few largest firms appear to be shielded from credit conditions set by bank supply shocks.**

We explore further to see whether firms with some particular characteristics (other than size) are more exposed to bank shocks than the average firm. In Column 3 in Table 9, we interact bank shocks and firm shocks with the average loan-to-asset ratio of each firm, based on a hypothesis that firms that rely more on bank borrowing for finance would have their investment more sensitive to bank shocks than firms that are less dependent on bank loans. We find that indeed **the impact of bank shocks on firm investment increases with the degree of loan dependence of the firms**. This result is robustly consistent with the findings by AW (2017) and Amador and Nagengast (2016).

5.2 Firm-Bank Relationships

A theoretical model and empirical evidence by Detragiache, et al. (2000) suggests that multiple bank relationships may ensure a more stable supply of credit and reduce liquidity risk that could otherwise affect the firm's investment project.

To test this hypothesis, in Column 4 and Column 5 of Table 6, we ask whether firms that have multiple bank relationships would be more insulated from idiosyncratic bank supply shocks compared to firms with only one bank borrowing relationship. We interact bank shocks and firm shocks with a dummy that is equal to 1 if a firm borrowed from more than one bank, and 0 otherwise. The coefficient on these interaction terms are negative and significant, implying that **having more bank relationships may be able to reduce the effect of bank loan supply shocks on firm investment.** In other words, firms with a single bank relationship are generally harder hit by changes in credit supply conditions. This is in line with previous literature that finds multiple bank relationships to be beneficial as they increase the ability of

[13] The number of listed firms on the Thai Stock Exchange has been around 500-600 during the recent period. Therefore, we arbitrarily choose to include the top 500 firms in our 'largest firms' sample with a presumption that most of these firms are listed companies, in an attempt to match the sample of AW. Changing the sample to include the top 400 or 600 firms does not change this result.

firms to mitigate the negative idiosyncratic loan supply changes by substituting them with loans from other banks. And this ability to diversify away bank supply risks is likely to be greater for firms that have more than one bank relationship to begin with.[14]

Table 6 : Bank shocks and firm investment
Baseline regressions

	Full Sample				
Dependent var: $Investment_{f,t}$ / $Capital_{f,t-1}$	(1)	(2)	(3)	(4)	(5)
$Net\ income_{f,t}/Capital_{f,t-1}$	0.006***	0.006***	0.006***	0.006***	0.006***
	(5.532)	(5.456)	(5.355)	(5.458)	(5.360)
$Current\ asset_{f,t}/Capital_{f,t-1}$	0.093***	0.093***	0.094***	0.093***	0.094***
	(38.616)	(39.683)	(39.924)	(39.677)	(39.910)
$ROA_{f,t-1}$	0.213***	0.168***	0.159***	0.169***	0.160***
	(10.103)	(8.139)	(7.727)	(8.207)	(7.788)
$Bank\ Shock_{f,t}$		0.082***	0.054***	0.097***	0.070***
		(12.918)	(5.857)	(12.800)	(6.595)
$Firm\ Shock_{f,t}$		0.068***	0.037***	0.074***	0.042***
		(39.670)	(15.054)	(30.276)	(14.036)
$Industry\ Shock_{f,t}$		0.115***	0.117***	0.116***	0.118***
		(6.244)	(6.375)	(6.271)	(6.391)
$Bank\ Shock_{f,t}$ * $Loan\text{-}to\text{-}Asset\ Ratio_f$			0.087***		0.081***
			(4.829)		(4.441)
$Firm\ Shock_{f,t}$ * $Loan\text{-}to\text{-}Asset\ Ratio_f$			0.093***		0.092***
			(12.938)		(12.761)
$Bank\ Shock_{f,t}$ * $More\ than\ one\ bank_{f,t}$				-0.041***	-0.036***
				(-3.512)	(-3.092)
$Firm\ Shock_{f,t}$ * $More\ than\ one\ banks_{f,t}$				-0.015***	-0.011***
				(-4.546)	(-3.521)
Constant	0.097***	0.079***	0.074***	0.078***	0.074***
	(28.104)	(23.204)	(22.040)	(23.150)	(22.014)
Observations	145,823	145,823	145,823	145,823	145,823
R-squared	0.067	0.099	0.104	0.099	0.104
Number of firms	32,353	32,353	32,353	32,353	32,353
Firm FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[14] The results on these interaction terms remain robust when we use the time-varying number of bank relationships (ranging from 1 to 18), or alternatively the time-invariant number of bank relationships over the whole sample period, instead of the time-varying dummy variable.

Table 7 reports the results when we divide the full sample into three subsamples by firm size as defined in the data section. Overall, the key results remain the same across different subsamples, though varying in magnitude of the effects.[15] Comparing the full specification in Column 5 between the small-firm, the medium-firm and the large-firm samples, the size of the coefficients on most variables are comparable with the exception of the interaction terms between bank and firm shocks and the mean loan-to-asset ratio. Interestingly, the additional effects from being highly dependent on bank loans are much more pronounced for a large and medium firm relative to a small firm. This could be due to the fact that the loan-to-asset ratio for the group of small firms is much more dispersed across the firms (mean = 0.52, std = 0.41), while the variation within the groups of large and medium firms is narrower (large: mean = 0.34, std = 0.25; medium: mean = 0.38, std = 0.28). Thus, an incremental increase in the loan ratio would make a bigger difference for the large and medium firms compared to the smaller firms.

5.3 Asymmetric Effects of Bank Shocks

We next examine whether the effects of bank shocks on firm investment are asymmetric. The past literature including AW (2017) and Khwaja and Mian (2008) does not make a distinction between the effects of positive and negative bank shocks. However, we conjecture that firm investment may respond differently to these two sides of shocks. More importantly, to be able to identify what types of firms are more prone to (or more isolated from) *adverse* shocks from bank loan supply, separating the positive and negative shocks is needed to make sure that the results are not driven by the positive side of the relationship.

To allow for the asymmetric effects, we interact all the bank shock variables in the baseline regression with a negative-shock dummy, which is equal to 1 if a firm-specific bank shock in year *t* is less than 0. We compare the full sample results with those from the subsamples of small-medium and large firms. The coefficients on the interaction term between bank shock and the negative shock dummy indicate that, for the full sample, the effects of positive and negative shocks on investment are not statistically different. However, this result is likely driven by the group of small and medium firms, while large firms appear to be much less sensitive to negative shocks.

The three-way interaction term between bank shock, more-than-one-bank dummy, and the negative shock dummy in Table 8 can provide a deeper insight on whether the baseline result—that having multiple bank relationships helps reduce overall sensitivity of firm investment to bank shocks—hold true both on the positive and negative sides of the shocks.

[15] Note that the lagged ROA is strongly correlated with firm investment only in the case of small firms, but hardly significant in the case of medium and large firms. This is consistent with the finding by Limjaroenrat (2016) that investment by small firms in Thailand are mostly determined by past profitability as well as supply of external finance while investment by larger firms are driven by demand outlook rather than firm performance.

Considering Column 3 and 4, we may infer that **for small and medium firms, multiple bank relationships help mitigate the impact of bank shocks on investment particularly when firms face negative bank shocks, while this additional effect is muted on the positive shocks.** Interestingly, in the case of large firms, having relationships with more than one bank does *not* help shield firm investment from bank supply shocks. In other words, we find that **large firms with multiple borrowing relationships are actually worse off in the face of negative bank shocks compared to large firms that stick to a single bank.**

This differential effect between small and large firms may at first appear puzzling. Nonetheless, we may refer to the theory of corporate finance literature in order to shed some light on this issue. On the one hand, there exist studies that argue in favor of establishing strong ties with a single bank. For example, Petersen and Rajan (1994) show that building close ties with one institutional creditor can help the firm better secure credit supply, while multiple sourcing weakens lending relationships and reduce the overall availability of credit. On the other hand, other studies argue that having multiple bank relationships is more beneficial for the firm on at least two counts. First, given the prevalence of information asymmetries and agent costs, establishing more than one lending relationship helps reduce the ability of the current creditor to extract rents based on an informational monopoly (Sharpe, 1990, Von Thadden, 1994). Second, it helps decrease the impact of the firm's liquidity risk on investment due to an exogenous reduction in credit supply from the single creditor (Detragiache, et al., 2000). Applying these two sides of the arguments to our findings, we think it is possible that for small firms, whose information asymmetries are likely to be more rampant, having multiple relationships helps relax market frictions and hence generates net benefits for the firms. In contrast, for large firms that generally face less financing constraint to begin with, the value of strong relationships or loyalty is high, and borrowing from multiple creditors may only result in weaker relationships and, as a consequence, lowers the availability of credit overall in the face of negative shocks.

Table 7: Bank shocks and firm investment
Subsamples by firm size

Dependent Variable:	**Small Firms**					**Medium Firms**					**Large Firms**				
Investment$_{f,t}$ / Capital$_{f,t-1}$	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Net income$_{f,t}$/Capital$_{f,t-1}$	0.006***	0.006***	0.006***	0.006***	0.006***	0.044***	0.042***	0.043***	0.042***	0.043***	0.033***	0.035***	0.035***	0.035***	0.035***
	(5.347)	(5.176)	(5.135)	(5.183)	(5.142)	(4.777)	(4.364)	(4.497)	(4.416)	(4.540)	(3.958)	(4.270)	(4.356)	(4.212)	(4.325)
Current asset$_{f,t}$/Capital$_{f,t-1}$	0.109***	0.111***	0.111***	0.111***	0.111***	0.145***	0.143***	0.142***	0.142***	0.142***	0.148***	0.143***	0.139***	0.142***	0.139***
	(30.941)	(31.631)	(31.730)	(31.635)	(31.732)	(29.176)	(30.245)	(30.894)	(30.161)	(30.807)	(21.207)	(22.078)	(22.228)	(22.036)	(22.163)
ROA$_{f,t-1}$	0.168***	0.150***	0.144***	0.150***	0.145***	0.009	-0.051	-0.075*	-0.049	-0.073*	0.067	-0.016	-0.055	-0.010	-0.052
	(5.420)	(4.863)	(4.703)	(4.881)	(4.721)	(0.219)	(-1.251)	(-1.870)	(-1.208)	(-1.831)	(1.385)	(-0.357)	(-1.223)	(-0.219)	(-1.153)
Bank Shock$_{f,t}$		0.068***	0.048***	0.078***	0.059***		0.102***	0.041***	0.101***	0.036**		0.092***	0.041**	0.134***	0.068***
		(6.785)	(3.199)	(7.115)	(3.703)		(10.717)	(2.791)	(9.030)	(2.258)		(8.468)	(2.481)	(7.552)	(3.128)
Firm Shock$_{f,t}$		0.047***	0.026***	0.052***	0.032***		0.079***	0.012***	0.089***	0.022***		0.078***	0.009*	0.104***	0.020***
		(19.570)	(7.870)	(16.449)	(8.385)		(26.404)	(3.239)	(20.500)	(4.682)		(22.394)	(1.730)	(14.830)	(2.746)
Industry Shock$_{f,t}$		0.111***	0.112***	0.112***	0.113***		0.073***	0.074***	0.075***	0.076***		0.117***	0.128***	0.116***	0.127***
		(3.613)	(3.633)	(3.651)	(3.674)		(2.891)	(2.933)	(2.972)	(3.009)		(3.694)	(4.159)	(3.696)	(4.145)
Bank Shock$_{f,t}$ * Loan-to-Asset Ratio$_f$			0.051**		0.050**			0.231***		0.234***			0.233***		0.220***
			(2.280)		(2.220)			(6.494)		(6.544)			(4.945)		(4.670)
Firm Shock$_{f,t}$ * Loan-to-Asset Ratio$_f$			0.051***		0.051***			0.237***		0.236***			0.288***		0.282***
			(6.932)		(6.977)			(16.269)		(16.062)			(11.895)		(11.629)
Bank Shock$_{f,t}$ * More than one bank$_{f,t}$				-0.036*	-0.036*				0.009	0.015				-0.063***	-0.036*
				(-1.662)	(-1.653)				(0.488)	(0.889)				(-3.050)	(-1.804)
Firm Shock$_{f,t}$ * More than one banks$_{f,t}$				-0.014***	-0.014***				-0.024***	-0.022***				-0.037***	-0.014**
				(-2.952)	(-3.112)				(-4.078)	(-4.118)				(-4.794)	(-1.991)
Constant	-0.034***	-0.045***	-0.047***	-0.045***	-0.047***	0.310***	0.281***	0.268***	0.280***	0.267***	0.337***	0.302***	0.282***	0.300***	0.282***
	(-5.572)	(-7.366)	(-7.725)	(-7.381)	(-7.743)	(42.589)	(41.079)	(39.342)	(40.911)	(39.210)	(33.676)	(32.351)	(30.448)	(32.286)	(30.401)
Observations	80,799	80,799	80,799	80,799	80,799	40,303	40,303	40,303	40,303	40,303	24,721	24,721	24,721	24,721	24,721
R-squared	0.067	0.078	0.080	0.079	0.080	0.171	0.238	0.265	0.239	0.266	0.161	0.242	0.287	0.247	0.287
Number of firms	21,920	21,920	21,920	21,920	21,920	10,662	10,662	10,662	10,662	10,662	5,621	5,621	5,621	5,621	5,621
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Bank shocks and firm investment
Asymmetric effects of bank shocks

	Full Sample		**Small & Medium Firms**		**Large Firms**	
Dependent var: $Investment_{f,t}$ / $Capital_{f,t-1}$	(1)	(2)	(3)	(4)	(5)	(6)
$Net\ income_{f,t}/Capital_{f,t-1}$	0.006***	0.006***	0.007***	0.007***	0.035***	0.035***
	(5.360)	(5.360)	(5.621)	(5.624)	(4.325)	(4.319)
$Current\ asset_{f,t}/Capital_{f,t-1}$	0.094***	0.094***	0.098***	0.098***	0.139***	0.139***
	(39.910)	(39.917)	(37.310)	(37.312)	(22.163)	(22.219)
$ROA_{f,t-1}$	0.160***	0.160***	0.155***	0.155***	-0.052	-0.054
	(7.788)	(7.791)	(6.637)	(6.631)	(-1.153)	(-1.194)
$Bank\ Shock_{f,t}$	0.070***	0.077***	0.066***	0.063***	0.068***	0.144***
	(6.595)	(4.124)	(5.612)	(3.094)	(3.128)	(3.597)
$Bank\ Shock_{f,t}$ * $NegativeShocks_{f,t}$		-0.013		0.007		-0.153**
		(-0.418)		(0.209)		(-2.399)
$Firm\ Shock_{f,t}$	0.042***	0.043***	0.042***	0.042***	0.020***	0.019***
	(14.036)	(14.084)	(13.309)	(13.371)	(2.746)	(2.633)
$Industry\ Shock_{f,t}$	0.118***	0.117***	0.120***	0.120***	0.127***	0.126***
	(6.391)	(6.371)	(5.560)	(5.556)	(4.145)	(4.095)
$Bank\ Shock_{f,t}$ * $Loan\text{-}to\text{-}Asset\ Ratio_{f}$	0.081***	0.085***	0.070***	0.083**	0.220***	0.237***
	(4.441)	(2.703)	(3.672)	(2.511)	(4.670)	(2.892)
$Bank\ Shock_{f,t}$ * $Loan\text{-}to\text{-}Asset\ Ratio_{f}$ * $NegativeShocks_{f,t}$		-0.008		-0.025		-0.030
		(-0.155)		(-0.454)		(-0.210)
$Firm\ Shock_{f,t}$ * $Loan\text{-}to\text{-}Asset\ Ratio_{f}$	0.092***	0.092***	0.075***	0.075***	0.282***	0.282***
	(12.761)	(12.736)	(10.343)	(10.314)	(11.629)	(11.693)
$Bank\ Shock_{f,t}$ * $More\ than\ one\ bank_{f,t}$	-0.036***	-0.006	-0.036**	0.005	-0.036*	-0.101***
	(-3.092)	(-0.326)	(-2.449)	(0.202)	(-1.804)	(-2.863)
$Bank\ Shock_{f,t}$ * $More\ than\ one\ bank_{f,t}$ * $NegativeShocks_{f,t}$		-0.057*		-0.078**		0.130**
		(-1.889)		(-2.111)		(2.347)
$Firm\ Shock_{f,t}$ * $More\ than\ one\ banks_{f,t}$	-0.011***	-0.012***	-0.017***	-0.017***	-0.014**	-0.013*
	(-3.521)	(-3.703)	(-4.539)	(-4.766)	(-1.991)	(-1.850)
Constant	0.074***	0.073***	0.044***	0.042***	0.282***	0.277***
	(22.014)	(20.656)	(11.087)	(10.390)	(30.401)	(29.339)
Observations	145,823	145,823	121,102	121,102	24,721	24,721
R-squared	0.104	0.104	0.094	0.094	0.287	0.288
Number of firms	32,353	32,353	28,787	28,787	5,621	5,621
Firm FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.4 Dynamic Firm-Bank Relationships: Bank Switching

The main results presented in section 5.2 point to a potential benefit of having multiple bank relationships for firms to hedge away loan growth shocks. We will investigate this issue further in this subsection.

Instead of counting the number of bank relationships for each firm at each point in time, we are interested to see whether firms actually reached out to find a new bank relationship during difficult times, and for firms that were able to do so what would be the effect of overall bank shock on the firm's investment. Thus, we create a dummy variable, $SwitchBank_{f,t}$, which is equal to 1 if at time *t+1* the firm managed to obtain new loans from a bank other than the bank(s) with existing borrowing relationships at time *t*.[16] This dummy variable is then interacted with the bank shock and the firm shock variables to see whether it makes a difference.

In column 1 of Table 9, the full sample specification presents a statistically insignificant coefficient on the interaction term between bank shock and the bank switching dummy. Interestingly, when we split the sample into the negative and positive bank shock subsamples (column 2 and 3 of Table 9), we find **asymmetric effects of bank switching on the influence of bank shocks on firm investment.** Specifically, **when firms face with negative bank shocks, the ability to secure new borrowing from a new bank significantly reduces the impact of the adverse shocks on their investment.** On the other hand, when firms experience positive bank shocks, the prospect of being able to expand their borrowing through a new bank actually helps spur their investment further.

Of course, notwithstanding the potential benefit of having multiple bank relationships, often than not this is not a choice to be made by a firm. As we show in the stylized facts section, more than half of the firms in our sample maintain only one bank relationship throughout their life time. Some firms seem to have easier access to the credit market and to be able to establish more lending ties than others.

To explore what types of firms have higher tendency to gain access to a new bank relationship, we look into the data and calculate the likelihood based on some specific firm characteristics. We find an interesting pattern as shown in Figure 9. On the whole, **the likelihood of a new bank relationship increases along the three dimensions that we consider: firm size, firm profitability as captured by ROA, and an existing number of bank relationships**. Put simply, a larger firm (economies of scale), a firm higher profitability (solvency), and a firm with already many bank relationships (established credit history) would have higher chance of obtaining loans from a new bank. This is intuitive as these qualities are likely related to firm creditworthiness against default risk. Since we find above that firms that are able to switch to a new bank would be in a more advantageous position, this implies that firms that are on the

[16] Note that firms may not switch completely to a new bank and terminate existing bank relationships. As long as there is a new bank relationship appearing at time *t+1* regardless of the existing ones, it would be captured by this dummy variable.

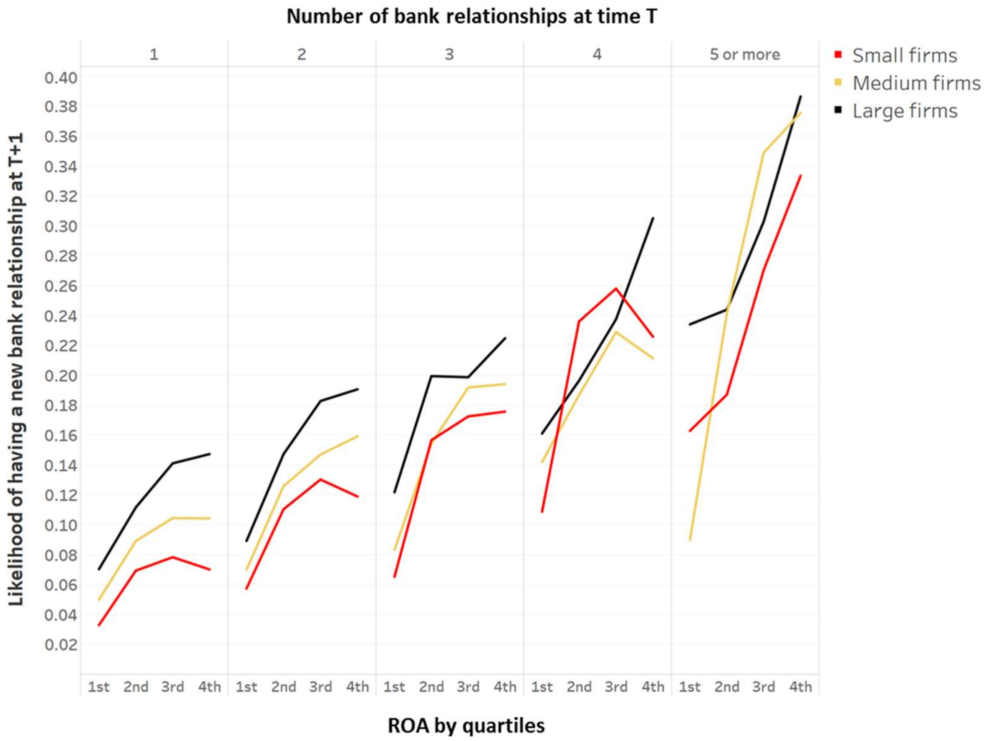
opposite spectrum, especially smaller firms with only one bank relationship, would likely be most affected by changes in bank loan supply. Overall the results suggest that bank shocks may have important distributional implications.

Table 9: Bank shocks and firm investment
Effects of bank-switching

Dependent var: $Investment_{f,t}$ / $Capital_{f,t-1}$	(1) Full Sample	(2) Negative Bank Shock	(3) Positive Bank Shock
Net $income_{f,t}$/$Capital_{f,t-1}$	0.007***	0.007***	0.007***
	(5.386)	(3.271)	(2.952)
Current $asset_{f,t}$/$Capital_{f,t-1}$	0.100***	0.097***	0.112***
	(38.694)	(24.132)	(28.645)
$ROA_{f,t-1}$	0.153***	0.185***	0.090***
	(6.909)	(4.888)	(2.807)
Bank $Shock_{f,t}$	0.086***	0.078***	0.106***
	(12.310)	(3.906)	(7.141)
Firm $Shock_{f,t}$	0.071***	0.075***	0.069***
	(35.922)	(22.592)	(24.141)
Industry $Shock_{f,t}$	0.103***	0.080**	0.122***
	(5.394)	(2.502)	(4.381)
Bank $Shock_{f,t}$ * $SwitchBank_{f,t}$	-0.006	-0.093***	0.074**
	(-0.336)	(-3.063)	(2.317)
Firm $Shock_{f,t}$ * $SwitchBank_{f,t}$	-0.015***	-0.022***	-0.016**
	(-3.161)	(-3.147)	(-2.330)
Constant	0.074***	0.064***	0.074***
	(22.205)	(10.473)	(12.377)
Observations	126,992	59,920	67,072
R-squared	0.103	0.105	0.107
Number of firms	29,764	25,610	24,033
Firm FE	YES	YES	YES
Time FE	YES	YES	YES

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 9: Likelihood of firms having a new bank relationship in the next period, by firm characteristics



5.5 Differential Bank Lending Policy

So far, our loan growth decomposition imposes that bank supply shocks of each particular bank are homogeneous across all of the bank's clients at each point in time. However, anecdotal as well as empirical evidence has suggested that banks may have different lending policies towards different groups of borrowers. This may be due to their market segmentation strategy or their balance sheet conditions that compel them to lend more to some particular types of firms. For example, Peek and Rosengren (2005), Caballero, et al. (2008), and Chakraborty and Peek (2017) found evidence of "evergreening" behavior by Japanese banks during the 'lost decade' in Japan, whereby banks extended additional credit to enable unhealthy and otherwise-insolvent firms to survive and avoid default. This suggests that banks may set different loan supplies for healthy firms and unhealthy firms.

In the case of Thailand, according to the Bank of Thailand's Senior Loan Officer Survey, we usually observe that banks do make distinction between large corporations small and medium enterprises (SMEs) when it comes to changes in credit standards.[17] And it appears that credit conditions for large corporations are more stable than those for SME firms.

[17] The Bank of Thailand's quarterly credit condition reports can be found at: https://www.bot.or.th/English/MonetaryPolicy/EconomicConditions/Pages/CreditCondition.aspx

To incorporate these insights into our analysis, we follow AW and first split our sample firms into two groups: healthy firms vs. unhealthy firms. Unhealthy firms are defined as firms whose interest payments exceed their operating income for two consecutive years.[18] Around 18 percent of our firm-year observations fall into this unhealthy category. We then repeat the decomposition exercise separately for these two groups of firms to obtain different estimates of bank shocks for healthy and unhealthy firms, denoted $\tilde{\beta}_{bt}^{H}$ and $\tilde{\beta}_{bt}^{U}$ respectively.

Interesting patterns emerge when we compare these two types of shocks. Figure 10 plots the average and the distribution of these differential shocks within each group of banks, for the ease of comparison: local large banks (panel A), local small and medium banks (panel B), and foreign banks (panel C). The box plots show a very narrow distribution of shocks to healthy firms (the green bars) across all types of banks, while the box plots for unhealthy-firm bank shocks are much wider and more volatile (the orange bars). What this suggests is that **healthy firms experienced more steady credit supply conditions, whereas bank supply shocks to unhealthy firms are much more erratic across time**.[19]

We then test whether our main results still hold once we allow banks to have different lending policies depending on firm health. The new bank shock variable will be calculated as a weighted average of the specific bank shocks in the firm's loan portfolio: $\sum_b \theta_{ft-1}\tilde{\beta}_{bt}^{h}$ where $h = H$ if the firm is healthy and $h = U$ if the firm is unhealthy, and the weight θ_{ft-1} is the share of each bank in the total borrowing by the firm. Then we replace this new bank shock variable in our baseline specification.

For comparison, in Table 10 we show the results from the main specification using the baseline bank shock (assuming that all of a bank's clients receive a common bank lending shock), along with the results from the new shock estimates (assuming that banks have different lending policies for unhealthy firms and healthy firms). In Column (3) of Table 10, we notice that the coefficients on all of the variables are rarely affected, except for the bank shock itself as well as its interaction with loan-to-asset ratio that see a significant drop in the size of the coefficients.

To check if this reduction in the impact of bank shocks on firm investment comes from the group of unhealthy firms, we interact the bank shock variables with a dummy indicating whether a firm belongs to the unhealthy category. Consider specification (4) of Table 10, the results show a stark difference between the effect of the new bank shock on a healthy firm and the effect on an unhealthy firm. For an unhealthy firm, the positive effect of bank shocks on

[18] This definition of unhealthy firms is used by AW which follows Hoshi, Kashyap, and Scharfstein (1990). Alternatively, we also try other criteria in defining unhealthy firms including return-on-asset and revenue growth. The resulting new bank shock estimates do not differ much.

[19] Another interesting observation is the large and persistent increases in bank lending to the financially distressed firms during the period leading to the global financial crisis, before slowing down and turned into a marked decline during 2010-2011 (around the time of high global risk aversion following the Greece debt crisis). We are inclined to relate this observation of increased lending to unhealthy firms to the risk-taking behavior of banks. However, it would require a separate study to analyze bank risk-taking behavior which is not a focus of this paper.

investment virtually disappears. The non-linear effect of the loan-to-asset ratio also becomes nil. Apparently, **once we allow banks to have differential supply shocks, we capture that the relationship between bank lending shocks and firm investment is now much weaker for an unhealthy firm than a healthy firm**. One plausible explanation may be that the troubled firms used new loans simply to make interest payments on existing loans and/or to meet their other expenses to avoid firm bankruptcy, thus the loan increases do not contribute to higher investment. This explanation is supported when we separate the sample into positive and negative bank shock subsamples and find that the negative coefficient (i.e. weaker correlation between bank shocks and firm investment) is actually driven by the result on the positive side of the shocks as shown in Column 5 of Table 10.

We also create another new bank shock variable, this time by allowing banks to have different lending policies towards small firms and larger firms. For this exercise, we do not observe that bank shocks to small firms are more volatile than larger firms (Figure 12). However, the dynamics of the small-firm bank shocks and large-firm bank shocks are clearly different through time. When we substitute this new bank shock variable by firm size in the baseline regressions (Table 15), we also find the results to differ from the baseline case, especially on the interaction term between bank shock and the small firm dummy. For the full sample regression in Column 4, it may appear puzzling that small firms' investment is less sensitive to bank shocks compared to larger firms. A closer investigation reveals that this result is driven mainly by the positive side of bank shocks, while the negative bank shocks render the opposite effect on investment sensitivity (Column 5 and 6). In essence, **small firms are more adversely affected by negative bank supply shocks, and at the same time observe smaller positive effects on investment from positive bank supply, compared to large firms**.[20]

An important departure from AW is our finding that the assumption of a common bank shock across all of a bank's clients of different types and health is in fact a very strong assumption that may not capture the true underlying bank supply shocks. AW find their results unchanged using either the common bank shock approach or the dual (eg. healthy vs. unhealthy firm) bank shock approach. In contrast, we find the two approaches give rise to strikingly different results on the impact of bank shocks on different types of firms. We believe that this discrepancy arises from the fact that firms in our sample are much more diverse than the group of listed Japanese firms used in AW. Therefore, the 'average' effects may not apply to all groups of vastly different firms. Although there is no way to prove what really are the true underlying bank supply shocks, this finding highlights multi-layered heterogeneity—across firms, across banks, and their interaction—that need to be unfolded to gain deeper understanding of economic relationships.

[20] Note that we do not find unhealthy firms to dominate in the small firm category. In fact, the proportion of unhealthy firms out of all the small firm observations is only 17 percent, compared to 21 percent in the medium and large firm group, and 19 percent in the full sample.

Figure 11: Differential Bank Shocks: Healthy Vs. Unhealthy Firms

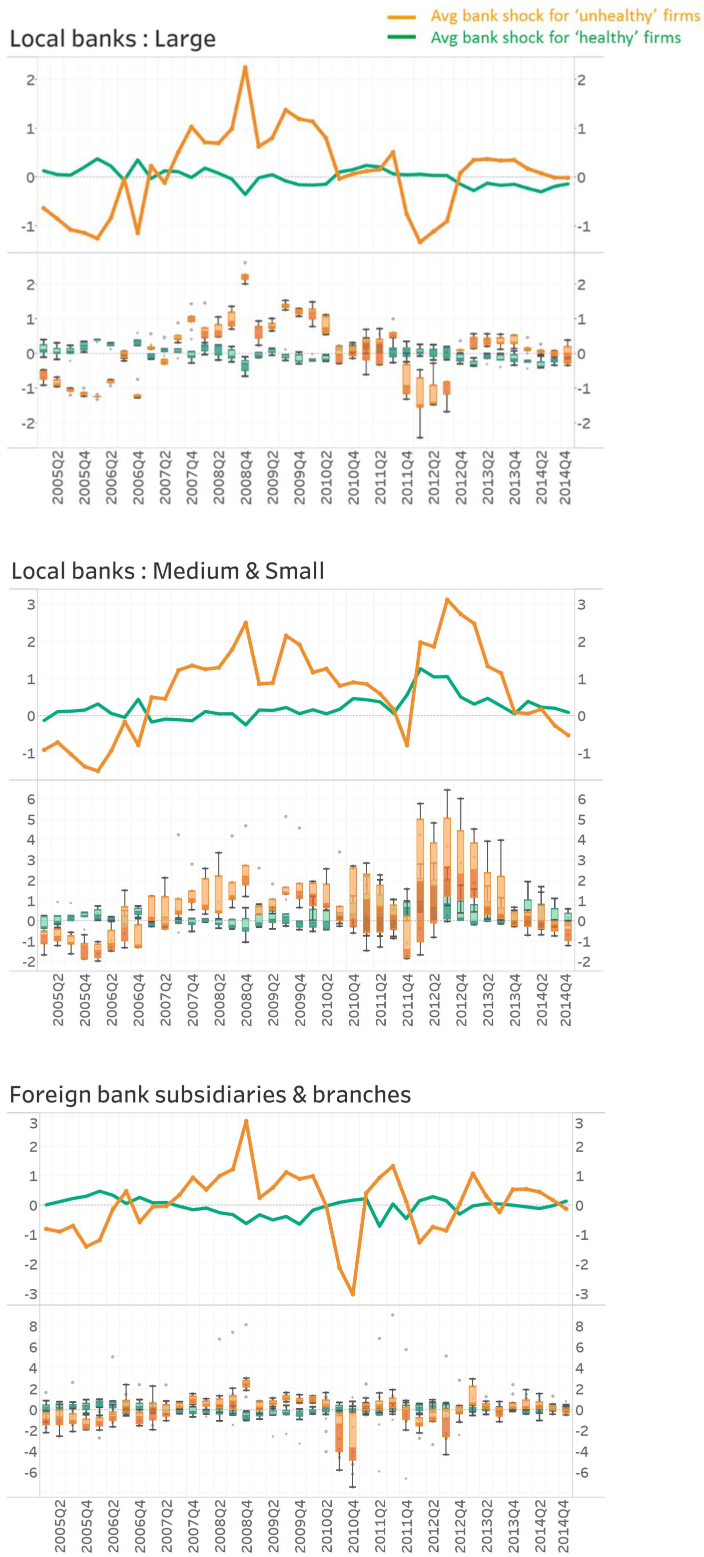


Table 10: Differential Bank Shocks: Healthy vs. Unhealthy Firms

	Common bank shocks		Differential Bank Shocks: Healthy-Unhealthy Firms			
Dependent var: Investment$_{f,t}$ / Capital$_{f,t-1}$	Full sample	Full sample	Full sample	Full sample	Positve shocks only	Negative shocks only
	(1)	(2)	(3)	(4)	(5)	(6)
Net income$_{f,t}$/Capital$_{f,t-1}$	0.006***	0.006***	0.006***	0.006***	0.006***	0.007***
	(5.355)	(5.349)	(5.539)	(5.508)	(2.681)	(4.242)
Current asset$_{f,t}$/Capital$_{f,t-1}$	0.094***	0.094***	0.094***	0.094***	0.114***	0.094***
	(39.924)	(39.935)	(39.498)	(39.540)	(28.522)	(27.059)
ROA$_{f,t-1}$	0.159***	0.158***	0.163***	0.159***	0.057*	0.176***
	(7.727)	(7.677)	(7.755)	(7.602)	(1.756)	(5.339)
Industry Shock$_{f,t}$	0.117***	0.116***	0.103***	0.112***	0.128***	0.108***
	(6.375)	(6.327)	(5.517)	(6.015)	(4.532)	(3.697)
Firm Shock$_{f,t}$	0.037***	0.037***	0.036***	0.037***	0.037***	0.036***
	(15.054)	(15.062)	(15.436)	(15.367)	(8.902)	(10.145)
Firm Shock$_{f,t}$*Loan-to-Asset Ratio$_f$	0.093***	0.093***	0.085***	0.088***	0.089***	0.087***
	(12.938)	(12.933)	(12.430)	(12.574)	(7.024)	(8.556)
Bank Shock$_{f,t}$	0.054***	0.046***	0.013***	0.053***	0.083***	0.022
	(5.857)	(4.636)	(3.593)	(6.658)	(5.106)	(1.379)
Bank Shock$_{f,t}$*UnhealthyFirm$_{f,t}$		0.057**		-0.055***	-0.083***	-0.029
		(2.397)		(-5.631)	(-4.388)	(-1.511)
Bank Shock$_{f,t}$*Loan-to-Asset$_f$	0.087***	0.090***	-0.003	0.032**	0.003	0.038
	(4.829)	(4.356)	(-0.477)	(2.351)	(0.155)	(1.641)
Bank Shock$_{f,t}$*Loan-to-Asset$_f$*UnhealthyFirm$_{f,t}$		-0.041		-0.038**	-0.010	-0.048*
		(-1.077)		(-2.535)	(-0.418)	(-1.904)
Constant	0.074***	0.074***	0.069***	0.055***	0.051***	0.046***
	(22.040)	(22.037)	(20.136)	(14.707)	(6.801)	(8.768)
Observations	145,823	145,823	143,808	143,808	66,826	76,982
R-squared	0.104	0.104	0.101	0.102	0.109	0.105
Number of firms	32,353	32,353	32,244	32,244	24,180	28,505
Firm FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 12: Differential Bank Shocks: Small Vs. Medium-Large Firms

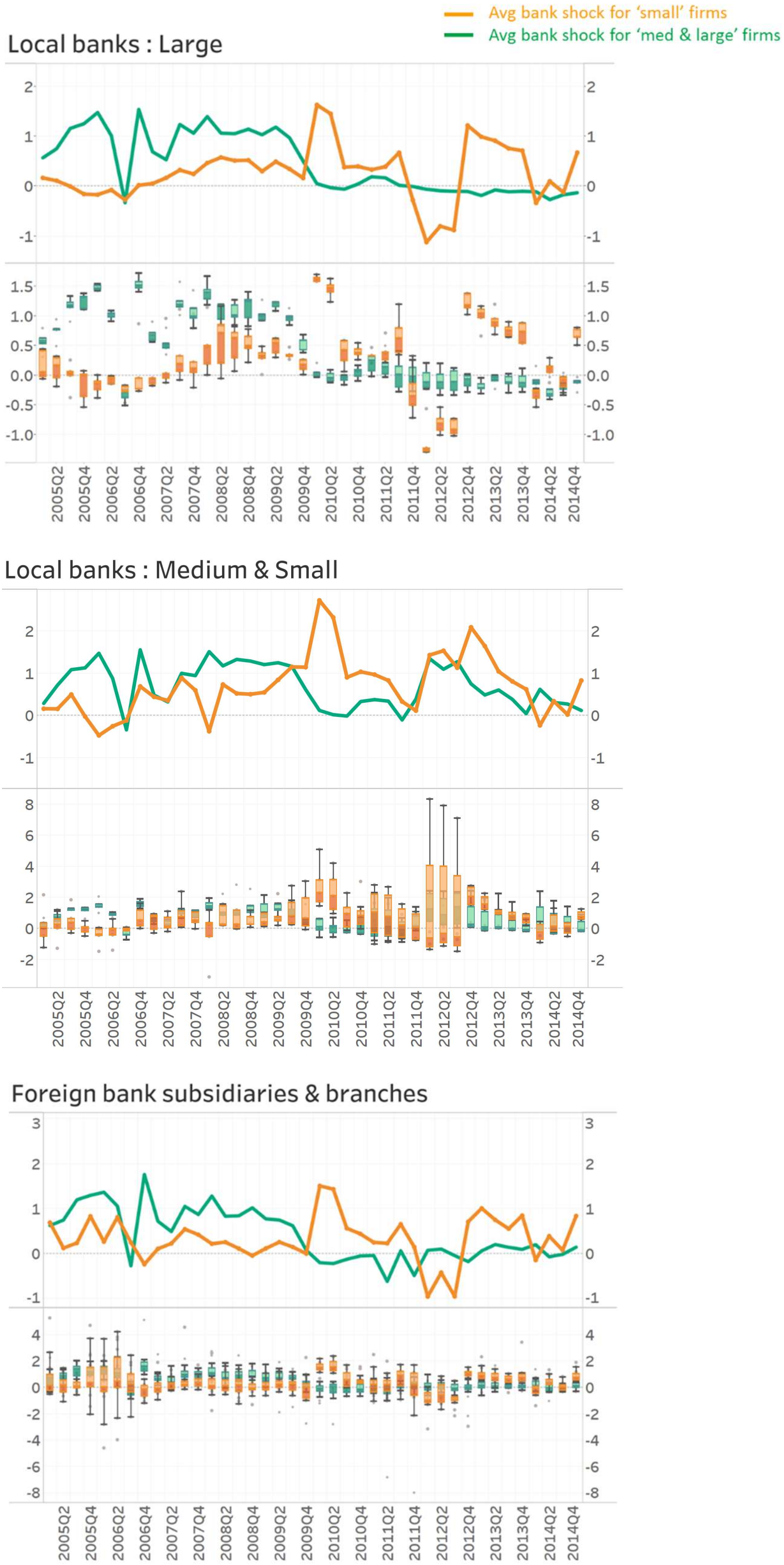


Table 11: Differential Bank Shocks: Small vs. Medium-Large Firms

	Common bank shocks		Differential Bank Shocks: Small-Large Firms			
Dependent var: Investment$_{f,t}$ / Capital$_{f,t-1}$	Full sample	Full sample	Full sample	Full sample	Positve shocks only	Negative shocks only
	(1)	(2)	(3)	(4)	(5)	(6)
Net income$_{f,t}$/Capital$_{f,t-1}$	0.006***	0.006***	0.006***	0.006***	0.006***	0.007***
	(5.355)	(5.356)	(5.562)	(5.553)	(2.643)	(4.421)
Current asset$_{f,t}$/Capital$_{f,t-1}$	0.094***	0.094***	0.093***	0.093***	0.112***	0.094***
	(39.924)	(39.927)	(39.726)	(39.863)	(28.698)	(27.462)
ROA$_{f,t-1}$	0.159***	0.159***	0.161***	0.161***	0.084***	0.172***
	(7.727)	(7.725)	(7.804)	(7.792)	(2.647)	(5.338)
Industry Shock$_{f,t}$	0.117***	0.117***	0.098***	0.097***	0.112***	0.100***
	(6.375)	(6.382)	(5.270)	(5.261)	(4.069)	(3.465)
Firm Shock$_{f,t}$	0.037***	0.037***	0.036***	0.037***	0.036***	0.037***
	(15.054)	(15.053)	(15.322)	(15.424)	(8.814)	(10.417)
Firm Shock$_{f,t}$*Loan-to-Asset Ratio$_f$	0.093***	0.093***	0.087***	0.087***	0.091***	0.084***
	(12.938)	(12.939)	(12.681)	(12.636)	(7.192)	(8.366)
Bank Shock$_{f,t}$	0.054***	0.046***	0.023***	0.032***	0.049***	-0.017
	(5.857)	(3.928)	(6.886)	(4.883)	(5.123)	(-1.413)
Bank Shock$_{f,t}$*SmallFirm$_{f,t}$		0.017		-0.022***	-0.045***	0.035**
		(0.916)		(-2.888)	(-3.970)	(2.532)
Bank Shock$_{f,t}$*Loan-to-Asset$_f$	0.087***	0.099***	-0.006	0.093***	0.083***	0.102***
	(4.829)	(3.232)	(-1.224)	(6.278)	(4.041)	(4.198)
Bank Shock$_{f,t}$*Loan-to-Asset$_f$ * SmallFirm$_{f,t}$		-0.020		-0.101***	-0.082***	-0.118***
		(-0.548)		(-6.429)	(-3.689)	(-4.639)
Constant	0.074***	0.075***	0.085***	0.073***	0.076***	0.062***
	(22.040)	(22.054)	(24.209)	(20.064)	(12.573)	(11.754)
Observations	145,823	145,823	144,324	144,324	67,048	77,276
R-squared	0.104	0.104	0.103	0.104	0.112	0.107
Number of firms	32,353	32,353	32,240	32,240	23,939	28,526
Firm FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.6 Robustness Checks

We perform various robustness checks in this section. First, among the control variables, some might argue that past ROA may not be a good predictor of investment opportunities. Since our sample consists mainly of non-listed firms, market-to-book value which is a widely-used indicator of future profitability is not available. We thus use three-year average forward ROA (current and two-year ahead ROA) as an alternative proxy for expected future profitability based on the assumption of perfect foresight (Abel and Blanchard, 1986). As shown in Column 1 of Table 12, the coefficients on other regressors hardly change with this replacement. Following AW, we also test whether current bank shocks are driven by past firm-level shocks, giving rise to endogeneity or a spurious relationship between bank shocks and firm-level investment. When lagged firm shocks are included in Column 2, we find that this does not change the key results that bank shocks are important determinants of firm investment, though the size of the effects become smaller.

To verify that our results are not driven by crisis events, we first interact the bank shock and firm shock variables with a global financial crisis dummy (GFC) which is equal to 1 for the year 2008 and 2009, 0 otherwise. The direct effect of the GFC that on investment across firms, if any, would already be accounted for by the time fixed effects. The results in Column 3 show that the effects of bank shocks on firm investment are similar to the baseline regressions. And the crisis interaction terms are not statistically significantly different from zero, indicating that there is no difference between crisis and non-crisis years. This makes intuitive sense given the low exposure of the Thai financial system to the global finance and the crisis-inflicted countries. Another shock event that struck the Thai economy during the sample period was the Great Flood that hit central Thailand in the last quarter of 2011, with its lingering effects on businesses throughout the first half of 2012. Interestingly, the flood interaction terms show significantly negative coefficients (Column 4), suggesting that the impact of bank shocks on firm investment are smaller during the flood period. We conjecture that government flood relief measures, which included various loan programs through government banks, are responsible for this alleviating effect of bank loan supply shocks on firm investment.[21]

Lastly, we divide the sample into manufacturing and non-manufacturing subsamples to show that our results are robust across different business sectors. Firms in our sample can actually be classified into 17 industries. However, since many of the industries have only a small number of firms, we group all the non-manufacturing industries together and compare against the manufacturing group. Column 5 and 6 show that the results remain robust across the two industry subsamples. We also run a separate regression for the wholesale/retail trade industry

[21] The Thai government disaster relief measures ranged from direct financial assistance to flood-hit households, to soft loan packages for working capital and reconstruction, credit extensions, and tax exemption for affected businesses. Most of these programs were implemented through government specialized financial institutions (SFIs), although some commercial banks also issued relief packages to provide assistance to their flood-affected clients. Note that loans under government SFIs are not included in our data.

since it has substantial number of firms within the industry. The coefficients are similar to those from the baseline regressions, confirming the robustness of the results.

Table 12: Robustness Checks

Dependent variable: Investment$_{f,t}$ / Capital$_{f,t-1}$	(1) ROA 3-yr average	(2) Lagged firm shock	(3) GFC interaction	(4) Great flood interaction	(5) Manufacturing firms	(6) Non-manufacturing firms
Net income$_{f,t}$/Capital$_{f,t-1}$	0.009***	0.009***	0.006***	0.006***	0.009**	0.006***
	(5.788)	(5.555)	(5.355)	(5.346)	(2.324)	(4.830)
Current asset$_{f,t}$/Capital$_{f,t-1}$	0.115***	0.106***	0.094***	0.094***	0.098***	0.093***
	(37.367)	(35.618)	(39.923)	(39.921)	(23.701)	(32.829)
ROA$_{f,t-1}$	0.110***	0.143***	0.159***	0.160***	0.115***	0.186***
	(3.359)	(5.959)	(7.727)	(7.752)	(4.134)	(5.749)
Bank Shock$_{f,t}$	0.058***	0.028***	0.055***	0.062***	0.042***	0.061***
	(5.279)	(2.619)	(5.439)	(6.320)	(3.547)	(4.335)
Firm Shock$_{f,t}$	0.039***	0.038***	0.037***	0.039***	0.035***	0.037***
	(12.688)	(13.066)	(14.162)	(15.133)	(9.406)	(11.353)
Firm Shock$_{f,t-1}$		0.018***				
		(12.702)				
Industry Shock$_{f,t}$	0.113***	0.099***	0.117***	0.119***	0.096***	0.129***
	(5.438)	(4.829)	(6.370)	(6.468)	(3.766)	(5.101)
Bank Shock$_{f,t}$ * Loan-to-Asset Ratio$_f$	0.081***	0.094***	0.087***	0.088***	0.104***	0.080***
	(3.550)	(4.536)	(4.818)	(4.867)	(3.819)	(3.290)
Firm Shock$_{f,t}$ * Loan-to-Asset Ratio$_f$	0.090***	0.064***	0.093***	0.093***	0.105***	0.088***
	(9.333)	(7.368)	(12.927)	(12.917)	(8.367)	(9.830)
Bank Shock$_{f,t}$ * Crisis			-0.004			
			(-0.259)			
Firm Shock$_{f,t}$ * Crisis			-0.001			
			(-0.352)			
Bank Shock$_{f,t}$ * Flood				-0.036**		
				(-2.350)		
Firm Shock$_{f,t}$ * Flood				-0.010***		
				(-2.706)		
Constant	0.064***	-0.087***	0.074***	0.074***	0.075***	0.077***
	(18.057)	(-27.800)	(21.978)	(21.951)	(17.485)	(14.866)
Observations	98,733	104,150	145,823	145,823	55,663	90,160
R-squared	0.116	0.091	0.104	0.104	0.117	0.100
Number of firms	25,159	25,271	32,353	32,353	11,312	22,698
Firm FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6. AGGREGATE-LEVEL REGRESSION ANALYSIS

Having explored the impact of bank supply shock on investment at the firm level, in this section we will turn to the macro-level relationship. We assess how much each of the four granular shocks obtained from the micro-level decomposition matters for aggregate loan and investment fluctuations.

First, in Table 13 left panel, the growth rate of total corporate loans is regressed on the granular bank, firm, industry and common shocks. Note that our loan data covers roughly 80 percent of the aggregate corporate loans and the two series have very similar dynamics. Since the four granular shocks provide a complete decomposition of the loan growth in our data, it is not surprising that the R^2 of this regression is exceptionally high at 87 percent. All coefficients are statistically significant and close to one indicating that the shocks identified in our data are the same as those we would find in economy-wide loan growth.

To gauge the relative importance of each shock in determining aggregate loan movements, we can interpret the results in terms of standard deviations of the variables. We find that a one standard deviation increase in the common shock, granular bank shock, and firm shock contributes to an increase in the aggregate loan growth by 1.9, 1.3 and 1.2 standard deviation, respectively. The granular industry shock appears to have the least influence on the aggregate loan fluctuations as it moves loan growth by merely 0.15 standard deviation.

A highlight from Table 13 is that, comparing Column 1 and 2, adding the bank shock component to the loan growth regression substantially increases the R^2 from 0.508 to 0.875. From this result, we can infer that **on average bank shock accounts for roughly 37 percent of aggregate credit expansion**.

Looking at the effect of granular bank shock on aggregate investment growth regressions (Table 13, right panel), adding bank shock improves R^2 from 0.085 to 0.248. This is equal to a 16 percentage-point increase in R^2 which is relatively low compared to the previous studies, implying that the overall financial shocks may not be a key determinant of aggregate investment in Thailand. Nevertheless, the R^2 decomposition reveals that **granular bank shock scores as the most important factor accounting for 39 percent of the overall financial shocks that drive aggregate investment dynamics**, followed by the common shock with 35 percent contribution.[22]

Turning to the effect of granular firm shock, we found that while granular firm shock is the major drivers of aggregate loan growth as it explains up to 50 percent of aggregate credit dynamics (Table 13, right and lower panel), its importance for aggregate investment is rather muted (Table 13, left and lower panel). Since the granular firm shocks are driven mainly by large firms by construction, this result implies that though large firms are a major source of

[22] Shapley-Owen R^2 decomposition measures the relative contribution of each regressor to the goodness-of-fit of the regression.

aggregate credit growth fluctuations, their borrowing may play a limited role in driving economy-wide investment growth.

Overall, our analysis shows that **the granular bank shock—i.e. the idiosyncratic bank lending decisions by large banks in isolation of common shocks and firm borrowing demand—can have a potentially large impact on the aggregate economy** through its influence on the macro-level credit and investment fluctuations.

Table 13: Aggregate loan growth and investment growth regressions

Variable	Aggregate loan growth						Aggregate investment growth					
	(1)			(2)			(3)			(4)		
	Coef.		S.E.	Coef.		S.E.	Coef.		S.E.	Coef.		S.E.
Common shock$_t$	0.372	***	0.092	1.145	***	0.077	0.047		0.163	0.732	***	0.254
Firm shock$_t$	0.985	***	0.142	1.436	***	0.085	-0.201		0.284	0.199		0.244
Industry shock$_t$	0.115		0.518	0.895	***	0.295	-1.603	**	0.733	-0.912		0.763
Bank shock$_t$				1.108	***	0.109				0.982	***	0.258
Constant	0.019	*	0.011	0.024	***	0.007	0.056	***	0.018	0.060	***	0.014
Observations	40			40			40			40		
R^2	0.508			0.875			0.085			0.248		
Shapley-Owen R-squared decomposition												
Common shock$_t$				31.03						35.59		
Firm shock$_t$				50.87						11.04		
Industry shock$_t$				2.85						14.30		
Bank shock$_t$				15.25						39.07		

7. CONCLUSION

The aim of this paper is to study the relationship between bank supply shocks and firm-level and aggregate-level investment in the case of Thailand during 2004-2015. We apply a novel methodology proposed by Amiti and Weinstein (2017) to the Thai credit registry data to obtain an exact decomposition of credit growth into bank supply, firm demand, industry, and common factors. The key advantage of this method is that the four components of the estimated shocks are summed up to match the aggregate-level lending and borrowing patterns, allowing us to not only to study the impact of shocks from different sources on firm investment but also to understand the underlying dynamics of the overall credit growth in the economy.

Our results indicate that bank supply shocks do matter for firm investment activity, particularly for smaller firms and firms that rely relatively more on bank loans in their total financing. In addition, we find that firms with multiple bank relationships and firms that are able to switch to a new bank are on average less affected by bank shocks. This mitigating effects of having diversified bank relationships are especially important for small firms when faced with negative bank shocks. We also show that banks are likely to have differential lending policy towards different groups of customers, thus assuming a common bank supply shock across all of the bank's clients may be too strong an assumption. Once we allow for bank shocks to differ across healthy and unhealthy firms, it appears that healthy firms may have experienced much more steady credit supply conditions, whereas bank supply shocks to unhealthy firms were much more volatile. At the aggregate level, we find evidence supporting the real effect of bank supply shocks on aggregate credit and investment dynamics, although the size of the impact on investment may be rather small in the case of Thailand relative to the previous studies.

From the perspective of policymakers, this shock decomposition methodology can be a potentially useful tool for the purpose of financial system monitoring. Since this approach relies only on a period-on-period estimation, the shock decomposition can thus be updated as frequently as the new data becomes available in the credit registry data system. This would provide an extra information for practitioners in identifying potential sources of financing shocks or liquidity risks that may have repercussions on the real economy in terms of derailing or holding back investment momentum. For example, considering the shock decomposition across times, policymakers can come up with a better idea of whether rapid increases or decreases in credit growth in the economy are driven by shocks that are common across most lenders and borrowers, or some systematic changes in the lending of some key creditors.

Overall, this paper lends empirical support to the granular hypothesis in the spirit of Gabaix (2011) that idiosyncratic bank shocks matter for the aggregate economy, given a high concentration of banks in the credit market. In this light, understanding the behavior of the key players in the banking system and the potential impact on the real sector deems essential not only for monitoring and supervisory purposes, but also for coming up with better forecasts at the macro level.

Our results also point to various policy implications. First, this study stresses the importance of granularity in analyzing macroeconomic phenomena. One should look beyond aggregate movements of economic variables, but rather pay attention to various layers of heterogeneity as well as the distributional effects of the shocks, in order to get a genuine understanding of what drives the aggregate outcome. Second, at the micro level, our results imply that financing frictions may still exist even for firms that already have access to bank finance. This is inferred from our finding on the differential impact of bank shock between firms with one bank relationship and firms with multiple-bank relationships, where the former tends to observe larger negative impact than the latter. Although there may be some unobserved characteristics of these two groups of firms related to their underlying creditworthiness or overall ability that we cannot verify, establishing a more diversified bank relationship appears, on average, to enhance resiliency of firms against idiosyncratic bank shocks. Towards this end, efforts to reduce supply-side informational frictions regarding creditworthiness of small- and medium-sized firms, whose access to finance remains limited, may prove beneficial for the flexibility of the system as a whole.

References

Amiti, Mary and David E. Weinstein. “How much do bank shocks affect investment? Evidence from matched bank-firm Loan data.” *Journal of Political Economy*, forthcoming (2017).

Amador, João, and Arne J. Nagengast. "The effect of bank shocks on firm-level and aggregate investment," European Central Bank Working Paper No. 1914 (2016).

Ananchotikul, Nasha, and Dulani Seneviratne. "Monetary policy transmission in emerging Asia: the role of banks and the effects of financial globalization,” IMF Working Paper No. 15/207 (2015).

Bernanke, Ben S., and Mark Gertler. “Inside the black box: the credit channel of monetary policy transmission,” National Bureau of Economic Research Working Paper No. 5146 (1995).

Bernanke, Ben S., Mark Gertler, and Simon Gilchrist. "The financial accelerator in a quantitative business cycle framework." *Handbook of macroeconomics* 1 (1999): 1341-1393.

Berglöf, Erik, and Ernst-Ludwig Von Thadden. "Short-term versus long-term interests: Capital structure with multiple investors." *The Quarterly Journal of Economics* 109, no. 4 (1994): 1055-1084.

Caballero, Ricardo J., Takeo Hoshi, and Anil K. Kashyap. "Zombie lending and depressed restructuring in Japan." *The American Economic Review* 98, no. 5 (2008): 1943-1977.

Cucinelli, Doriana. "The impact of non-performing loans on bank lending behavior: evidence from the italian banking sector." *Eurasian Journal of Business and Economics* 8, no. 16 (2015): 59-71.

Detragiache, Enrica, Paolo Garella, and Luigi Guiso. "Multiple versus single banking relationships: Theory and evidence." *The Journal of Finance* 55, no. 3 (2000): 1133-1161.

Detragiache, Enrica, Paolo Garella, and Luigi Guiso. "Multiple versus single banking relationships: Theory and evidence." *The Journal of Finance* 55, no. 3 (2000): 1133-1161.

Gabaix, Xavier. "The granular origins of aggregate fluctuations." *Econometrica* 79, no. 3 (2011): 733-772.

Hahm, Joon-ho, Hyun Song Shin, and Kwanho Shin. "Noncore bank liabilities and financial vulnerability." *Journal of Money, Credit and Banking* 45, no. s1 (2013): 3-36.

Hoshi, Takeo, Anil Kashyap, and David Scharfstein. "The role of banks in reducing the costs of financial distress in Japan." *Journal of financial economics* 27, no. 1 (1990): 67-88.

Klemperer, Paul. "Competition when consumers have switching costs: An overview with applications to industrial organization, macroeconomics, and international trade." *The review of economic studies* 62, no. 4 (1995): 515-539.

Knittel, Christopher R. "Interstate long distance rates: search costs, switching costs, and market power." *Review of industrial Organization* 12, no. 4 (1997): 519-536.Degryse, et al. (2017)

Kashyap, Anil K., and Jeremy C. Stein. "What do a million observations on banks say about the transmission of monetary policy?" *American Economic Review* (2000): 407-428.

Kashyap, Anil K., and Jeremy C. Stein. "The impact of monetary policy on bank balance sheets." In *Carnegie-Rochester Conference Series on Public Policy*, vol. 42, pp. 151-195. North-Holland, 1995.

Khwaja, Asim Ijaz, and Atif Mian. "Tracing the impact of bank liquidity shocks: Evidence from an emerging market." *The American Economic Review* 98, no. 4 (2008): 1413-1442.

Kishan, Ruby P., and Timothy P. Opiela. "Bank size, bank capital, and the bank lending channel." *Journal of Money, Credit and Banking* (2000): 121-141.

Kiyotaki, Nobuhiro, and John Moore. "Credit cycles." *Journal of political economy* 105, no. 2 (1997): 211-248.

Peek, Joe, and Eric S. Rosengren. "Unnatural selection: Perverse incentives and the misallocation of credit in Japan." *The American Economic Review* 95, no. 4 (2005): 1144-1166.

Petersen, Mitchell A., and Raghuram G. Rajan. "The benefits of lending relationships: Evidence from small business data." *The journal of finance* 49, no. 1 (1994): 3-37.

Sharpe, Steven A. "Asymmetric information, bank lending, and implicit contracts: A stylized model of customer relationships." *The journal of finance* 45, no. 4 (1990): 1069-1087.

Stiglitz, Joseph E., and Andrew Weiss. "Credit rationing in markets with imperfect information." *The American economic review* 71, no. 3 (1981): 393-410.

APPENDIX A: Firm-Bank Shock Decomposition Methodology

We describe briefly our firm-bank shock decomposition methodology. Readers are kindly referred to AW (2017) for further detailed of the methodology. Here, vector A_t is defined as a full set of firm shocks and Φ_t matrix is the full set of bank-lending weight described as

$$A_t \equiv \begin{bmatrix} \alpha_{1t} \\ \vdots \\ \alpha_{Ft} \end{bmatrix},\ \Phi_t \equiv \begin{pmatrix} \phi_{11t} & \cdots & \phi_{F1t} \\ \vdots & \ddots & \vdots \\ \phi_{1Bt} & \cdots & \phi_{FBt} \end{pmatrix}$$

By rewriting firm and bank shock relative to its median as $\dot{A_t} \equiv A_t - \bar{A}_t 1_F$ and $\dot{B_t} \equiv A_t - \bar{B}_t 1_B$ we would obtain

$$\begin{aligned} \mathrm{D}_t^B &= B_t + \Phi_{t-1} A_t \\ &= \dot{B_t} + \overline{B_t}\, 1_B + \Phi_{t-1}\dot{A_t} + \overline{A}_t \Phi_{t-1} 1_F \\ &= \dot{B_t} + \Phi_{t-1}\dot{A_t} + (\bar{A}_t + \overline{B_t})\, 1_B \end{aligned}$$

and

$$\begin{aligned} \mathrm{D}_t^F &= A_t + \theta_{t-1} B_t \\ &= \dot{A_t} + \overline{A_t}\, 1_F + \Phi_{t-1}\dot{B_t} + \overline{B}_t \theta_{t-1} 1_B \\ &= \dot{A_t} + \theta_{t-1}\dot{A_t} + (\bar{A}_t + \overline{B_t})\, 1_F \end{aligned}$$

We further decompose firm industry shock by define $\widetilde{A_t} \equiv \dot{A}_t - median_f(\dot{A}_t)$ where f is part of industry n. Similarly, define $\widetilde{B_t} \equiv \dot{A}_t - median(\dot{B}_t)$ where $median(\dot{B}_t)$ = 0.

Finally, we define N_t as Fx1 vector of industry median corresponding to F firms in the sample. We thus can rewrite the equation, corresponding to the main text as

$$\mathrm{D}_t^F = \widetilde{A}_t + N_t + \theta_{t-1}\widetilde{B}_t + (\overline{A}_t + \overline{B}_t)\, 1_F$$

$$\mathrm{D}_t^B = \widetilde{B}_t + \Phi_{t-1}\widetilde{A}_t + \Phi_{t-1} N_t + \theta_{t-1}\widetilde{B}_t + (\overline{A}_t + \overline{B}_t)\, 1_B$$

APPENDIX B: Validity of Shock Estimates

We have seen in the previous section that the decomposition methodology yields bank shocks that are heterogeneous across banks at each point in time. Although the evolution of the bank, firm, and common shocks at aggregate level appear to be consistent with the overall credit dynamics in the Thai economy as discussed above, how can we be sure that these estimates of bank and firm shocks are sensible at the individual bank and firm level? In this section, we will evaluate the validity of the estimated bank and firm shocks to reassure that they meaningfully capture the idiosyncratic bank lending shocks and firm borrowing shocks, respectively. Be reminded that the bank and firm shock measures are derived purely from the decomposition of loan growth rate at the bank-firm level without relying on any balance sheet information. One way to check external validity of the estimates is thus to compare them with balance sheet variables that generally found to be related to bank-lending channel in the case of bank shocks, and related to firm's demand or ability to borrow in the case of firm shocks.

B.1 Bank shock validity

The concept of bank supply shocks is closely related to that of the bank lending channel (Bernanke and Gertler, 1995) which emphasizes the role of financial frictions and external finance premium that induce changes in the supply of bank credit in face of (monetary policy) shocks. One important implication from the bank lending channel is that banks that are more financially constrained will need to reduce their loan supply by more when faced with negative shocks. Financial constraints are commonly proxied by bank size and capitalization (for example, Kashyap and Stein, 1995 and 2000, Kishan and Opiela, 2000, Khwaja and Mian, 2008). According to the bank lending literature, we expect banks that are more financially constrained, as captured by low capitalization (proxied by the BIS risk-based capital adequacy ratio) and smaller size (proxied by log of bank assets) to have bank shocks that are more negative.

In addition to the above common proxies of bank supply shocks, we also consider other balance sheet variables that may influence banks' credit supply policy. The outlook of the quality of loans in bank's portfolio and credit default risk have been found to affect bank lending behavior (Cucinelli, 2015). The argument is that when banks expect loan quality to deteriorate and/or default risk to escalate, banks would tend to limit the overall bank risk by adopting more stringent lending policy. This conforms to the credit rationing theory in imperfect market with adverse selection problem (Stiglitz and Weiss, 1981). We use the loan loss provision ratio—an expense set aside as an allowance for anticipated loan losses, as a ratio to bank's gross loans—as a forward-looking measure of bank's credit risk outlook, and test its relationship with our estimates of bank supply shocks.

Regarding bank funding structure, it has been evident that banks in emerging markets including in Thailand has been increasingly resorted to non-core funding as an alternative to the traditional deposit funding (Hahm, Shin, Shin, 2011, Ananchotikul and Seneviratne, 2015). We posit that in general banks that deviate from the traditional funding sources should have more flexibility in financing their loan expansion and thus should be more able to insulate their loan supply from negative shocks that affect the cost of deposit funding. Thus, we expect banks that rely more on non-core funding to be correlated with more positive bank supply shocks.[23] Here we use the ratio of debt (including loans and debt securities both in local and foreign currencies) to total liabilities as a measure of non-core funding ratio.

Figure B1 provides the scatter plots between our bank shock estimates and bank loan growth as well as some of the bank balance sheet variables described above, averaged over the whole sample period 2005-2014. Each of the dots represents each bank in our sample. The top left chart shows that bank shocks is closely correlated with the overall bank loan growth, but not perfectly. This is reassuring since it can be inferred that the bank shock measures generally go in the same direction as the overall bank loan growth, but sometimes it was something else other than bank supply shocks that drove bank credit growth. The rest of the charts show that there seem to be some relationships between the average bank shocks and the average balance sheet characteristics of each bank, all in the expected direction.

We then examine the significance of these correlations in a regression analysis, using quarter-by-quarter data rather than sample-period averages. The regressors are in lagged terms to avoid endogeneity biases. Table B1 confirms that our bank shock estimates are statistically significantly correlated with the capital adequacy ratio, loan loss provision ratio, and the non-core liabilities ratio, with expected signs. The coefficient on the asset size is also significant but only once we control for the other balance sheet characteristics. These results suggest that at each point in time, banks with larger asset size, higher capitalization, better outlook on the quality of loan portfolio, and greater reliance on non-core funding, generally produce more positive bank supply shocks. This is consistent with previous findings on the determinants of bank supply shocks and reassures that the decomposition method used in this paper is able to correctly identify the idiosyncratic factors that affected the loan supply of individual banks.

To further investigate the reasonableness of the bank shock estimates, and with our prior that local banks and foreign banks may behave differently especially during the global financial crisis period, we conduct a mean test of bank shocks between these two groups of banks. Table B2 shows that the t test cannot reject the null hypothesis of equal means between the two groups for the full sample period, pre-crisis period (2005-2007), and the post-crisis period (2010-2014), implying that the bank shocks of both local and foreign banks are similarly distributed around the same mean during the normal periods. Only during the crisis period (2008-2009) that foreign banks produced statistically significantly more negative bank shocks than the Thai local banks. This result is intuitive provided that fact that most local Thai banks were largely insulated from the direct effects of the global financial crisis due to their low exposure to the U.S. and European banking system, while foreign bank branches and

[23] However, one could also argue that banks with high core funding ratio may feel more secure and more likely to expand loan supply to a greater extent than non-core funded banks. The relationship between bank shocks and this funding ratio is thus less clear-cut than the other balance sheet characteristics.

subsidiaries were perceivably impacted by the crisis due to their linkages to the parent banks in the crisis-inflict countries. The more negative bank shocks of the foreign banks during the crisis thus appear to lend further support to the validity of our bank supply shock measures.

Figure B1: Bank shocks and bank characteristics, average 2005-2014

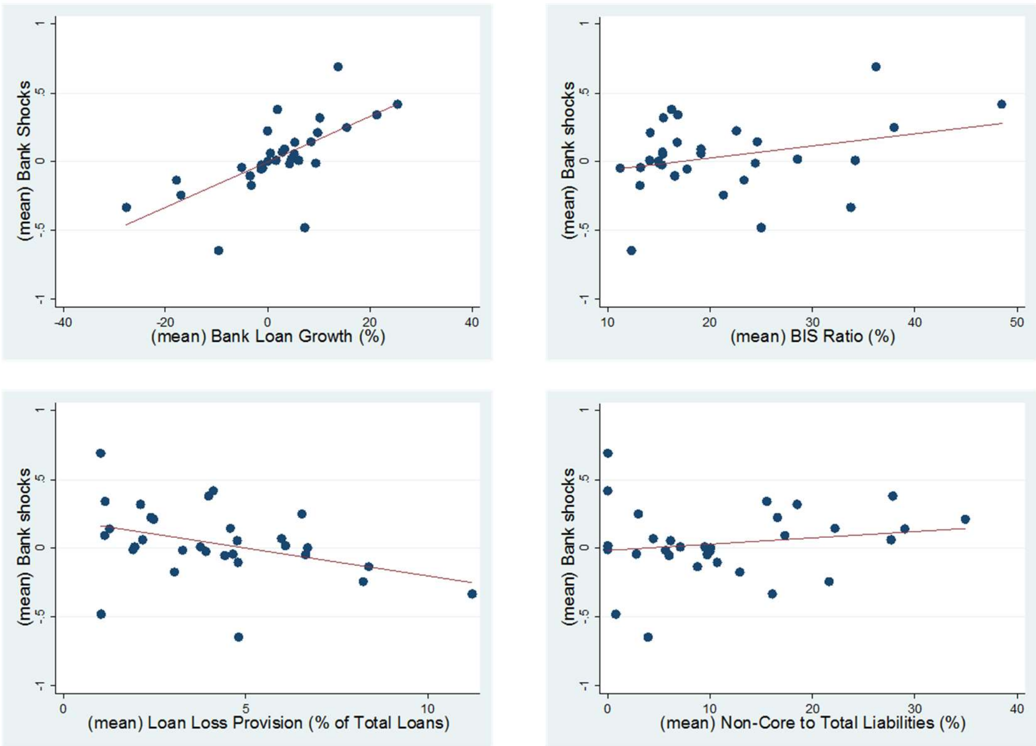


Table B1: Validation of bank shocks

Dependent Variable: Bank Shock$_{b,t}$	(1)	(2)	(3)	(4)	(5)
Ln(Bank asset)$_{b,t-1}$	-0.010				0.029***
	(-0.893)				(2.675)
BIS ratio$_{b,t-1}$		0.006**			0.011***
		(2.032)			(3.223)
Loan loss provision ratio$_{b,t-1}$			-0.019***		-0.019***
			(-3.683)		(-3.901)
Non-core funding$_{b,t-1}$/Total liabilities$_{b,t-1}$				0.003**	0.003**
				(2.345)	(2.327)
Constant	0.213	-0.119	0.086	0.087	-0.341
	(1.209)	(-1.390)	(1.175)	(0.697)	(-1.637)
Observations	1,034	1,022	1,030	1,030	1,022
R-squared	0.022	0.030	0.036	0.027	0.062
Time FE	YES	YES	YES	YES	YES

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B2: Mean test of bank shocks between local and foreign banks

Two-sample t test of the equality of bank shock means: Local banks VS. Foreign banks

Group	Obs	Mean	Std. Dev.	Diff(Mean)	H_0: diff = 0			
					Equal variances		Unequal variances	
					t value	Prob	t value	Prob
Full period (2005-2014)								
Local	13	0.029	0.338	*0.054*	0.455	0.652	0.451	0.656
Foreign	19	-0.025	0.322					
Pre-GFC (2005-2007)								
Local	12	0.007	0.130	*-0.072*	-0.775	0.445	-0.894	0.380
Foreign	18	0.078	0.301					
GFC (2008-2009)								
Local	13	0.326	0.537	***0.478***	**2.745**	**0.010**	**2.653**	**0.014**
Foreign	17	-0.152	0.418					
Post-GFC (2010-2014)								
Local	13	-0.016	0.541	*0.006*	0.037	0.971	0.034	0.973
Foreign	17	-0.022	0.304					

B.2 Firm shock validity

Next, we examine whether the firm-specific shocks generated from our decomposition method are reasonable and consistent with what we would expect based on firm characteristics. Firm-specific shocks to loan growth could be driven either by varying loan demand, or by some other characteristics of the particular firms that are often associated with more or less favorable loan growth compared to the average bank supply shocks. We consider the following firm attributes for the external validity test: firm size, level of leverage, profitability, growth prospect, and the number of bank relationships. Except for the leverage, we expect all of these variables to be positively correlated with firm shocks. Firm size and the number of borrowing relationships are likely to be positively associated with firms' creditworthiness or political (crony) connection, hence leading to more favorable firm-specific lending. At the same time, firms with higher profitability and greater growth prospect should have greater demand for loans as well as higher probability of loan approval by banks, hence receiving larger loan growth than the average firm.

As for leverage, the arguments could be both ways. On the one hand, firm shocks and leverage could be positively correlated simple because larger firm shocks cause firm leverage to be higher, or because high level of access to bank loans may also signify greater creditworthiness of the firms. On the other hand, highly-leveraged firms could also be viewed as riskier and thus associated with smaller shocks. We postulate that the former effects should dominate in the general sample, while the latter effect would become important above some threshold level of borrowing.

We use log of fixed assets as a measure of firm size (to be consistent with how we define small, medium and large size later in the regression analysis section). Leverage is measured as the amount of outstanding loans to asset ratio. For profitability and growth prospect, we proxy by return-on-asset (ROA) and revenue growth, respectively. The number of bank relationships is captured by counting the number of different banks with which each firm has outstanding loans within a particular year. Since we are not testing the causality here—only a simple correlation to assess the pattern between firm shocks and firm characteristics—we use the mean of firms shocks as well as the mean of other firm variables across the sample period and run simple linear regressions. As shown in Table B3, we find that all variables, with the exception of ROA, are positively correlated with the firm shocks as expected. ROA alone is negatively correlated with firm-specific shocks, but the coefficient turns positive once other firm characteristics are taken into account as in Column 6. Overall, the results appear to be consistent with our priors on the pattern of firm-specific shocks in association with firm characteristics and balance sheet quality, supporting the validity of the firm shock estimates.

Table B3: Firm shocks and firm characteristics

Dependent Var: Mean of Firm Shock$_f$	(1)	(2)	(3)	(4)	(5)	(6)
Mean Ln(Fixed Assets$_f$)	0.009***					0.006***
	(7.277)					(4.283)
Mean Loan-to-Asset Ratio$_f$		0.154***				0.067***
		(17.117)				(8.552)
Mean Return-On-Asset$_f$			-0.204***			0.230***
			(-3.655)			(4.632)
Mean Revenue Growth$_f$				0.082***		0.085***
				(12.153)		(12.362)
Mean Number of Bank Relationships$_f$					0.046***	0.042***
					(14.081)	(14.710)
Constant	0.041*	0.124***	0.197***	0.168***	0.128***	-0.025
	(1.898)	(21.618)	(57.767)	(60.469)	(22.106)	(-1.030)
Observations	34,733	33,556	34,408	27,203	34,733	26,363
R-squared	0.001	0.008	0.000	0.018	0.005	0.032

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX C: Summary Statistics

Aggregate Variables *(Quarterly)*	**Obs**	**Mean**	**S.D.**	**p25**	**Median**	**p75**
Δln(Aggregate loan$_t$)	40	0.057	0.065	0.014	0.043	0.117
Δln(Aggregate investment$_t$)	40	0.037	0.087	-0.010	0.041	0.095
Δln(LAR total loan$_t$)	40	1.441	4.779	-1.367	2.221	4.721
Granular bank shock$_t$	40	0.012	0.076	-0.047	0.026	0.062
Granular firm shock$_t$	40	0.062	0.054	0.014	0.063	0.096
Granular industry shock$_t$	40	0.002	0.011	-0.003	0.001	0.004
Granular common shock$_t$	40	-0.061	0.109	-0.172	-0.041	0.021
Bank-Level Variables *(Quarterly)*	**Obs**	**Mean**	**S.D.**	**p25**	**Median**	**p75**
Bank shock$_{b,t}$	1,086	0.051	0.541	-0.183	0.002	0.229
Firm shock$_{b,t}$	1,086	0.040	0.395	-0.101	0.054	0.210
Industry shock$_{b,t}$	1,086	-0.003	0.032	-0.013	0.000	0.011
Bank asset$_{b,t}$ (logged)	1,079	11.92	1.64	10.81	12.17	13.08
BIS ratio$_{b,t}$ (%)	1,062	19.13	8.65	14.11	16.17	21.28
Loan loss provision/Gross loans$_{b,t}$ (%)	1,072	4.15	3.39	2.07	3.24	5.27
Debt/Total liabilities$_{b,t}$ (%)	1,072	12.42	14.67	0.73	7.13	18.11

Firm-Level Variables *(Yearly)*	**Obs**	**Mean**	**S.D.**	**p25**	**Median**	**p75**
Bank shock$_{f,t}$	145,823	-0.018	0.180	-0.136	-0.020	0.081
Firm shock$_{f,t}$	145,823	0.189	0.877	-0.183	0.032	0.301
Industry shock$_{f,t}$	145,823	0.004	0.064	-0.029	0.013	0.042
Investment$_{f,t}$/Capital$_{f,t-1}$	145,823	0.027	0.348	-0.105	-0.035	0.087
Return-on-asset$_{f,t-1}$	145,823	0.010	0.068	-0.006	0.012	0.039
Current asset$_{f,t}$/Capital$_{f,t-1}$ (logged)	145,823	0.370	2.263	-0.897	0.376	1.704
Net Income$_{f,t}$/Capital$_{f,t-1}$	145,823	0.328	2.664	-0.013	0.041	0.187
Loan to asset ratio$_f$ (mean)	145,823	0.465	0.355	0.221	0.384	0.601
Number of bank relationships	126,992	1.8	1.5	min: 1	1	max: 18