How is Chinese Monetary Policy Transmitted? Disentangling Loan Supply and Loan Demand Effects

Max Breitenlechner* Riikka Nuutilainen†

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Abstract

We study the transmission of Chinese monetary policy in a structural vector autoregressive framework. Using combinations of zero and sign restrictions we are able to quantify transmission channels, which are linked to demand and supply responses on the loan market. This distinction is consistent with an interpretation in favor of the money and credit view of monetary policy. We find that monetary policy in China is associated with both transmission channels. Furthermore, our results show that at least half of the transmission effects are linked to loan supply responses and therefore provide empirical evidence for a distinct credit channel in China. Finally, our results confirm existing evidence that monetary policy accounts for a relatively high share of business cycle dynamics in China's economy.

Keywords: China, Monetary Policy, Transmission Effects, Structural Vector Autoregression, Zero and Sign Restrictions

JEL codes: C32, E44, E52

*University of Innsbruck, Department of Economics, Universitaetsstrasse 15, A-6020 Innsbruck, Austria, Phone: +43 (512) 507 71025, E-mail: max.breitenlechner@uibk.ac.at.

†Bank of Finland Institute for Economies in Transition (BOFIT), Snellmaninaukio, PO Box 160, FI-00101 Helsinki, Finland, E-mail: riikka.nuutilainen@bof.fi.

1 Introduction

Over the last twenty years China's economy has experienced a steady transition to become more market-orientated. In this process, the direct state control of the banking sector is decreasing and the financial markets are becoming more mature. At the same time, China's traditionally quantity-based monetary policy relies increasingly on price-based policy measures (Fernald et al., 2014). While this transition potentially results in similar transmission mechanism of monetary policy as in western economies, empirically little is known about the transmission of Chinese monetary policy. The purpose of this paper is to provide new insights in the propagation of Chinese monetary policy.

A broad field of research studies the transmission of monetary policy in western economies, providing a growing number of potential transmission channels. The different transmission mechanism can be broadly classified by the *money* and *credit* view of monetary policy (Bernanke and Blinder, 1988).[1] The money view holds that monetary policy influences economic activity through changes in the interest level and hence, the cost of credit. Firms potentially adjust their investment activities in response to changing credit costs, and therefore influence economic activity. This mechanism is also frequently referred to as the interest rate channel. In addition, the credit view describes that monetary policy changes the availability of loans and thereby limits firms' funding possibilities, which ultimately matters for investments and the real economy. While in the money view the volume of loans changes due to firms' demand of loans, the credit view emphasizes that changes in the supply of loans potentially amplify the effects on output. In this paper we propose a novel approach that allows us to quantify the relative importance of loan supply and demand responses in the transmission of Chinese monetary policy.

We fit structural vector autoregressive models to monthly Chinese data ranging from October 2004 through June 2016. To identify monetary policy and the two transmission channels we combine a block recursive approach (Christiano et al., 1999) with sign restrictions on the impulse responses (Faust, 1998; Uhlig, 2005). Specifically, we identify a block of monetary policy shocks, which are consistent with the standard recursive assumption of monetary policy, but within this block are not exactly identified.[2] As the policy shock is not exactly identified we are able

[1] Originally, the credit view consists of the bank lending channel and the borrower net-worth channel or also called balance sheet channel (Bernanke and Blinder, 1988; Bernanke and Gertler, 1995). More recently, it also captures the risk-pricing channel (Disyatat, 2011; Kishan and Opiela, 2012), the bank balance sheet channel (Jimènez et al., 2012), and the deposit channel (Drechsler et al., 2016).

[2] The recursive structure is frequently used to identify monetary policy in China (see e.g. He et al., 2013;

to impose sign restrictions to distinguish between policy shocks that are linked to supply or demand dynamics on the loan market. Consider for instance a contractionary monetary policy shock. Given that loan supply effects dominate on the loan market, then the supply curve of loans should shift stronger inwards as compared to the demand curve of loans. Therefore, we should observe that prices of loans increase while volumes decline. In contrast, when monetary policy is mainly linked to changes in the demand for bank loans, prices and volumes of loans should respond with similar signs. Hence, with sign restrictions on the loan volume and the loan rate we are able to distinguish between policy shocks that are linked to supply and demand responses on the loan market.

We find that policy induced output dynamics in China are associated with both loan supply and loan demand effects, regardless whether monetary policy is conducted with price-based or quantity based policy measures. Hence, our results suggest that monetary policy in China is transmitted consistently with the money and credit view of monetary policy. Concerning the relative importance of the credit and money view, we find that loan supply effects dominate the transmission of Chinese monetary policy. Furthermore loan supply effects appear especially pronounced when monetary policy relies on interest rates as policy instrument. After two years, up to 80% of policy induced output dynamics are associated with loan supply responses. Together, the transmission effects account for roughly 10% to 17% of the forecast variance of output after 2 years, depending on the policy instrument. The magnitude of the effects is in line with earlier findings in the literature about the overall effect of Chinese monetary policy on output fluctuations (see e.g. Fernald et al., 2014; Chen et al., 2016).

As we evaluate loan supply responses in the transmission of Chinese monetary policy, our study is related to a small number of studies which study policy induced loan supply responses in China. In contrast to our approach, these studies use bank-level micro data to identify loan supply dynamics, an approach which was originally introduced by Kashyap and Stein (1995).[3] This approach relies on the idea that after changes in monetary policy loan supply responds asymmetrically across banks, depending on specific bank characteristics, while loan demand responds symmetrically. The analyzed bank characteristics depend on the specific transmission channel. Gunji and Yuan (2010) study the bank lending channel in China and evaluate whether

Fernald et al., 2014).

[3] As loans are generally reported as total volumes, the identification of changes in the supply of loans is essential in this field of literature. Only if loan application data is available, no identification assumptions are required (see e.g. Jimènez et al., 2012; Jiménez et al., 2014). However, these data is not available for China.

loan growth responds asymmetrically across banks depending on their creditworthiness. The findings are mixed and therefore provide no clear support for loan supply responses. Fungáčová et al. (2016) show that in response to policy changes the growth rate of loans does not depend on banks' creditworthiness but rather on their ownership structure. Therefore, their results suggest that loan supply effects might be present through a China specific ownership channel. In contrast to these studies, we evaluate the transmission channel using a macroeconomic framework which allows us to identify monetary policy as well as loan dynamics at the aggregate level. Therefore we can abstract from specific transmission mechanism and evaluate the credit channel from a broader perspective.

The reminder of the paper is structured as follows. In Section 2 we provide a short overview of Chinese monetary policy. Section 3 describes the empirical model, the identification approach and the data. Section 4 presents our main findings, and all robustness exercises are summarized in Section 5. Finally, Section 6 summarizes our main findings.

2 Chinese Monetary Policy

Monetary policy in China differs from developed economies in terms of policy instruments as well as monetary policy objectives. The People's bank of China's (PBoC) stated objective is to "maintain the stability of the value of the currency and thereby promote economic growth" (Law of the People's Republic of China on the People's Bank of China I:3§).[4] Currency stability is interpreted to include both domestic price stability as well as external exchange rate stability. In addition to the target stated in the law, the PBoC is assigned with additional policy objectives, such as full employment, financial market stability, support of certain sectors or geographical areas and stability in the balance of payments.

Various policy instruments are utilized in order to achieve the multiple policy objectives. These include both quantity- and price-based instruments as well as non-market based moral suasion policies. China's monetary policy transition into more market-oriented framework started in 1998 with the abolishment of direct credit controls. Still, the PBoC retains some control over commercial bank lending through the so called "window guidance policy", where the central bank advises banks directly on the quantity and structure of their lending.[5] In our estimation

[4] Adopted March 18, 1995. Available at `http://www.npc.gov.cn/englishnpc/Law/2007-12/12/content_1383712.htm`

[5] The literature on Chinese monetary policy tend to find window guidance as an effective policy instrument

period, the PBoC toolbox include the benchmark interest rates, bank reserve requirements, open market operations, central bank lending and the window guidance policies. Changes in PBoC policy stance are often implemented using a mixture of different policy tools.

Therefore, to capture this policy variety we use two different measures of Chinese monetary policy, one quantity based instrument, the reserve requirement ratio (RRR), and one price based instrument, the deposit benchmark rate (DBR).[6] In our estimation period, October 2004 – June 2016, reserve requirements as well as benchmark interest rates have been the most important and most frequently altered policy instruments. Different from other central banks, the PBoC uses the RRR as an active policy instrument. Over time the RRR has become the favored policy instrument by the central bank and the sophistication of the instrument has also increased. Between October 2004 and June 2016 the ratio was changed 44 times compared to the benchmark lending and deposit rates that were altered on 27 and 25 occasions, respectively (see Figure 1). To make the RRR a more targeted tool, the RRRs were differentiated for different types of banks in 2008, and in 2011 the PBoC adopted a "dynamically differentiated RRR" scheme, where the RRRs for individual banks are adjusted taking into account, for example, the credit portfolio, soundness and systemic importance of the bank (PBC, 2012).[7] In our analysis, we use the average of the three different RRRs.

Interest rate liberalization in China started in 1996 and has proceeded in small steps (see Table A.1 in the Appendix). Prior to 2004, banks were allowed to add only small surcharge to the corresponding benchmark lending rate. In October 2004, lending rate ceiling and deposit rate floor were removed, allowing banks to freely charge higher rates on loans to their customers and offer lower deposit rates compared to the benchmarks. Commercial bank lending rates were liberalized in 2013, and in October 2015 the PBoC removed the final ceiling of banks deposit rates.[8] The interest rate liberalization enables us to analyze whether banks change the supply of bank loans in response to changes in monetary policy.

Finally, while the PBoC still operates in less developed financial environment as compared to other major central banks, the loan market is the major source of funding for firms and

(see, for example Chen et al., 2013). Details about the discussions between central bank and commercial banks representatives are not disclosed, however, so little is known about the actual functioning of the window guidance policy.

[6]In the robustness analysis (Section 5) we also consider the benchmark deposit rate as an alternative price based policy measure.

[7]See Ma et al. 2013 for a detailed analysis on the use of the RRR as policy instrument in China.

[8]Other interest rates, namely money and bond market rates, have been largely liberalized prior to the start of our estimation period in 2004 (He et al., 2015).

households in China. Therefore, the credit channel is likely to play a relevant role for the transmission of Chinese monetary policy. In 2015, still almost 70% of non-bank corporate sector and households' new financing were in the form of bank loans.

3 Empirical Approach

3.1 Estimation

We evaluate the transmission effects of Chinese monetary policy using a structural vector autoregressive approach. As the reliability of Chinese data is difficult to verify we follow the literature and use a broad set of economic activity and price indicators to control for Chinese output and inflation (see Fernald et al., 2015, 2014; He et al., 2013). Therefore, we estimate a factor-augmented vector autogression (FAVAR) in the spirit of Bernanke et al. (2005), in which the latent output and inflation factors are treated as observables variables.[9]

The model is specified as follows:

$$\begin{bmatrix} F_t \\ X_t \end{bmatrix} = \sum_{j=1}^{p} A_j \begin{bmatrix} F_{t-1} \\ X_{t-1} \end{bmatrix} + e_t, \tag{1}$$

where F_t represents the output and inflation factor, and X_t consists of the observable variables including a policy measure, the growth rate of loans and an average lending rate. The variables appear in the estimation in the same ordering. A_j are matrices containing the reduced-form coefficients, and e_t is a vector of white noise reduced-form residuals with $E(e_t) = 0$ and $\Sigma_e = E(e_t e_t')$.

We extract the output and price factors using a principal component analysis on a broad set of economic activity and price indicators, respectively. In particular, we extract the factors applying the replication files provided by Fernald et al. (2014) on an updated dataset described in Section 3.3. The algorithm follows Stock and Watson (1998) and imputes missing data observations iteratively (please refer to Fernald et al., 2014, for details).[10]

In line with the standard approach in the sign-restriction literature, we estimate the reduced-

[9] Bernanke et al. (2005) shows that treating estimated factors as data provides results, which are consistent with estimates from Bayesian methods that consider the uncertainty involved with the estimation of the factors.

[10] The replication files are available at `http://www.frbsf.org/economic-research/economists/jfernald/wp2014-07supplement_replication_files.zip`.

form model in Equation 1 with Bayesian methods using an uninformative Normal-Inverse-Wishart prior for the coefficients and the variance-covariance matrix.[11] The reduced form posterior distribution, which is also a Normal-Wishart density, is derived analytically using the estimates of A_j and Σ_e as location parameters (see Uhlig, 1994). However, as we impose sign restrictions for identification, our system is set-identified and therefore we are not necessarily uninformative over the structural coefficients (Baumeister and Hamilton, 2015; Moon and Schorfheide, 2012). According to the Bayesian (or Schwarz) information criterion we use $p = 2$ lags in our baseline estimation.

3.2 Identification

To identify monetary policy shocks that are associated with loan supply or loan demand responses, we follow Breitenlechner and Scharler (2017) and combine a block-recursive identification approach with sign restrictions. With the contemporaneous zero restriction we impose that consistent with the idea of a standard Taylor rule, monetary policy responds simultaneously to changes in output and prices, but influences these variables only with a lag (Christiano et al., 1999).[12] However, to distinguish between different dynamics on the loan market in response to policy shocks, we allow for contemporaneous effects between the policy variable and the loan market variables. Therefore, the monetary policy shock is not exactly identified and sign restrictions can be imposed to identify policy shocks which specific dynamics on the loan market. Specifically, we identify one contractionary monetary policy shock that coincides with a decrease in the supply of loans (MP Loan Supply), and a second policy shock, which is linked to a decline in the demand for loans (MP Loan Demand).

Table 1 summarses the identification restrictions. We normalize both shocks to be contractionary imposing a positive response on the policy variable. The restrictions on the loan market variables are consistent with the idea that an inward shift of the supply curve of loans implies a decline of loan volumes but an increase in the price. In contrast, an inward shift of the demand curve implies that volume and prices of loans decline simultaneously.[13] All remaining dynamics

[11] See Moon et al. (2013) for a frequentist perspective on the sign-restriction approach.

[12] As we order the policy variable behind the latent factors, the block-recursive structure implies that no further identification assumption on the underlying observables are required (see Bernanke et al., 2005).

[13] Sign restrictions are already widely used to distinguish between supply and demand side effects across various markets. So far sign restrictions have already been used to evaluate aggregate demand and supply shocks (see e.g. Fry and Pagan, 2011), identify loan supply shocks (see e.g. Bijsterbosch and Falagiarda, 2015; Gambetti and Musso, 2012; Hristov et al., 2012), distinguish between supply and demand effects on the oil market (Kilian and Murphy, 2014; Cashin et al., 2014) or the broad money market (Chadha et al., 2010). In contrast to these studies

on the loan market, which coincide with an increase in the policy rate are captured by a separate residual shock.

To implement our identification approach we follow the model selection algorithm proposed by Arias et al. (2014). This means we use the Gram-Schmidt process to construct random factorizations of the reduced form model. The reduced form model is transformed with an orthonormal matrix Q that considers the zero restrictions appropriately. To obtain a distribution of accepted draws we draw 3,000 models from the reduced from posterior distribution and check a maximum of 1,000 Q-transformations for each draw. To improve the efficiency of the algorithm we check the sign-identified shocks sequently for each transformation and re-arrange the matrix Q if applicable. Unless otherwise stated we impose sign restrictions upon impact and three consecutive month.

As we identify loan supply and demand responses at the aggregate level we differ from the standard approach in the credit channel literature. Introduced by Kashyap and Stein (1995), changes in loan supply are commonly identified by exploring possible asymmetric responses of loan growth across specific groups of banks.[14] The identification assumption is that after a change in the policy rate, banks should adjust the supply of bank loans subject to their individual ability to absorb the fluctuation in reserves, while the demand of loans should change independently from bank specific characteristics. Therefore, asymmetric responses in the loan growth rate across differently sized, liquid or capitalized banks are interpreted in favor of loan supply responses (see e.g. Kashyap and Stein, 2000; Kishan and Opiela, 2000; Gambacorta, 2005, among many others). However, this approach requires an exact understanding of the underlying transmission mechanism, such that possible asymmetric loan responses across the selected groups of banks can indeed be interpreted in favor of loan supply responses. In contrast, we identify loan supply responses, which are consistent with any transmission mechanism that implies loan supply effects. Furthermore, as we identify the dynamics at the aggregate level we do not require to obtain detailed bank level data, which appears especially challenging in the context of China. Finally, our approach allows us to identify exogenous changes in monetary policy, as well as to evaluate the effects on the macroeconomy.

However, the identification of loan supply and demand responses at the aggregate level also

however, we do not identify exogenous supply or demand shocks. In contrast, we identify policy shocks that coincide with endogenous changes in the demand or supply of bank loans.

[14] In contrast, if loan application data is available, no identification assumptions are required (see e.g. Jimènez et al., 2012; Jiménez et al., 2014). However, these data is not available for China.

faces some limitations. First, as we identify supply and demand dynamics at the aggregate level, we cannot control for compositional effects in the supply or demand of loans (see Peersman, 2011). This means, if banks may over-proportionally decrease the supply of loans to firms and households with relatively weak financial characteristics, then the average loan rate might actually decrease as banks' loan portfolios improve. While this special case actually represents a decline in the supply of bank loans, our identification approach captures these effects as a decline in loan demand.

Second, as we allow for contemporaneous effects between the loan market and the policy variable the sign restrictions are also required to rule out autonomous loan market shocks. In the empirical literature, which evaluates exogenous loan supply shocks (see Bijsterbosch and Falagiarda, 2015; Gambetti and Musso, 2016; Hristov et al., 2012), monetary policy is expected to respond expansionary to a contractionary loan supply shock. While generally loan demand shocks are not separately identified, they are captured as aggregate demand shocks. Therefore, monetary policy is also expected to respond expansionary to a contractionary loan demand shock. However, as the policy rate increases in our identification, we can rule out that the identified monetary policy shocks are driven by exogenous dynamics on the loan market. Put differently, the imposed sign restrictions imply that the identified dynamics on the loan market represent only endogenous responses to the policy shocks. Any exogenous loan market shocks are potentially captured by the last residual shock (Residual MP, AVLR, LNGR).

3.3 Data

For the estimation we use monthly data ranging from October 2004 to June 2016. The observation period is determined by data availability. Specifically, the average lending rate cannot be constructed before our starting date, as restrictions on lending rate ceiling were still at place (see Table A.1). All the data are obtained from the CEIC China Premium Database.

To extract the economic activity (EA) and the price (PR) factors we use a broad set of Chinese economic indicators. As mentioned before, we use exactly the same time series as in Fernald et al. (2014) but on an updated dataset. Figure 4 shows the estimated factors and Table A.2 in the Appendix lists all variables. The EA factor constructed with all economic activity measures (wide EA factor) is highly correlated to industrial production in China, but is less volatile. In the baseline we follow the data transformation as suggested in Fernald et al.

(2014): we seasonally adjust the level variables, then obtain monthly growth rates (taking first-log differences times 100), and finally remove local trends from each time-series by applying a biweight filter (see also Stock and Watson, 2012).[15]

As policy instruments, we consider a quantity based measurement, the average reserve requirement ratio (RRR), and two different price based measurements, the one year lending benchmark rate (LBR) and the one year deposit benchmark rate (DBR). As there is very little variation between the two benchmark rates (see Figure 1), in the remaining of the paper we show the results only for the one year deposit benchmark rate. The results for the lending benchmark rate are very similar, and for compactness we present them only in the Appendix.

The loan volume variable is the total banking sector loan stock in domestic currency available from the PBoC monthly financial statistics. Loan growth (LNGR) is the month-on-month change in the total loan stock (similar to the factor variables we remove in our baseline local means by applying a biweight filter).

Obtaining data for an average lending rate is challenging for China. The PBoC reports average banking sector lending rate only at quarterly frequency and starting from 2009 (PBoC AVLR in Figure 2). Fortunately, the PBoC publishes monthly statistics of the share of loans priced above/below its benchmark lending rate (Figure 3). We utilize this data to construct an average monthly lending rate measure from October 2004 onwards. In the baseline estimation, we construct our average lending rate variable (AVLR) using the mean value in every loan category times the lending benchmark rate (LBR in Figure 3) for that period. (I.e. we use the value 1.40 x benchmark rate for the share of the loans in the category 30%– 50% above the benchmark rate and 0.95 x benchmark for the category 0%–10% below the benchmark rate, ect.). Our average monthly lending rate constructed this way is in line with the quarterly rate reported by the PBoC after 2011 (see Figure 2).[16]

[15] In the robustness analysis we consider different biweight parameters as well as unfiltered data.

[16] We were also able to obtain data on monthly average lending rate from one of the big-five banks in China for 2014-2016 (BIG5 AVLR in Figure 2). Our lending rate is broadly in line also with this measure.

4 Results

4.1 Impulse Responses

Figure 5 shows point-wise median impulses to the two identified monetary policy shocks, together with 68% of the distribution of accepted draws. In the top panel we see impulse responses from the estimation with the RRR as monetary policy measure and in the bottom panel monetary policy is captured with the deposit benchmark rate. In the first row of each panel we see the impulse responses to monetary policy shocks associated with loan supply responses and the second row shows the responses to policy shocks that are linked to demand dynamics on the loan market.

Starting with the top panel we see that contractionary monetary policy shocks have a clear negative effect on economic activity regardless of the transmission channels. While prices decline immediately when monetary policy shocks are linked to loan demand effects, prices initially increase and only decline over time in case of an transmission of monetary policy through loan supply. The remaining responses are restricted with the sign restrictions on impact and the first month.

In the bottom panel, we see that the response of economic activity is less clear cut when monetary policy is captured with the deposit benchmark rate. We only observe a systematic negative response when monetary policy is transmitted through loan supply.

Our findings support the view of Fernald et al. (2014) and Chen et al. (2017) that the transmission of monetary policy conducted via RRR and benchmark rates to output and prices seems to be very similar to developed countries, despite the fact that the policy framework in China is still rather different. After policy tightening output falls and also inflation is reduced (with a lag) over the two years, except for the interest rate shock associated with loan demand effects, where the response is not systematic. In contrast to most earlier papers for China, including He et al. (2013), we find also the interest rate instrument effective to the policy transmission, but interestingly only when monetary policy is linked to the credit channel.

To asses the relative importance of loan demand and loan supply effects in the transmission of Chinese monetary policy we now turn to the forecast error variance decomposition of economic activity.

4.2 The Transmission of Chinese Monetary Policy

How important are loan supply and demand responses for the transmission of monetary policy? Hence, what is the effect of monetary policy shocks on economic activity depending whether they are associated with loan supply or demand effects. Table 2 shows the effects of monetary policy shocks on the dynamics of the economic activity factor that are linked to loan supply or loan demand responses. Furthermore, the table also reports the sum of both transmission channels indicating the overall effect of monetary policy.

The quantitative policy has a somewhat stronger effect as compared to the price based instrument. The RRR instrument monetary policy shocks together account for 17.20% of the variation in economic activity after the effects stabilize at a forecast horizon of 24 month. For the interest rate instrument the overall effect is clearly weaker (10.84%), indicating that in our estimation period overall the quantitative policy instrument has been more effective in output stabilization, compared to the price based instrument. In comparison to results from western economies over similar observation periods, these shares are exceptionally high (see e.g. Ramey, 2016).

The effect of monetary policy shocks associated with loan supply effects are found to have a stronger effect on economic activity, compared to the ones associated with loan demand effects, irrespective of the policy instrument. Therefore, in addition to a traditional interest rate channel with demand effects, loan supply effects also play an important role in China. This is especially the case with the interest rate instrument. When interest rates are used as a policy variable, almost all policy-induced effects on output are due to loan supply responses.

Furthermore, we can provide insights how monetary policy influences the loan market itself. From Table 3 we see that the two monetary policy instruments have different effects on the loan market. Policy shocks identified with the RRR influence the loan market to a similar extend through changes in loan supply and demand. In contrast, interest rates based policy shocks influence the loan market predominantly through changes in loan supply and especially through changes in the average lending rate. In other words, when the PBoC changes the benchmark rates, our results indicate that Chinese banks can easily adjust their lending rates.

5 Robustness Analysis

The main findings are consistent across a broad set of robustness checks:

1. To control for a possible pass-through of interest rates, we re-estimate the model using a spread between the average lending rate and the lending benchmark rate.

2. As we calculate the average lending rate using the mean values of the shares that banks set their lending rate above or below the benchmark rate, we also consider two alternative calculations. In the first check we take not the mean of the categories but the upper bound. In the second alternative, we calculate the average lending rate using the first principal component of the six lending share time series.

3. In the baseline we follow Fernald et al. (2014) and filter the data with a bi-weight filter parameter of 36. We consider also estimations with unfiltered data and a parameter of 120.

4. As a broad set of observables might induce unnecessary noise, we also consider a narrow set of economic activity indicators to derive the economic activity factor (Fernald et al., 2014).

5. We also check estimations in which we use a shorter horizon for the sign restrictions, imposing the restrictions only on impact and the consecutive month.

6. While the Bayesian information criteria suggest only two lags of the endogenous variables in the FAVAR, due to the monthly frequency of our data set we also check the results when we use twelve lags.

7. China's economy is an open economy heavily depending on world output and commodity prices. Therefore we re-estimate the baseline model including US output and Oil prices denoted in dollars (Fernald et al., 2014).

8. After the global financial crisis hit China in 2008, the Chinese government supported the economy with a huge stimulus package. Majority of the increased funding was channeled through the banking sector, and monetary authorities encouraged banks to provide bank loans to mainly state-owned firms. Therefore, we also consider an estimation excluding the period from July 2008 to March 2010. Indeed without this observation period the share of policy shocks associated with loan supply effects drops substantially as compared

to our baseline estimation.

9. Finally, we also re-estimate our models using only the observation period in which we have monthly data available to calculate the average lending rate (2008M1 to 2016M6). As the Great Recession becomes more weight, consistent with the previous robustness check, the effects of monetary policy on economic activity appears stronger and monetary policy is relatively stronger transmitted through loan supply responses.

The results of the different robustness checks are presented in Table 4 and confirm our main findings from the baseline specifications.

6 Summary

How is Chinese monetary policy transmitted? We propose a novel identification scheme, which allows us to obtain new insights in the transmission of monetary policy in China using aggregated time-series data. We find that Chinese monetary policy is linked to demand and supply dynamics on the loan market. However, Chinese monetary policy influences economic activity to a larger extent when loan supply responses are present. Therefore our results provide empirical evidence for a distinct credit channel in China. Loan supply effects are especially pronounced when monetary policy relies on benchmark interest rates as policy instruments. Furthermore, we find that in line with existing literature monetary policy in China accounts for a relative high share of business cycle dynamics, when measured by the reserve requirement ratio. While we also find that interest benchmark rates are effective monetary policy instruments, they only account for roughly half of the effects arising from changes in the reserve requirements.

References

Arias, J. E., Rubio-Ramirez, J. F., Waggoner, D. F., 2014. Inference based on svars identified with sign and zero restrictions: Theory and applications. International Finance Discussion Papers 1100, Board of Governors of the Federal Reserve System (U.S.).

Baumeister, C., Hamilton, J. D., 2015. Sign restrictions, structural vector autoregressions, and useful prior information. Econometrica 83 (5), 1963–1999.

Bernanke, B. S., Blinder, A. S., 1988. Credit, money, and aggregate demand. The American Economic Review 78 (2), 435–439.

Bernanke, B. S., Boivin, J., Eliasz, P., 2005. Measuring the effects of monetary policy: A factor-augmented vector autoregressive (favar) approach. The Quarterly Journal of Economics 120 (1), 387–422.

Bernanke, B. S., Gertler, M., 1995. Inside the black box: The credit channel of monetary policy transmission. The Journal of Economic Perspectives 9 (4), 27–48.

Bijsterbosch, M., Falagiarda, M., 2015. The macroeconomic impact of financial fragmentation in the euro area: Which role for credit supply? Journal of International Money and Finance 54, 93–115.

Breitenlechner, M., Scharler, J., 2017. How does monetary policy influence bank lending? evidence from the market for banks wholesale funding. Unpublished manuscript (March, 2017), University of Innsbruck.

Cashin, P., Mohaddes, K., Raissi, M., Raissi, M., 2014. The differential effects of oil demand and supply shocks on the global economy. Energy Economics 44, 113–134.

Chadha, J. S., Corrado, L., Sun, Q., 2010. Money and liquidity effects: Separating demand from supply. Journal of Economic Dynamics and Control 34 (9), 1732–1747.

Chen, H., Chen, Q., Gerlach, S., 2013. The implementation of monetary policy in china: The interbank market and bank lending. Ch. 2, pp. 31–69.

Chen, H., Chow, K., Tillmann, P., 2017. The effectiveness of monetary policy in china: Evidence from a qual var. China Economic Review 43 (Supplement C), 216–231.

Chen, K., Higgins, P., Waggoner, D. F., Zha, T., 2016. Impacts of monetary stimulus on credit allocation and macroeconomy: Evidence from china. Working Paper 22650, National Bureau of Economic Research.

Christiano, L. J., Eichenbaum, M., Evans, C. L., 1999. Monetary policy shocks: What have we learned and to what end? In: Taylor, J. B., Woodford, M. (Eds.), Handbook of Macroeconomics. Vol. 1, Part A of Handbook of Macroeconomics. Elsevier, Ch. 2, pp. 65–148.

Disyatat, P., 2011. The bank lending channel revisited. Journal of Money, Credit and Banking 43 (4), 711–734.

Drechsler, I., Savov, A., Schnabl, P., 2016. The deposits channel of monetary policy. Working Paper 22152, National Bureau of Economic Research.

Faust, J., 1998. The robustness of identified VAR conclusions about money. Carnegie-Rochester Conference Series on Public Policy 49, 207–244.

Fernald, J. G., Hsu, E., Spiegel, M. M., 2015. Is china fudging its figures? evidence from trading partner data. BOFIT Discussion Papers 29/2015, Bank of Finland, BOFIT Institute for Economies in Transition.

Fernald, J. G., Spiegel, M. M., Swanson, E. T., 2014. Monetary policy effectiveness in China: Evidence from a FAVAR model. Journal of International Money and Finance 49, Part A, 83–103.

Fry, R., Pagan, A., 2011. Sign restrictions in structural vector autoregressions: A critical review. Journal of Economic Literature 49 (4), 938–960.

Fungáčová, Z., Nuutilainen, R., Weill, L., 2016. Reserve requirements and the bank lending channel in China. Journal of Macroeconomics 50, 37–50.

Gambacorta, L., 2005. Inside the bank lending channel. European Economic Review 49 (7), 1737–1759.

Gambetti, L., Musso, A., Sep 2012. Loan supply shocks and the business cycle. Working Paper Series 1469, European Central Bank.

Gambetti, L., Musso, A., 2016. Loan supply shocks and the business cycle. Journal of Applied Econometrics, forthcoming.

Gunji, H., Yuan, Y., 2010. Bank profitability and the bank lending channel: Evidence from China. Journal of Asian Economics 21 (2), 129–141.

He, D., Wang, H., Yu, X., 2015. Interest rate determination in china: Past, present, and future. International Journal of Central Banking 11 (4), 255–277.

He, Q., Leung, P.-H., Chong, T. T.-L., 2013. Factor-augmented VAR analysis of the monetary policy in China. China Economic Review 25, 88–104.

Hristov, N., Hülsewig, O., Wollmershäuser, T., 2012. Loan supply shocks during the financial crisis: Evidence for the euro area. Journal of International Money and Finance 31 (3), 569–592.

Jimènez, G., Ongena, S., Peydrò, J.-L., Saurina, J., 2012. Credit supply and monetary policy: Identifying the bank balance-sheet channel with loan applications. American Economic Review 102 (5), 2301–2326.

Jiménez, G., Ongena, S., Peydró, J.-L., Saurina, J., 2014. Hazardous times for monetary policy: What do twenty-three million bank loans say about the effects of monetary policy on credit risk-taking? Econometrica 82 (2), 463–505.

Kashyap, A. K., Stein, J. C., 1995. The impact of monetary policy on bank balance sheets. Carnegie-Rochester Conference Series on Public Policy 42 (0), 151–195.

Kashyap, A. K., Stein, J. C., 2000. What do a million observations on banks say about the transmission of monetary policy? The American Economic Review 90 (3), 407–428.

Kilian, L., Murphy, D. P., 2014. The role of inventories and speculative trading in the global market for crude oil. Journal of Applied Econometrics 29 (3), 454–478.

Kishan, R. P., Opiela, T. P., 2000. Bank size, bank capital, and the bank lending channel. Journal of Money, Credit and Banking 32 (1), 121–141.

Kishan, R. P., Opiela, T. P., 2012. Monetary policy, bank lending, and the risk-pricing channel. Journal of Money, Credit and Banking 44 (4), 573–602.

Moon, H. R., Schorfheide, F., 2012. Bayesian and frequentist inference in partially identified models. Econometrica 80 (2), 755–782.

Moon, H. R., Schorfheide, F., Granziera, E., 2013. Inference for VARs identified with sign restrictions. Working paper, University of Pennsylvania.

PBC, 2012. China financial stability report 2012. Financial Stability Analysis Group of the Peoples Bank of China. Tech. rep.

Peersman, G., Dec 2011. Bank lending shocks and the euro area business cycle. Working Papers of Faculty of Economics and Business Administration, Ghent University, Belgium 11/766, Ghent University, Faculty of Economics and Business Administration.

Ramey, V. A., 2016. Macroeconomic shocks and their propagation. Working Paper 21978, National Bureau of Economic Research.

Stock, J. H., Watson, M. W., 1998. Diffusion indexes. Working Paper 6702, National Bureau of Economic Research.

Stock, J. H., Watson, M. W., 2012. Disentangling the channels of the 2007–09 recession. Brookings Papers on Economic Activity: Spring 2012, 81–135.

Uhlig, H., 1994. What macroeconomists should know about unit roots: A bayesian perspective. Econometric Theory 10 (3-4), 645–671.

Uhlig, H., 2005. What are the effects of monetary policy on output? Results from an agnostic identification procedure. Journal of Monetary Economics 52 (2), 381–419.

A Additional Tables and Figures

INSERT TABLES A.6, A.6, A.4, A.3, A.2, and A.1 HERE.

INSERT FIGURES A.1 and A.2 HERE.

Table 1: Zero and sign restrictions on impulse response functions

Shock	EA Factor	Prize Factor	MP	AVLR	LNGR
Residual EA					
Residual Prize	0				
MP Loan Supply	0	0	↑	↑	↓
MP Loan Demand	0	0	↑	↓	↓
Residual MP, AVLR, LNGR	0	0	↑		↑

Notes: Sign restrictions hold on impact and the subsequent period; zero restrictions hold contemporaneously.

Table 2: Forecast error variance decomposition of the economic activity factor

Policy		FEVD			Relative Effects	
Variable	h	MP Loan Supply	MP Loan Demand	Total	MPLS	MPLD
RRR	12	8.66 (3.33, 16.12)	5.94 (2.59, 11.56)	14.60	59.31	40.69
	24	10.61 (4.35, 18.93)	6.59 (2.89, 12.49)	17.20	61.67	38.33
DBR	12	6.26 (2.20, 13.04)	1.09 (0.36, 2.95)	7.35	85.18	14.82
	24	9.32 (3.57, 18.17)	1.51 (0.52, 3.50)	10.84	86.03	13.97

Notes: The values correspond to the point-wise median values of the FEVD distribution of the accepted draws. Values in parentheses represent 68% of the distribution.

Table 3: Forecast error variance decomposition of loan market variables

Policy Variable	h	FEVD MP Loan Supply	FEVD MP Loan Demand	FEVD Total	Relative Effects MPLS	Relative Effects MPLD
1. Average Lending Rate						
RRR	24	28.85 (12.77, 47.68)	22.99 (8.64, 42.36)	51.84	55.66	44.34
DBR	24	28.85 (11.62, 48.41)	3.73 (0.90, 11.16)	32.58	88.55	11.45
2. Loan Growth						
RRR	24	14.92 (5.62, 37.22)	14.37 (4.68, 36.65)	29.30	50.94	49.06
DBR	24	20.58 (6.98, 42.37)	11.61 (4.36, 26.57)	32.19	63.94	36.06

Notes: The values correspond to the point-wise median values of the FEVD distribution of the accepted draws. Values in parentheses represent 68% of the distribution.

Table 4: Robustness analysis: Relative contributions to the policy induced forecast error variance of the economic activity factor

Robustness	EA T	EA S	EA D	AVLR T	AVLR S	AVLR D	LNGR T	LNGR S	LNGR D
Reserve Requirement Ratio									
Spread	11.73	53.93	46.07	56.38	65.12	34.88	31.86	49.06	50.94
AVLR diff.	13.96	60.22	39.78	44.65	60.57	39.43	30.35	49.22	50.78
AVLR with PC	10.77	48.79	51.21	50.59	74.77	25.23	29.16	57.64	42.36
No BW-filter	10.76	79.83	20.17	37.83	87.42	12.58	42.73	29.33	70.67
BW-filter 120	10.76	78.81	21.19	36.90	79.58	20.42	29.76	56.53	43.47
Narrow set	4.81	67.59	32.41	65.19	56.30	43.70	37.77	52.69	47.31
SR horizon 1	17.40	61.23	38.77	51.21	48.65	51.35	29.69	53.85	46.15
Lag 12	21.41	58.58	41.42	35.12	37.52	62.48	34.84	49.15	50.85
Open Economy	12.46	48.76	51.24	44.50	54.30	45.70	26.67	51.61	48.39
Great Recession	13.52	33.50	66.50	62.77	54.42	45.58	48.57	55.50	44.50
Short sample	22.62	76.56	23.44	44.14	72.51	27.49	29.87	58.24	41.76
2. Deposit Benchmark Rate									
Spread	12.71	73.55	26.70	67.71	82.18	17.82	30.03	52.67	47.33
AVLR diff.	10.38	87.62	12.38	32.88	91.24	8.76	32.63	63.77	36.23
AVLR with PC	8.03	70.04	29.96	64.59	90.17	9.83	27.42	66.27	33.73
No BW-filter	9.25	53.04	46.96	29.66	87.60	12.40	38.46	68.38	31.62
BW-filter 120	7.88	73.10	26.90	32.50	90.27	9.73	37.05	66.91	33.09
Narrow set	4.56	64.63	35.37	43.79	94.03	5.97	37.18	66.90	33.10
SR horizon 1	11.30	84.37	15.63	33.05	87.02	12.98	33.42	58.90	41.10
Lag 12	16.27	66.69	33.31	15.44	85.90	14.10	28.60	63.32	36.68
Open Economy	7.63	81.75	18.25	27.74	90.81	9.19	27.81	65.43	34.57
Great Recession	7.38	54.64	45.36	32.63	90.86	9.14	46.27	68.61	31.39
Short sample	13.24	83.05	16.95	27.40	91.35	8.65	29.25	62.68	37.32

Notes: Total Contribution (T) corresponds to the sum of the effects of the two monetary policy shocks in the FEVD of the economic activity factor (EA), the average lending rate (AVLR), and loan volumes (LV). The relative contributions correspond to policy shocks associated with loan supply effects (S) and loan demand effects (D). All values are reported in percent and correspond to the point-wise median values of the FEVD distribution of the accepted draws at a forecast horizon of 14 months.

Table A.1: Interest rate liberalization in China

Time	Lending rates	Deposit rates
1996	Rates allowed to float (0.9 – 1.1 x) against the benchmark	
1998	Rural lending institutions allowed to set lending rate at 1.5 x benchmark	
1999	Lending ceiling to small businesses and mid-sized enterprises raised to 1.3 x benchmark	
01/2004	Ceiling for commercial banks and urban credit cooperatives expanded to 1.7 x benchmark and for rural credit cooperatives to 2.0 x benchmark (floor remained at 0.9 x benchmark)	
10/2004	**Ceiling removed** (excluding urban and rural credit cooperatives, for whom the ceiling was raised to 2.3 x benchmark)	**Floor is removed** (ceiling still fixed at benchmark)
2012	Floor lowered first to 0.8 x benchmark and then to 0.7 x benchmark	Ceiling raised to 1.1 x benchmark
2013	**Floor removed**; ceiling removed for urban and rural credit cooperatives	
2014		Ceiling raised to 1.2 x benchmark; interest rates of 5-year and longer liberalized
03/2015		Ceiling raised to 1.3 x benchmark
05/2015		Ceiling raised to 1.5 x benchmark
10/2015		**Ceiling is removed**

Table A.2: Data

Data series	Code	Start	End
Broad Economic Activity Factor			
No of employees: industrial enterprise	263578101 (CBRABOE)	2005M12	2016M09
Consumer Confidence Index	5198401 (CHGAA)	1990M01	2016M09
Exports FOB[1]	5823501 (CJAA)	1992M01	2016M09
Trade Balance	6094301 (CJAE)	1992M01	2016M09
Imports (Materials)	6168101 (CJBAEB)	1994M01	2016M09
Foreign Reserve	7012201 (CKNA)	1989M01	2016M09
FX Rate: PBOC: Month End: RMB to USD	7058001 (CMEBAE)	1994M01	2016M10
Fixed Asset Investment	7872901 (COBDJU)	1994M01	2016M09
FAI:: New Construction	7876701 (COBDLI)	1999M08	2016M09
FAI:: Equipment Purchase	7877101 (COBDLM)	2004M01	2016M09
PMI: Non Mfg: Business Activity	230798301 (CSAAJG)	2007M01	2016M09
Index: Shanghai Stock Exchange: Composite	13092401 (CZIC)	1990M12	2016M10
Index: Shenzhen Stock Exchange: Composite	13088801 (CZIA)	1991M04	2016M09
Index: Shanghai Shenzhen 300 Index	66006801 (CZAAUI)	2005M04	2016M10
PE Ratio: Shanghai SE: All Share	13100801 (CZMA)	1996M08	2016M09
PE Ratio: Shenzhen SE: All Share	13074901 (CZDA)	1994M01	2016M09
Real Estate Climate Index (RECI)	64391101 (CEABPQ)	2004M01	2016M09
Electricity consumption	50194201 (CRBACGD)	2002M12	2016M09
Electricity production[1]	3662501 (CBGN)	1996M01	2016M09
Rail freight traffic	12915101 (CTCAA)	1998M08	2016M09
Real Estate Investment: Residential Building	3948701 (CECAA)	1995M12	2016M09
Crude steel production	12931101 (CWAAAAJ)	2001M01	2016M09
Trucks sales	56398301 (CRAACGD)	2005M01	2016M09
Purchasing Managers' Index	69851501 (CBAWLX)	2005M01	2016M09
PMI: Mfg: New Export Order	69852101 (CBAWMD)	2005M01	2016M09
Consumer Expectation Index	5198601 (CHGAC)	1990M01	2016M09
Floor Space Started: Commodity Building[1]	3963901 (CECD)	1995M12	2016M09
Retail Sales of Consumer Goods	5190001 (CHBA)	1990M01	2016M09
Industrial production	3640701 (CBEOA)	1995M01	2016M09
Gas consumption index	ICOLCONC	2003M01	2013M03
Price Factor			
Consumer Price Index	5716201 (CIAHJZ)	1995M01	2016M09
CPI Core (excl. Food & Energy)	314418701 (CIAIEN)	2006M01	2016M09
CPI Food	5716301 (CIAHKA)	1995M01	2016M09
Consumer Price Index: 36 City	5718901 (CIAHLA)	2002M01	2016M09
Loan Market			
Loan	7029101 (CKSAC)	1997M01	2016M09
% of Ex. Benchmark Lending Rate: as Benchmark	242950301 (CMAAWK)	2004M10	2016M06
% of Ex. Benchmark Lending Rate: below	242950401 (CMAAWL)	2004M10	2016M06
% of Ex. Benchmark Lending Rate: above	242950501 (CMAAWM)	2004M10	2016M06
% of Ex. Benchmark Lending Rate: 10% above	242950601 (CMAAWN)	2008M01	2016M06
% of Ex. Benchmark Lending Rate: 10-30% above	242950701 (CMAAWO)	2004M10	2016M06
% of Ex. Benchmark Lending Rate: 30-50% above	242950801 (CMAAWP)	2004M10	2016M06
% of Ex. Benchmark Lending Rate: 50-100% above	242950901 (CMAAWQ)	2004M10	2016M06
% of Ex. Benchmark Lending Rate: 100% above	242951001 (CMAAWR)	2004M10	2016M06
Average Lending Rate	Authors calculation	2004M10	2016M06
Monetary Policy Instruments			
CB Benchmark Interest Rate: Loan to FI: 1 Year	7055601 (CMCAD)	1993M05	2016M09
Household Savings Deposits Rate: Time: 1 Year	7054401 (CMBBC)	1993M05	2016M09
Required Reserve Ratio	7036401 (CMAAAA)	1985M01	2016M09
US Variables			
Industrial Production Index, Index 2012=100	INDPRO	2004M10	2016M06
Crude Oil Prices: West Texas Intermediate (WTI)	MCOILWTICO	2004M10	2016M06

Notes: All data are obtained from the CEIC Asia database, except the US variables which are taken from the St. Louis Federal Reserve Economic Data (FRED) and the Gas consumption index which is taken from Bloomberg.
[1]The selected indicators are used for the calculation of the narrow economic activity factor.

Table A.3: Forecast error variance decomposition of the economic activity factor

Horizon	Residual EA	Residual PR	MP Loan Supply	MP Loan Demand	Residual MP, AVLR, LNGR
1. Reserve Requirement Ratio					
0	100.00	0.00	0.00	0.00	0.00
	(100.00, 100.00)	(0.00, 0.00)	(0.00, 0.00)	(0.00, 0.00)	(0.00, 0.00)
12	70.65	3.96	8.66	5.94	7.11
	(62.41, 77.97)	(1.79, 7.53)	(3.33, 16.12)	(2.59, 11.56)	(2.71, 14.12)
24	67.30	4.49	10.61	6.59	7.60
	(57.28, 75.10)	(1.96, 8.84)	(4.35, 18.93)	(2.89, 12.49)	(2.87, 14.92)
2. Deposit Benchmark Rate					
0	100.00	0.00	0.00	0.00	0.00
	(100.00, 100.00)	(0.00, 0.00)	(0.00, 0.00)	(0.00, 0.00)	(0.00, 0.00)
12	80.19	2.46	6.26	1.09	7.18
	(72.89, 86.67)	(0.94, 5.22)	(2.20, 13.04)	(0.36, 2.95)	(2.88, 13.32)
24	73.37	2.93	9.32	1.51	9.69
	(63.97, 81.40)	(1.07, 6.63)	(3.57, 18.17)	(0.52, 3.50)	(3.59, 17.68)
3. Lending Benchmark Rate					
0	100.00	0.00	0.00	0.00	0.00
	(100.00, 100.00)	(0.00, 0.00)	(0.00, 0.00)	(0.00, 0.00)	(0.00, 0.00)
12	77.51	2.40	8.74	1.67	6.64
	(68.72, 85.13)	(0.90, 4.96)	(3.61, 16.15)	(0.51, 4.57)	(2.76, 12.55)
24	71.79	2.66	10.09	2.16	9.95
	(62.23, 80.17)	(0.99, 5.78)	(4.18, 18.80)	(0.71, 5.26)	(4.01, 17.81)

Notes: Values correspond to the point-wise median of the sign-identified posterior distribution; values in parentheses show the 16^{th} and 84^{th} percentiles; all values are in percent.

Table A.4: Forecast error variance decomposition of the economic activity factor (extension of Fernald et al. (2014) with loan market)

Horizon	Residual EA	Residual PR	MP Shock	Residual AVLR	Residual LNGR
0	100.00	0.00	0.00	0.00	0.00
	(100.00, 100.00)	(0.00, 0.00)	(0.00, 0.00)	(0.00, 0.00)	(0.00, 0.00)
12	70.81	4.10	14.52	7.48	1.18
	(62.44, 77.77)	(1.96, 7.48)	(8.14, 21.79)	(3.44, 13.14)	(0.43, 2.93)
24	67.34	4.55	13.63	10.62	1.23
	(56.60, 74.90)	(2.12, 8.83)	(8.15, 20.41)	(5.21, 18.75)	(0.46, 3.19)

Notes: Values correspond to the point-wise median of the sign-identified posterior distribution; values in parentheses show the 16^{th} and 84^{th} percentiles; all values are in percent.

Table A.5: Forecast error variance decomposition of economic activity using the lending benchmark rate as monetary policy instrument

Policy		FEVD			Relative Effects	
Variable	h	MPLS	MPLD	Total	MPLS	MPLD
DPR	12	8.74 (3.61, 16.15)	1.67 (0.51, 4.57)	10.41	83.94	16.06
	24	10.09 (4.18, 18.80)	2.16 (0.71, 5.26)	12.25	82.39	17.61

Notes: Please refer to notes of Table 2.

Table A.6: Robustness analysis: Relative contributions to the policy induced forecast error variance of the economic activity factor using the lending benchmark rate as monetary policy instrument

Robustness	EA			AVLR			LNGR		
	T	S	D	T	S	D	T	S	D
Spread	12.71	73.55	26.45	69.15	83.56	16.44	32.09	54.05	45.95
AVLR diff.	12.47	81.43	18.57	28.85	88.02	11.98	33.51	64.74	35.26
AVLR with PC	9.19	80.60	19.40	67.73	90.77	9.23	28.61	67.44	32.56
No BW-filter	19.51	79.67	20.33	24.57	90.46	9.54	43.63	65.56	34.44
BW-filter 120	15.78	79.16	20.84	26.87	86.96	13.04	42.16	65.80	34.20
Narrow set	4.81	63.31	36.69	34.17	83.38	16.62	37.62	68.32	31.68
SR horizon 1	12.25	81.10	18.90	23.61	81.84	18.16	36.10	60.09	39.91
Lag 12	17.01	44.99	55.01	18.68	66.79	33.21	28.65	58.25	41.75
Open Economy	8.53	73.05	26.95	18.18	84.85	15.15	29.48	61.39	38.61
Great Recession	13.84	63.09	36.91	32.15	80.46	19.54	45.63	67.56	32.44
Short sample	11.86	81.98	18.02	26.69	90.90	9.10	30.67	67.81	32.19

Notes: Please refer to notes of Table 4.

Figure 1: Different monetary policy instruments

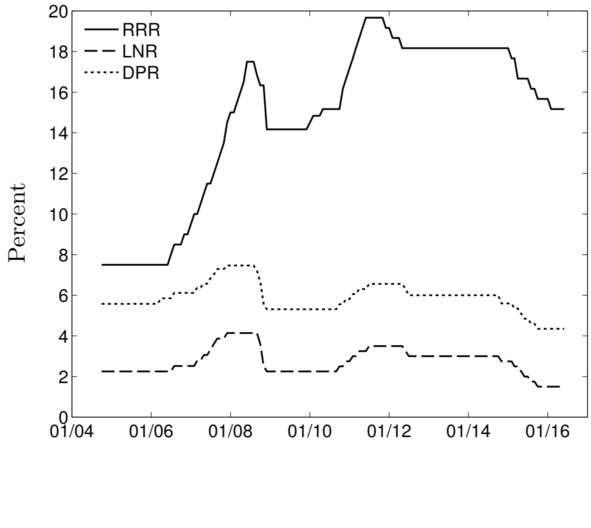


Figure 2: Comparison of different lending rates

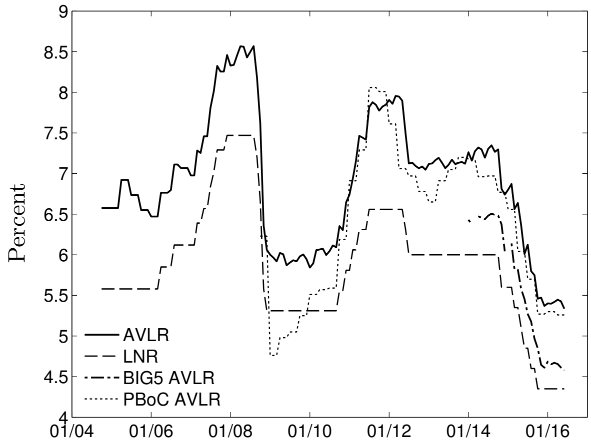


Figure 3: Shares of different lending rates

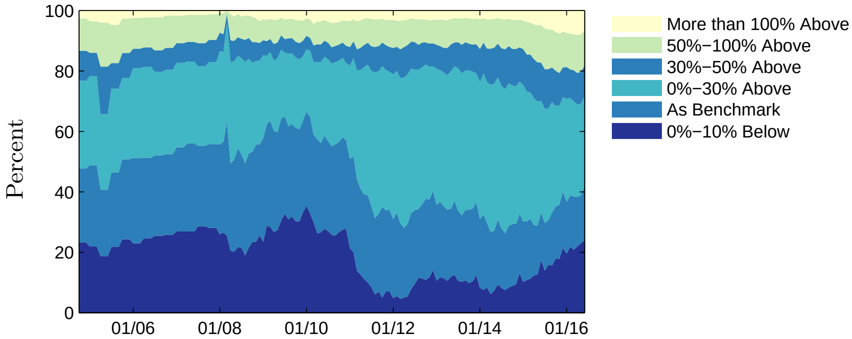
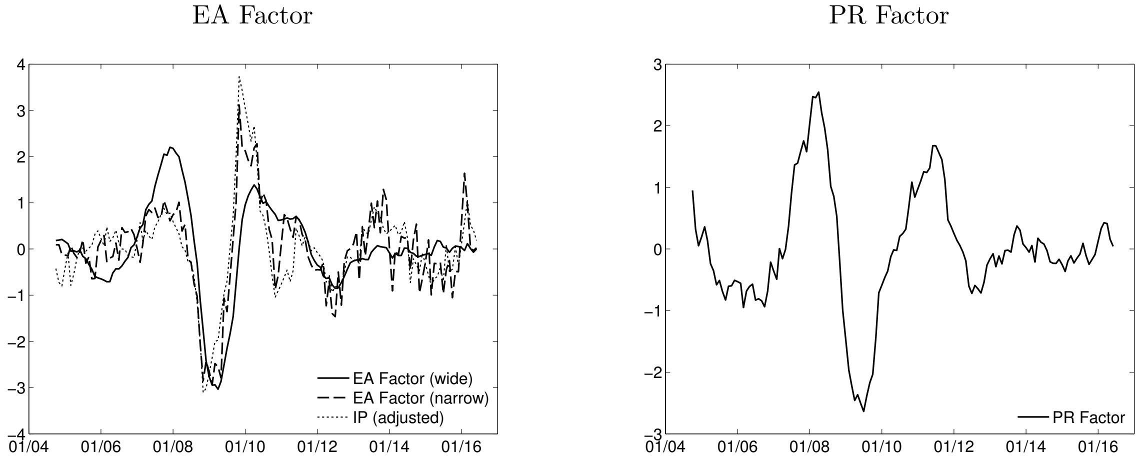
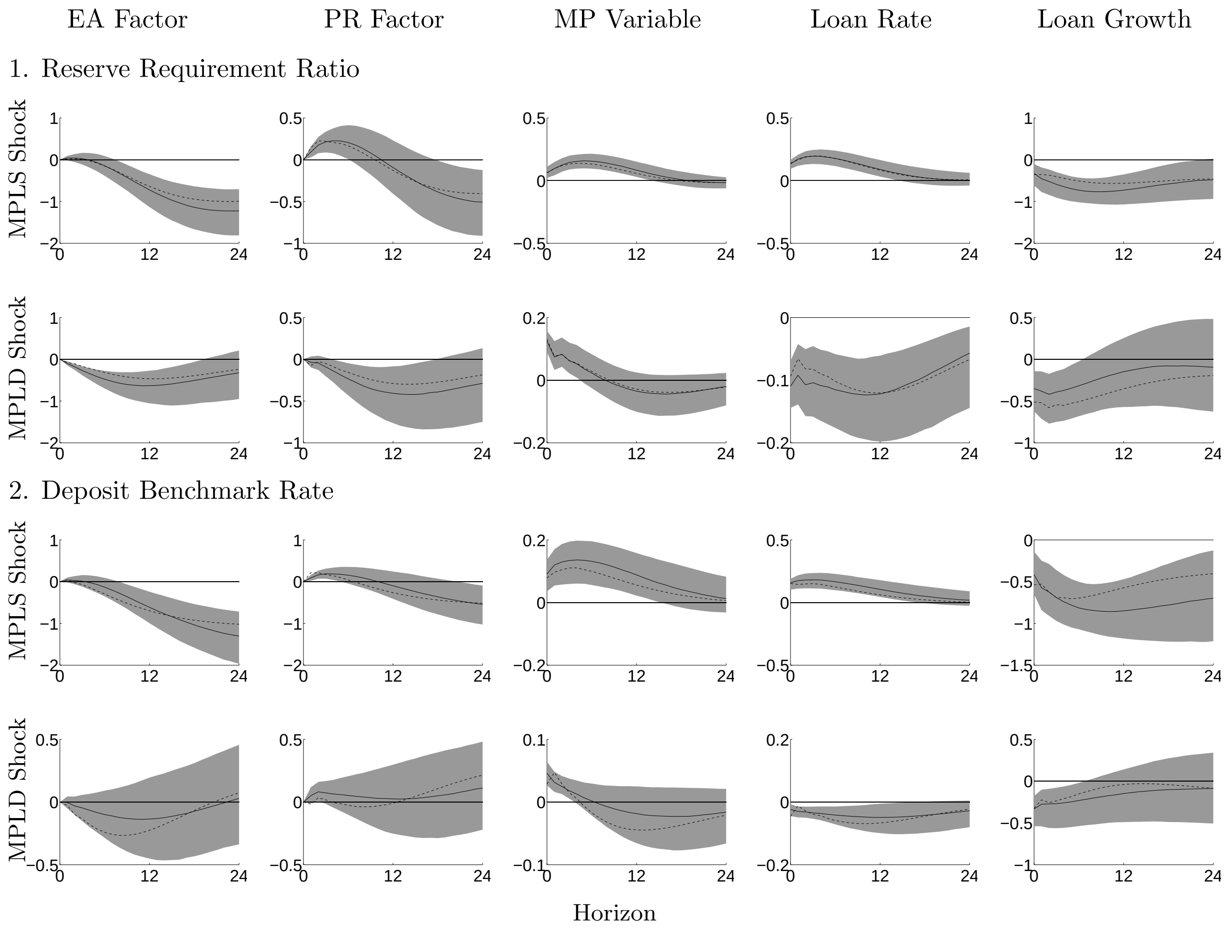


Figure 4: Economic activity and price factors



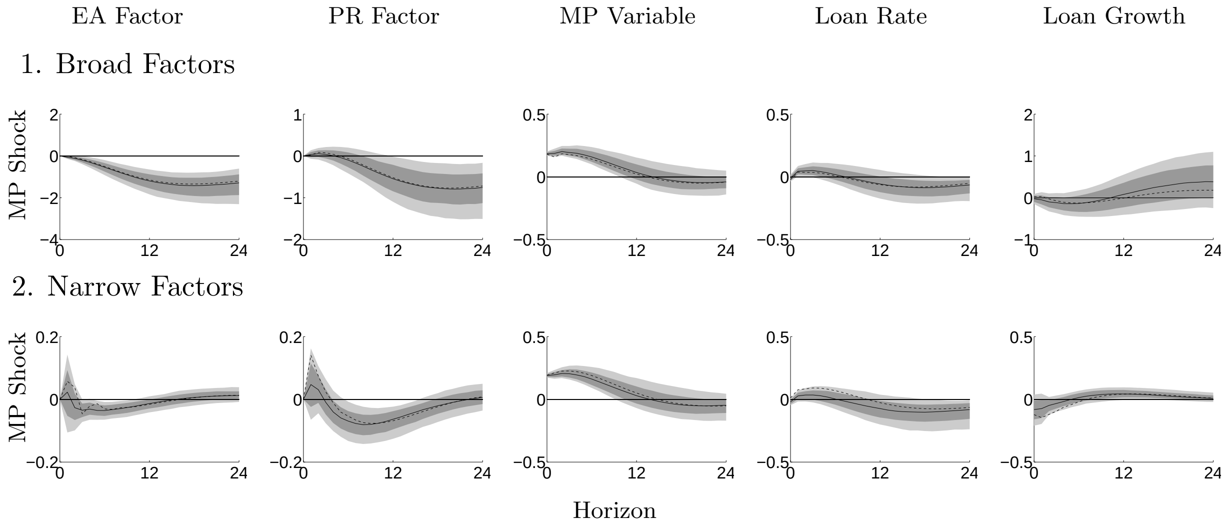
Notes: normalized 12-month moving averages (mean zero and unit variance); IP from adjusted Fernald et al. (2014) dataset (i.e. data is Chinese new year adjusted; transformed to month on month growth rates and seasonally adjusted)

Figure 5: Impulse responses to contractionary monetary policy shocks with different loan dynamics



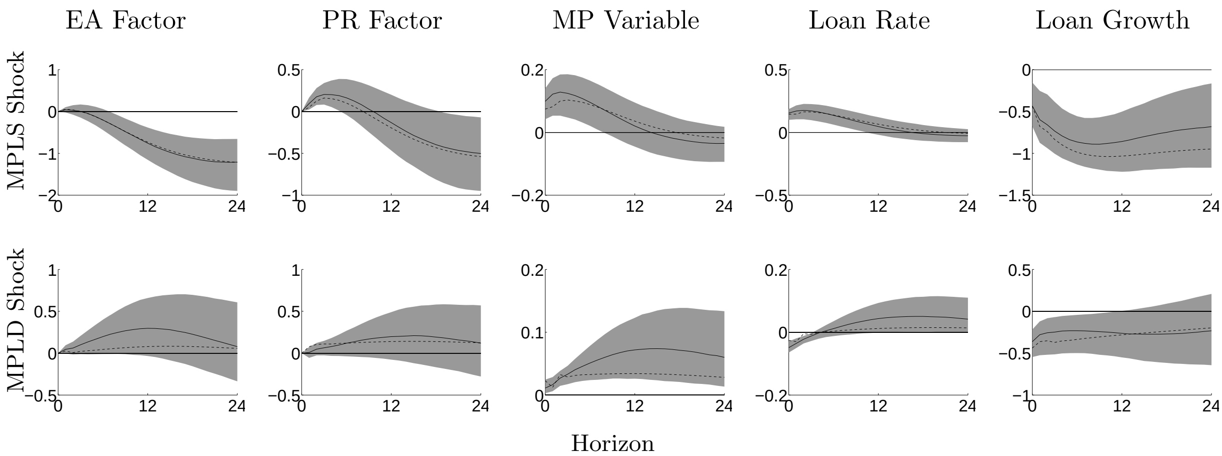
Notes: The impulse responses of the variables in first-differences are cumulated to provide the same level interpretation as in the case of the policy variable and the loan rate. The solid lines show the point-wise median values of of the impulse responses of all accepted draws. The light gray and dark gray areas represent 68% of the distribution. The dashed lines represent responses of the closest to median model (see Fry and Pagan, 2011, for details).

Figure A.1: Replication of Fernald et al. (2014) with updated data set additional loan market: Impulse responses to a recursively identified monetary policy shock



Notes: The light gray and dark gray areas represent 90% and two third of the sign-identified posterior distribution. The solid line shows the point-wise median response and the dashed line represents responses of the closest to median model (which is calculated as suggested by Fry and Pagan, 2011).

Figure A.2: Impulse responses to different monetary policy shocks using the lending benchmark rate as monetary policy instrument



Notes: Please refer to notes of Figure 5.