China's Monetary Policy and the Loan Market: How Strong is the Credit Channel in China?

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August 2018

Abstract

We study the credit channel of Chinese monetary policy in a structural vector autoregressive framework. Using combinations of zero and sign restrictions we identify monetary policy shocks that are either linked to supply or demand responses on the loan market. We find that policy shocks that coincide with loan supply effects, account for roughly 10 percent of output dynamics after two years. Loan demand effects account for up to 7 percent depending on the policy measure. Hence, the credit channel represent an economically relevant and important transmission channel for monetary policy in China. Additionally, our results confirm existing evidence that monetary policy in China accounts for a relatively high share of business cycle dynamics.

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

JEL codes: C32, E44, E52

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1 Introduction

Over the last twenty years China's economy has experienced a steady transition to become more market-orientated. In this process, Chinese monetary policy has decreased its direct control of credit markets, known as "window guidance," and increasingly relies on market based policy measures (Fernald et al., 2014). In this paper we evaluate how market-based policy measurers, such as benchmark rates and reserve requirements, propagate through the loan market and ultimately, affect the Chinese economy.

The focus on the loan market is motivated by the credit channel of monetary policy. In a seminal paper, Bernanke and Blinder (1988) argue that changes in reserve requirements influence the supply of bank loans, which in turn amplify the effects of monetary policy on the real economy. A drain in bank reserves, for instance, requires that banks substitute reservable deposits with external sources of funding. However, depending on banks' solvency and the costs of external funds, banks might not be able to fully balance their deposits and therefore decrease the supply of bank loans. While monetary policy is generally viewed to determine the cost of credit, which influences firms' investment decisions and their demand for external funds, an additional decline of loan supply potentially amplifies the effects on the economy (see also Bernanke and Gertler, 1995). More recently, Disyatat (2011) and Kishan and Opiela (2012) emphasize that changes in the policy rate should also influence loan supply, as they trigger adjustments in banks' external financing costs, which are finally passed onto borrowers.

To evaluate whether the loan market matters for the propagation of Chinese monetary policy, we apply a novel identification approach that allows us to quantify aggregate output effects of monetary policy shocks, depending on the transmission of the shocks. In the analysis we fit structural vector autoregressive models to monthly Chinese data ranging from October 2004 through June 2016. To identify monetary policy shocks and the respective dynamics on the loan market we combine block-recursive zero restrictions with sign restrictions. The zero restrictions identify a block of policy shocks, which is consistent with the standard recursive assumption that monetary policy responds simultaneously to macroeconomic aggregates, such as prices and output, but affects these variables with a lag (Christiano et al., 1999).[1] Within this block, we do not exactly identify the policy shock but impose sign restrictions to distinguish between policy shocks that are linked to supply or demand dynamics on the loan market. Consider,

[1]The recursive structure is also frequently used to identify monetary policy in China (see e.g. He et al., 2013; Fernald et al., 2014).

for instance, a contractionary monetary policy shock. When loan supply effects dominate the transmission of monetary policy, the supply curve of loans shifts inwards and we should observe that prices of loans decline while volumes increase. In contrast, when a monetary tightening primarily coincides with a decline in loan demand we should observe that both prices and volumes of loans decline. Hence, by imposing sign restrictions on the responses of the loan rate and loan volumes, we are able to disentangle policy shocks that are linked to different transmission channels of monetary policy.

We find that the overall effects of market based monetary policy shocks account for up to 20 percent of the forecast variance of Chinese output after two years. The magnitude of these effects is in line with existing empirical evidence and supports the view that market based policy measures have become effective instruments of the People's bank of China's to stabilize the Chinese economy (Chen et al., 2017; Fernald et al., 2014). Monetary policy shocks that coincide with loan supply dynamics account for roughly 10 percent of the dynamics in output, regardless of the specific policy measure. In contrast, we find that policy shocks that are linked to loan demand responses capture roughly 2 and 7 percent of the fluctuations in output depending on whether monetary policy is measured with the reserve requirement ratio or benchmark rates, respectively. Therefore, loan supply dynamics coincide with at least 50 percent of policy induced output dynamics. Both the absolute and relative importance of loan supply dynamics in the transmission of Chinese monetary policy, provides empirical evidence for an economically relevant credit channel of monetary policy in China.

As we evaluate loan supply responses in the transmission of Chinese monetary policy, our analysis 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).[2] This approach relies on the idea that after changes in monetary policy loan supply responds asymmetrically across banks, depending on banks' ability to absorb the policy shock, while loan demand should responds independently from these characteristics. Gunji and Yuan (2010) study whether loan growth responds asymmetrically across banks depending on their solvency. 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

[2] 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.

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. Hou and Wang (2013) conclude that the increasing financial liberalization in China generally decreases the transmission of Chinese monetary policy through loan supply. In contrast to these studies, we evaluate loan supply effects using a macroeconomic framework. While this approach allows us to abstract from specific bank characteristics to identify loan supply, we are also able to quantify the effects of identified policy shocks at the aggregate level.

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 concludes.

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 (hereafter 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§).[3] 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 a 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 window guidance policies, where the central bank advises banks directly on the quantity and structure of their lending.[4] In our estimation period, the PBoC toolbox include the benchmark interest rates, bank reserve requirements,

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

[4] The literature on Chinese monetary policy tend to find window guidance as an effective policy instrument (see, for example Chen et al., 2013).

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.

As we are interested in the transmission of Chinese monetary policy through the credit channel, we focus on market based policy measures (see Bernanke and Blinder, 1988; Disyatat, 2011; Kishan and Opiela, 2012). To capture, however, somehow the policy variety of the PBoC we evaluate both quantity and price based policy measures. Specifically we study the reserve requirement ratio (RRR) and the deposit benchmark rate (DPR) as policy instruments.[5] In our estimation period, October 2004 – June 2016, reserve requirements as well as benchmark interest rates have been important and 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, in 2008 the RRRs were differentiated for different types of banks, 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).[6] Hence, in our analysis, we use the average of the three different RRRs, represented in Figure 1.

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.[7] As we describe in detail below, we exploit the lending rate of banks to distinguish between supply and demand dynamics on the loan market. Hence, the interest rate liberalization enables us to analyze whether banks adjust the supply of bank loans in response to changes in monetary policy.

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

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

[7] 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).

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 households in China. Therefore, the credit channel is likely to play a relevant role for the transmission of Chinese monetary policy. In 2016, still almost 70% of non-bank corporate sector and households' new financing were in the form of bank loans.[8]

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 aggregates on economic activity and prices are difficult to verify we follow the literature and use a broad set of economic activity and price indicators to measure 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 captures 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. In the estimation the variables appear 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

[8]The share is calculated by the ratio of loans denoted in local and foreign currency to an aggregate financing statistic reported by the PBoC. The corresponding series codes in the CEIC Asia database are: 365867287 (CKABAVF), 365867297 (CKABAVG), and 365867277 (CKABAVE), respectively.

[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.

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-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 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 with 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 policy shocks to be contractionary by imposing a positive response on the policy variable. The restrictions on the loan market variables in case of policy shocks that are linked to loan supply responses are

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

[11]See Moon et al. (forthcoming) 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).

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 of loans. In contrast, when monetary policy shocks coincide with loan demand effects we require that volumes and prices of loans decline simultaneously, consistent wich an inward shift of the demand curve of loans.[13] All remaining dynamics on the loan market, which coincide with an increase in the policy rate are captured by the third residual shock.

As we allow for contemporaneous effects between the loan market variables and the policy measure, the question arises whether we are able to distinguish between monetary policy shocks and 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 interpreted as aggregate demand shocks. Therefore, monetary policy is also expected to respond expansionary to contractionary loan demand shocks. Hence, 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 endogenous responses to the policy shocks.

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.[14]

[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 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]Please refer to Arias et al. (2014) for technical details and Breitenlechner and Geiger (2018) for details on the applied estimation algorithm.

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 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. We use exactly the same time series as in Fernald et al. (2014) but with an updated dataset. Figure 2 shows the estimated factors and Table A.2 in the Appendix lists all variables. The wide EA factor is constructed with all economic activity measures, while the narrow EA factor is constructed with a small subset of economic activity measures. Both EA factors are clearly correlated with industrial production, but to various extent. 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).

As the PBoC only reports an average banking sector lending rate from late 2008 onwards on a quarterly frequency (see PBoC AVLR in Figure 3), we exploit monthly statistics of the share of loans priced above/below its benchmark lending rate. Specifically, we construct the average

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

lending rate (AVLR_t) as follows:

$$\text{AVLR}_t = \text{LNR}_t \left(\sum_{i=1}^{k} \frac{\text{SHARE}_{i,t} \cdot \text{CHANGE}_i}{100} \right), \tag{2}$$

where LNR_t captures the short term benchmark lending rate (see LBR in Figure 4), SHARE_t represents the shares of differently prices loans (see Figure 4 for the individual time series) and k is the number of different price categories. In the baseline estimation, we define the variable CHANGE_t as the mean value of the respective surcharge or discount in each price category, respectively. To construct the average lending rate from October 2004 onwards we accept that until 2008 the shares of loans priced above/below its benchmark rate are only reported on a quarterly frequency. Hence, the average lending rate changes only on a quarterly frequency prior to 2008. In Figure 3 we compare our constructed lending rate with the benchmark lending rate and the average lending rate reported by the PBoC. Furthermore, we were also able to obtain data on the monthly average lending rate from one of the big-five banks in China for 2014-2016 (BIG5 AVLR in Figure 3). Generally our average lending rate is broadly in line with the two other measures of the average lending rate in China.

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 reserve requirement ratio 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 case of policy shocks that are linked to loan supply effects we see that the increase of the reserve requirement ratio coincides with an increase of the average lending rate while the growth rate of loans decreases. In contrast, we see that in case of policy shocks that are linked to loan demand responses both the average lending rate and loan growth decline.

In the bottom panel, we see that the responses of economic activity generally reveal the same pattern when monetary policy is captured with the deposit benchmark rate as compared to the reserve requirement ratio. However, we only observe a systematic negative response when monetary policy is transmitted through loan supply responses. The response of the price factor is generally weaker when monetary policy is conducted through changes in the deposit rate as compared to adjustments in the reserve requirement ratio.

Overall, our findings support the findings of Fernald et al. (2014) and Chen et al. (2017) that market based policy instruments affect output and prices in China. While in contrast He et al. (2013) does not find that changes in benchmark interest rates matter for output dynamics in China, our results reveal that this might be the case when the shock is transmitted through adjustments in firms' and households' demand for bank loans. The effects on output are predominantly present through the transmission of benchmark rates on the supply of bank loans.

To asses the economic and 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 the economic activity measure.

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 loan 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.[16] In Table 2 we show the results for the estimation with the reserve requirement ratio as policy measure and in Table 3 we report the findings related to the deposit benchmark rate. Furthermore, the tables also report the sum of both transmission

[16]Table A.3 in the Appendix shows the complete FEVD of the economic activity factor including the residual shocks.

channels indicating the overall effect of monetary policy, as well as the relative contribution of each channel.

Starting with the reserve requirement ratio as policy instrument, we see in Table 2 that the effects of monetary policy increase steadily over time and after two years account for roughly 20 percent of the forecast variance in the economic activity factor.[17] While these shares are exceptionally high in comparison to results from western economies over similar observation periods (see e.g. Ramey, 2016), the results support existing findings in the literature that market based monetary policy instruments are effective policy tools of the PBoC (Fernald et al., 2014; Chen et al., 2017).

Turning to policy shocks that are associated with loan supply effects (first column of Table 2), we see that it takes roughly a year until reasonable output effects materialize. In contrast, policy shocks that are linked to loan demand dynamics affect economic activity relatively faster as compared to the supply effects. Therefore, our results suggest that firms' and households' adjust their demand for bank loans faster as compared to the changes in banks' supply of credit. After two years however, we see higher output effects in case of policy shocks that correspond to loan supply responses. Specifically, monetary policy shocks associated with loan supply effects account for roughly 11 percent of output dynamics after two years, while policy shocks linked to loan demand effects account for 7 percent. The relative contributions show that the transmission effects are first dominated by loan demand effects but from the end of the first year onwards loan supply effects become relatively more important.

With the deposit benchmark rate as policy measure, in Table 3 we generally see similar patterns as compared to the results with the reserve requirement ratio. Again the overall effects of monetary policy increase over time and policy shocks that are linked to loan supply dynamics finally reveal larger effects on the economic activity as compared to loan demand effects. However, the absolute effects on output are weaker. After two years exogenous adjustments in the deposit benchmark rate account for roughly 11 percent of output fluctuations, as compared to 17 percent in case of changes in the reserve requirement ratio. Interestingly, the decline in the absolute share is mainly due to the relative weak policy effects connected to loan demand responses. The values of policy shocks associated with loan supply effects are similar to the values reported in Table 2. Therefore loan supply responses represent the dominant transmis-

[17] The order of magnitude of the overall effect of monetary policy is relatively similar to a recursively identified monetary policy shock (see Table A.4).

sion channel when monetary policy is conducted through adjustments in the benchmark rates.[18] The relative share varies between 66 and 86 percent across the different forecast horizons.

To sum up, we find that loan supply dynamics represent an economically relevant transmission mechanism for both policy instruments, the reserve requirement ratio and the deposit benchmark rates. Furthermore, in comparison to loan demand effects, loan supply dynamics account for at least half of policy induced output dynamics after two years. Therefore, we find that the credit channel represents an important transmission channel for market based policy instruments in China.

5 Robustness Analysis

As we provide the first quantification of the credit channel at the aggregate level in China, we perform extensive robustness checks to validate our findings in the FEVD analysis. The sensitivity checks focus on the identification restrictions, the construction of the average lending rate, the model specification, data transformations, and the sample selection. All robustness checks are summarized in Table 4.[19]

Identification First, we control for a possible pass-through of interest rates. This means, we re-estimate the baseline model using a spread between the average lending rate and the lending benchmark rate. While we require in our baseline that the average lending rate increases or decreases in case of a policy contraction, depending on the transmission of the shock, with the spread we require that the lending rate changes relatively stronger as compared to the lending benchmark rate. Furthermore, we also check estimations in which we apply a shorter sign restrictions horizon, imposing the restrictions only on impact and the subsequent month.

Average Leinding Rate As we have to construct an average lending rate we check different definitions. In the baseline estimation we include an average lending rate which is calculated using the mean values of the above described price categories. Therefore, we firstly take the upper bound of each price category instead of the mean value (for the category with the largest

[18] Table A.5 in the Appendix also reports results for an estimation with the lending benchmark rate as policy instrument.

[19] We also perform all robustness checks on a model in which we use the lending benchmark rate as policy instrument (see Table A.6).

surcharge we assume a markup of 200 percent). Secondly, as we are primarily interested in the dynamics of an average lending rate, we use the principal component analysis to summarize the dynamics in the shares of loans priced above or below the benchmark rate in one average landing factor.

Data Transformation 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. Furthermore, while we follow in our baseline the literature and improve data reliability by approximate economic activity with a broad set of observables indicators we also check whether we find similar results with a small set of economic activity indicators (see also Fernald et al., 2014).

Specification 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 further check wether our results change when we use twelve lags instead. Additionally, China's economy is an open economy strongly depending on world output and commodity prices. Therefore we re-estimate the baseline model including US output and Oil prices denoted in US Dollars (see also Fernald et al., 2014).[20]

Sample After the global financial crisis hit China in 2008, the Chinese government supported the domestic economy with a huge stimulus package. The 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 it is likely that banks' supply of loans also responded relatively stronger to policy shocks during this period. We re-estimate the baseline models and exclude the period from July 2008 to March 2010 to test whether indeed strong loan supply effects are present during this period. 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).

Overall, the results of the various robustness checks confirm our main findings from the baseline specifications. The relative shares of policy induced output dynamics after two years (reported in the fourth column of Table 4) show that loan supply effects account for generally

[20]Please refer to Table A.2 for the data description.

more as half of the transmission effects on economic activity. The only reasonable exception is the estimation in which we exclude the recovery period of the Great Recession. The drop in the policy effects associated with loan supply responses support the hypothesis that loan supply played an important role during this period. However, we also see that loan supply dynamics still matter for the remaining period, albeit to a somewhat smaller extent. Analogously, when we re-estimate the model with the shorter sample starting in January 2008, in which the Great Recession becomes more weight in the sample, the effects of monetary policy on economic activity appears more pronounced and monetary policy is relatively stronger transmitted through loan supply responses. While we find considerably lower effects of overall monetary policy when economic activity is measured with the narrow set of indicators,[21] we still find the same relative importance of loan supply and loan demand effects. Hence, also in this estimation loan supply effects represent an important transmission channel for Chinese monetary policy.

6 Conclusion

How important is the credit channel in the transmission of Chinese monetary policy? We apply a novel identification scheme, which allows us to evaluate monetary policy shocks that are linked to loan supply effects using aggregated time-series data.

We find that both market based policy measures, the reserve requirement ratio and the deposit benchmark rate, are linked to loan supply dynamics. After two years monetary policy shocks that are associated with loan supply effects account for roughly 10 percent of the dynamics in economic activity. In comparison, monetary policy shocks that are linked to loan demand effects account for up to 7 percent of fluctuations in output over the same forecast horizon. Hence, over half of the transmission effects on output are linked to loan supply effects.

Overall, our results provide empirical evidence that the credit channel represents an economically relevant transmission channel for market based monetary policy measures in China.

[21]The same observation actually holds when we identify monetary policy recursively (see Table A.4 in the Appendix

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A Additional Tables and Figures

INSERT TABLES A.1, A.2, A.3, A.4, A.5, and A.6 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 (using the reserve requirement ratio as policy measure)

Horizon	FEVD MP with		Total	Relative Effects	
	Loan Supply	Loan Demand		Loan Supply	Loan Demand
1	0.47 (0.04, 1.87)	2.24 (0.61, 4.75)	2.71	17.34	82.66
6	2.88 (1.17, 5.83)	6.22 (2.57, 11.69)	9.10	31.61	68.39
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

Notes: Total contributions correspond to the sum of the effects of the two monetary policy shocks in the FEVD. The relative contributions correspond to policy induced output dynamics associated with either loan supply or loan demand effects. All values are reported in percent and 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 the economic activity factor (using the deposit benchmark rate as policy measure)

Horizon	FEVD MP with		Total	Relative Effects	
	Loan Supply	Loan Demand		Loan Supply	Loan Demand
1	0.43 (0.04, 1.90)	0.22 (0.02, 0.87)	0.65	65.96	34.04
6	2.22 (0.82, 4.69)	0.84 (0.23, 2.32)	3.06	72.55	27.45
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: Please refer to notes of Table 2.

Table 4: Summary of the robustness analyses of the forecast error variance decomposition of the economic activity factor at a forecast horizon of 24 month

Robustness Checks	FEVD MP with Loan Supply	FEVD MP with Loan Demand	Total	Relative Effects MP with Loan Supply	Relative Effects MP with Loan Demand
1. Using the reserve requirement ratio as policy measure					
Spread	6.33 (2.35, 12.61)	5.40 (2.01, 11.52)	11.73	53.93	46.07
SR horizon 1	10.65 (4.24, 18.51)	6.75 (2.96, 12.67)	17.40	61.23	38.77
AVLR diff.	8.41 (3.28, 15.39)	5.55 (2.23, 11.14)	13.96	60.22	39.78
AVLR with PC	5.25 (1.80, 11.25)	5.51 (2.27, 10.65)	10.77	48.79	51.21
No BW-filter	8.59 (4.34, 14.30)	2.17 (0.88, 4.58)	10.76	79.83	20.17
BW-filter 120	8.48 (3.98, 14.38)	2.28 (1.00, 4.57)	10.76	78.81	21.19
Narrow set	3.25 (1.58, 5.77)	1.56 (0.63, 3.50)	4.81	67.59	32.41
Lag 12	12.54 (7.65, 19.95)	8.87 (5.61, 13.86)	21.41	58.58	41.42
Open Economy	6.08 (2.36, 12.85)	6.39 (2.88, 12.11)	12.46	48.76	51.24
Great Recession	4.53 (1.66, 9.94)	8.99 (3.65, 17.47)	13.52	33.50	66.50
Short sample	17.32 (7.92, 28.27)	5.30 (1.97, 11.72)	22.62	76.56	23.44
2. Using the deposit benchmark rate as policy measure					
Spread	8.27 (3.03, 15.73)	3.01 (0.96, 7.46)	11.28	73.30	26.70
SR horizon 1	9.53 (3.31, 18.00)	1.77 (0.60, 4.08)	11.30	84.37	15.63
AVLR diff.	9.10 (3.44, 17.54)	1.29 (0.44, 3.08)	10.38	87.62	12.38
AVLR with PC	5.62 (1.85, 12.56)	2.40 (0.80, 5.84)	8.03	70.04	29.96
No BW-filter	4.91 (1.53, 11.47)	4.34 (1.62, 9.18)	9.25	53.04	46.96
BW-filter 120	5.76 (1.94, 12.31)	2.12 (0.78, 4.83)	7.88	73.10	26.90
Narrow set	2.95 (1.29, 5.68)	1.61 (0.50, 4.01)	4.56	64.63	35.37
Lag 12	10.85 (6.64, 16.95)	5.42 (3.29, 8.79)	16.27	66.69	33.31
Open Economy	6.24 (2.25, 13.87)	1.39 (0.54, 3.28)	7.63	81.75	18.25
Great Recession	4.03 (1.43, 10.01)	3.35 (1.39, 7.47)	7.38	54.64	45.36
Short sample	11.00 (4.06, 21.37)	2.24 (0.79, 5.50)	13.24	83.05	16.95

Notes: Please refer to notes of Table 2.

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: All values are reported in percent and correspond to the point-wise median values of the distribution of accepted draws. Values in parentheses represent 68% of the distribution.

Table A.4: Forecast error variance decomposition of the economic activity factor (replication of Fernald et al. (2014) with updated data set and additional loan market variables)

Horizon	Residual EA	Residual PR	MP Shock	Residual AVLR	Residual LNGR
1. Broad EA factor					
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)
2. Narrow EA factor					
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	91.13	1.90	2.11	2.10	1.52
	(87.00, 94.38)	(0.82, 3.69)	(0.63, 4.95)	(1.09, 3.91)	(0.64, 2.93)
24	89.60	2.19	2.14	3.01	1.73
	(84.80, 93.42)	(0.95, 4.17)	(0.65, 4.95)	(1.50, 5.31)	(0.82, 3.37)

Notes: Please refer to notes of Table A.3.

Table A.5: Forecast error variance decomposition of the economic activity factor (using the lending benchmark rate as policy measure)

Horizon	FEVD MP with		Total	Relative Effects	
	Loan Supply	Loan Demand		Loan Supply	Loan Demand
1	0.50 (0.04, 2.18)	0.48 (0.04, 1.81)	0.98	51.20	48.80
6	3.26 (1.34, 6.42)	1.32 (0.38, 3.76)	4.58	71.18	28.82
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

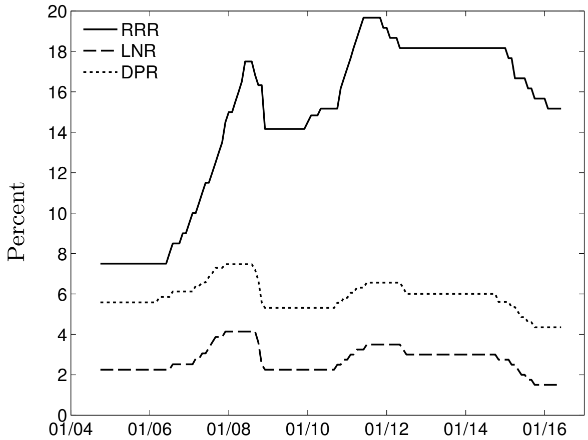
Notes: Please refer to notes of Table 2.

Table A.6: Summary of the robustness analyses of the forecast error variance decomposition of the economic activity factor at a forecast horizon of 24 month (using the lending benchmark rate as policy measure)

Robustness	FEVD MP with		Total	Relative Effects MP with	
Checks	Loan Supply	Loan Demand		Loan Supply	Loan Demand
Spread	9.35 (3.77, 17.53)	3.36 (1.09, 8.14)	12.71	73.55	26.45
SR horizon 1	9.94 (3.85, 18.34)	2.32 (0.75, 5.71)	12.25	81.10	18.90
AVLR diff.	10.16 (3.98, 18.79)	2.32 (0.78, 5.44)	12.47	81.43	18.57
AVLR with PC	7.41 (2.56, 15.34)	1.78 (0.55, 4.71)	9.19	80.60	19.40
No BW-filter	15.54 (7.25, 26.59)	3.96 (1.32, 8.93)	19.51	79.67	20.33
BW-filter 120	12.49 (5.78, 21.22)	3.29 (1.09, 7.05)	15.78	79.16	20.84
Narrow set	3.05 (1.32, 5.74)	1.77 (0.65, 4.04)	4.81	63.31	36.69
Lag 12	7.66 (4.64, 12.55)	9.36 (5.50, 14.97)	17.01	44.99	55.01
Open Economy	6.23 (2.55, 13.48)	2.30 (0.78, 5.64)	8.53	73.05	26.95
Great Recession	8.73 (2.87, 17.65)	5.11 (1.77, 12.21)	13.84	63.09	36.91
Short sample	9.72 (3.52, 20.11)	2.14 (0.74, 5.10)	11.86	81.98	18.02

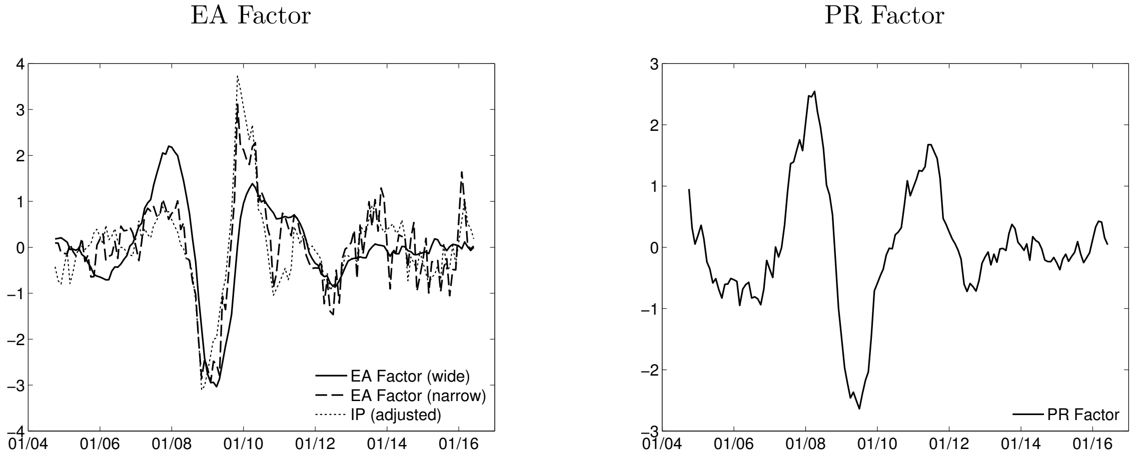
Notes: Please refer to notes of Table 2.

Figure 1: Different monetary policy instruments



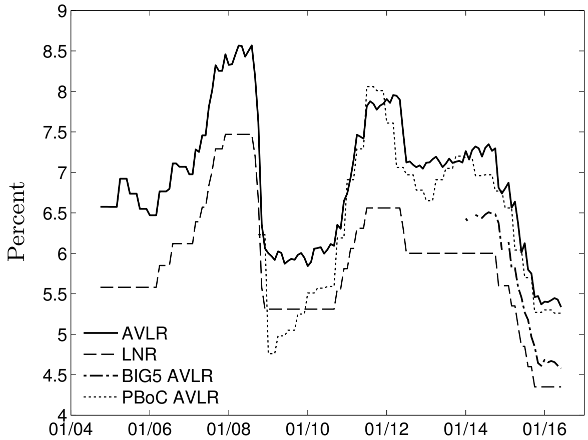
Notes: The solid line shows the average reserve requirement ratio (RRR), the dashed line is the lending benchmark rate (LNR), and the dotted line shows the deposit benchmark rate (DPR).

Figure 2: Economic activity and price factors



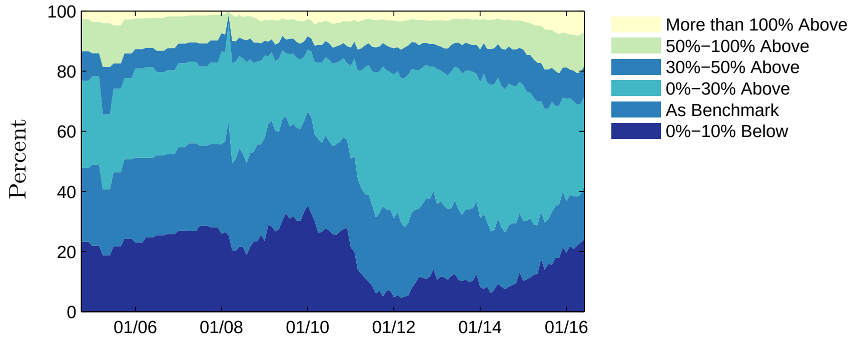
Notes: For the visualization we show 12-month moving averages of the economic activity (EA) and the price (PR) factors. IP data is adjusted as described inFernald et al. (2014): IP is Chinese new year adjusted; transformed to month on month growth rates, and seasonally adjusted (using the X12-ARIMA method).

Figure 3: Comparison of different lending rates



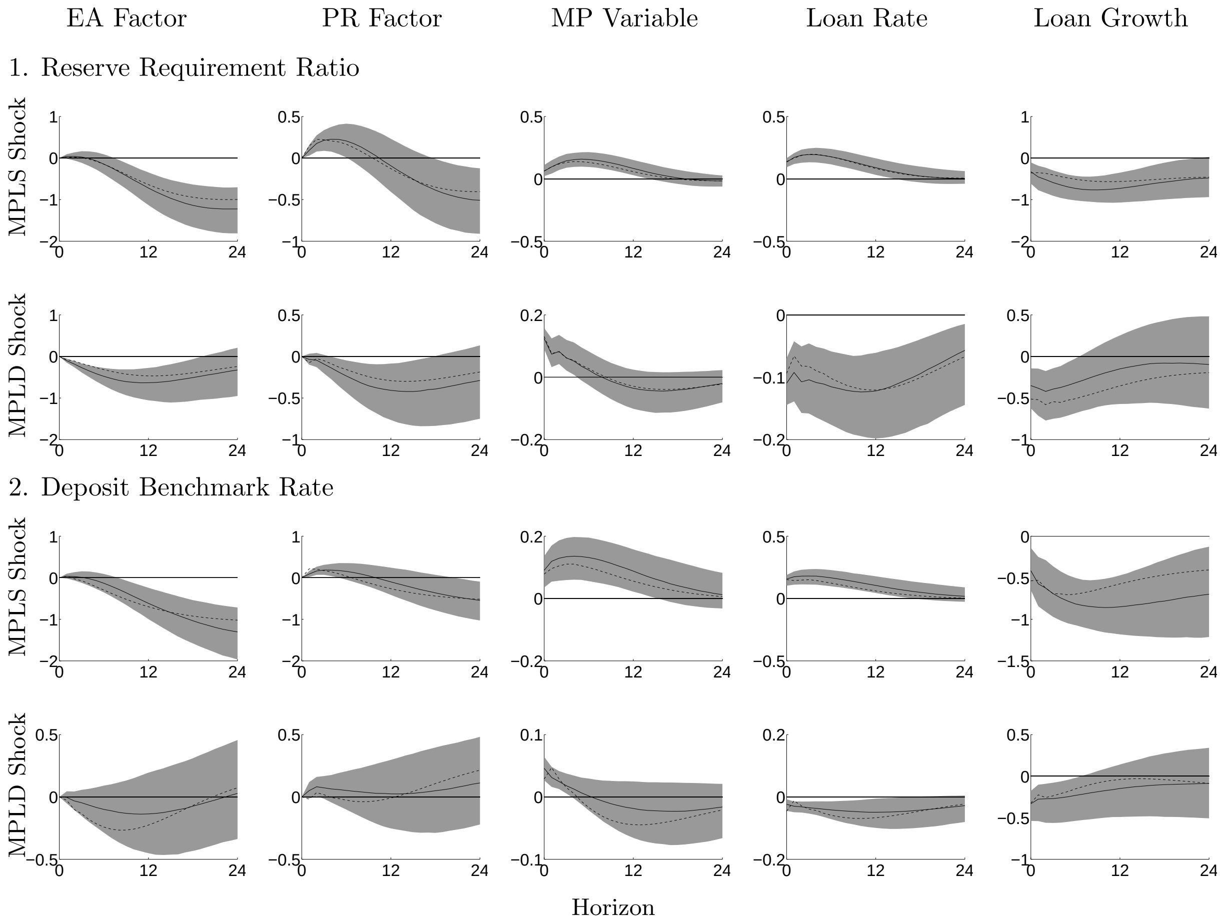
Notes: The solid line shows the constructed average lending rate (AVLR), the dashed line is the lending benchmark rate (LNR), the dotted line is the average lending rate reported by one of the 5 largest banks in China (BIG5 AVLR), and the dash-dotted line shows the average private sector lending rate reported by the PBoC (PBoC AVLR).

Figure 4: Shares of different lending rates



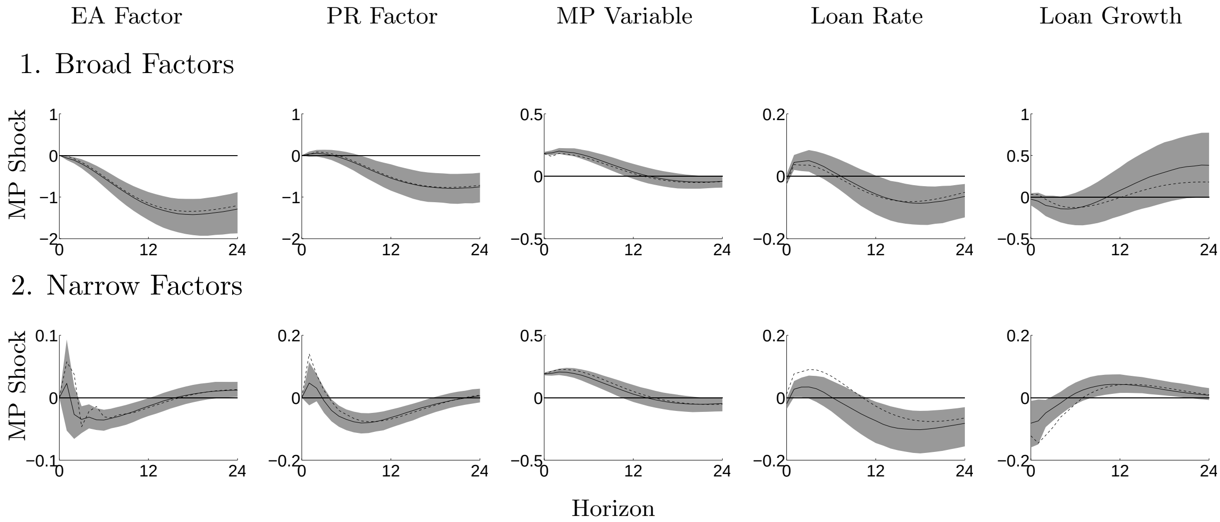
Notes: The shares report the percentage of banks which charge a higher or lower lending rate as compared to the bench mark lending rate. The categories capture the magnitude of the surcharge or discount.

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



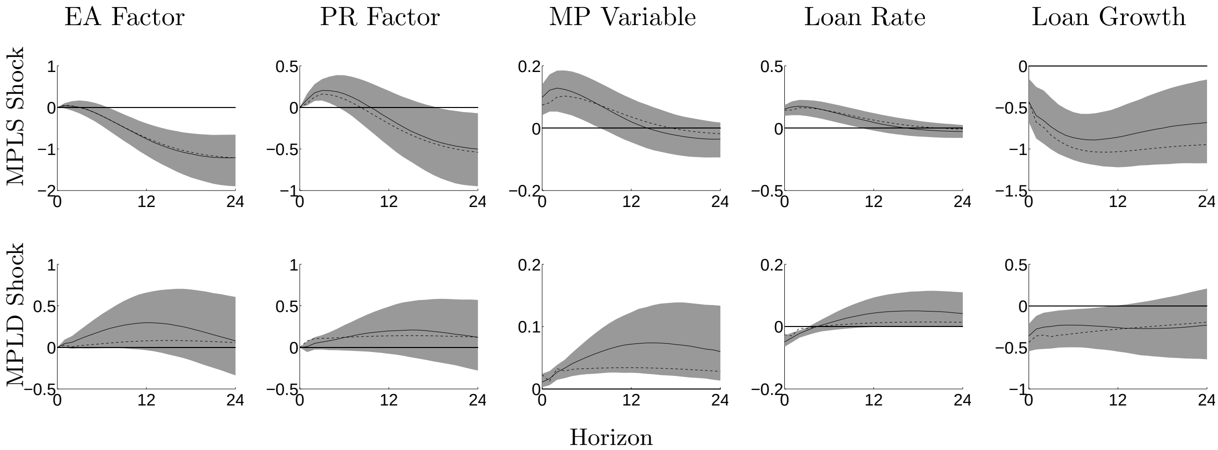
Notes: The impulse responses of the variables in first-differences are cumulated to provide the same level interpretation as in the case of the policy variable and the loan rate. The solid lines show the point-wise median values of the impulse responses of all accepted draws and the gray areas represent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

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



Notes: Please refer to notes of Figure 5.

Figure A.2: Impulse responses to to contractionary monetary policy shocks with different loan dynamics (using the lending benchmark rate as monetary policy instrument)



Notes: Please refer to notes of Figure 5.