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

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

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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 linked to supply and demand responses in the loan market. Our results show that policy shocks coinciding with loan supply effects account for roughly 10 percent of output dynamics after two years, while loan demand effects represent up to 7 percent of output dynamics depending on the policy measure. The credit channel thus constitutes an important and economically relevant transmission channel for monetary policy in China. Monetary policy in China also 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, China's monetary policymakers have moved away from reliance on direct controls of credit markets to more market-based monetary policy measures (Fernald et al., 2014). According to the credit channel literature, changes in these newer policy measures (e.g. benchmark rates and reserve requirements) influence the supply of bank loans and thereby amplify the effects on the economy (Bernanke and Blinder, 1988; Bernanke and Gertler, 1995; Disyatat, 2011; Kishan and Opiela, 2012). In this paper we evaluate how market-based monetary policy shocks propagate through the loan market and quantify to what extent loan supply ultimately affects the Chinese economy.

In the analysis we fit structural vector autoregressive models with monthly Chinese data that extend from October 2004 through June 2016, a time period when monetary policy was primarily conducted via changes in the reserve requirement ratio and benchmark interest rates. To identify monetary policy shocks and supply 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 immediately to macroeconomic aggregates (e.g. prices and output) but affects the relevant variables with a lag (Christiano et al., 1999; Ramey, 2016).[1] Within this block, we do not precisely identify the policy shock, but rather impose sign restrictions to distinguish between policy shocks linked to supply or demand dynamics in the loan market. Consider, for instance, a contractionary monetary policy shock. When loan supply effects dominate the transmission of monetary policy, the supply curve of loans shifts inwards. In such case, we should observe that prices of loans decline and 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 disentangle policy shocks linked to various transmission channels of monetary policy.[2]

We find that the overall effects of market-based monetary policy shocks account for up to 20% of the forecast variance of Chinese output after two years. The magnitude of these effects

[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).

[2] Jarociński and Karadi (2019) and Andrade and Ferroni (2018) use a similar approach to disentangle policy shocks linked to information effects or standard monetary policy effects.

is in line with existing empirical evidence and supports the view that market-based policy measures have become effective instruments in the efforts of the People's Bank of China to influence the economy (Chen et al., 2017; Fernald et al., 2014; Kamber and Mohanty, 2018). Monetary policy shocks that coincide with loan supply dynamics account for roughly 10% of the dynamics in output, regardless of the specific policy measure. Moreover, we find that policy shocks linked to loan demand responses capture roughly between 2% and 7% of the fluctuations in output, depending on whether monetary policy is measured with the reserve requirement ratio or the benchmark rate. In other words, loan supply dynamics coincide with at least 50% of policy-induced output dynamics. Both the absolute and relative importance of loan supply dynamics in the transmission of Chinese monetary policy shocks provides empirical evidence for an economically relevant credit channel of monetary policy in China.

Our analysis relates to the small group of studies on loan supply responses in the transmission of Chinese monetary policy. In contrast to our approach, these studies use bank-level micro data to identify loan supply dynamics. The alternative approach, originally proposed by Kashyap and Stein (1995),builds on the idea that loan supply responds asymmetrically across banks to a shift in monetary policy, depending on the ability of banks to absorb the policy shock. In contrast, loan demand responds independently from these characteristics. Gunji and Yuan (2010) study whether loan growth responds asymmetrically across banks depending on their solvency. Their findings are mixed, providing no clear support for loan supply responses. Fungáčová et al. (2016) show that in response to policy changes the growth rate of loans depends on bank ownership structure rather than bank creditworthiness. Their results suggest that loan supply effects might be present through a China specific ownership channel. Hou and Wang (2013) conclude that increased financial deregulation in China generally decreases the transmission of Chinese monetary policy through the supply of loans. In contrast to these studies, we evaluate loan supply effects using a macroeconomic framework. This approach allows us to abstract from specific bank characteristics to identify loan supply, as well as quantify effects at the aggregate level.

The remainder 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 robustness exercises are summarized in Section 5. Section 6 concludes.

2 Chinese Monetary Policy

Monetary policy in China is unlike that of developed economies. The People's Bank of China (PBoC) uses a large monetary policy toolbox in pursuit of its overarching monetary policy objective of maintaining "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 cover both domestic price stability and external exchange rate stability. In addition to the target stated in the law, the PBoC's other policy objectives include full employment, financial market stability, support of certain sectors or geographical areas, and stability in the balance of payments.

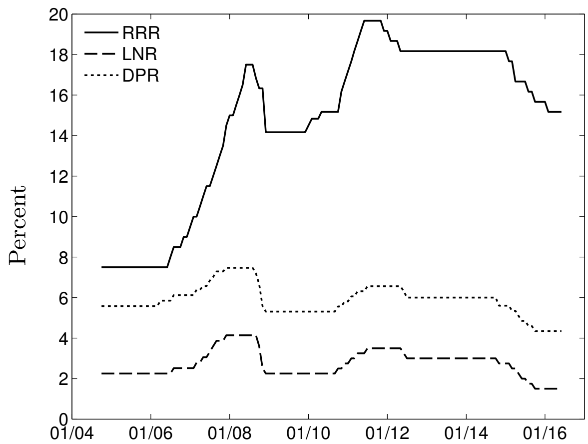
The policy instruments used to achieve these multiple policy objectives include both quantity- and price-based instruments, as well as non-market-based moral suasion policies. China's monetary policy transition into a more market-oriented framework started in 1998 with the abolition of direct credit controls. The PBoC today retains some control over commercial bank lending through window guidance policies, whereby the central bank advises banks directly on the quantity and structure of their lending ('window guidance').[4] The composition of the PBoC's monetary toolbox during our estimation period includes benchmark interest rates, bank reserve requirements, open market operations, central bank lending, and window guidance policies. Changes in PBoC policy stance are often implemented with several policy tools at the same time.

Given the range of available policy instruments, we narrow our analysis to the most important market-based policy measures that potentially relate to loan supply effects (see Bernanke and Blinder, 1988; Disyatat, 2011; Kishan and Opiela, 2012) and study the reserve requirement ratio (RRR), the benchmark deposit rate, and the benchmark lending rate. During our October 2004–June 2016 estimation period, reserve requirements and benchmark interest rates were the most prominent and frequently adjusted policy instruments. Notably, the PBoC uses the RRR as an active policy instrument. The sophistication of the RRR framework has increased over time to become the central bank's preferred policy instrument. The reserve requirement ratio was adjusted 44 times between October 2004 and June 2016. In comparison, the benchmark lending rate was changed 27 times and deposit rate adjusted 25 times (see Figure 1). After 2016, and

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

[4] Much of the literature on Chinese monetary policy finds window guidance to be a fairly effective policy instrument (see, for example Chen et al., 2013).

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).

with the abolishment of the requirement that commercial banks need to follow the benchmark rates, the PBoC has relied more on targeted policy measures such as various lending programs and targeted reserve requirement changes.

To make the RRR a more targeted tool, RRRs were differentiated for various types of banks in 2008. In 2011, the PBoC adopted a "dynamically differentiated RRR" scheme in which the RRRs for individual banks considered, e.g. the credit portfolio, soundness, and systemic importance of the bank (PBC, 2012).[5] Our analysis uses the average of the three RRRs as shown in Figure 1.

Incremental interest-rate deregulation in China started in 1996 (see Table A.1 in Appendix A). Prior to 2004, banks were allowed to add only small surcharge to the corresponding benchmark lending rate. In October 2004, the 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. In October 2015, the PBoC removed the final ceiling of banks deposit rates.[6] Despite being liberalized on paper, commercial banks still use the benchmark rates as reference in their loan pricing and the PBoC still publishes the benchmark rates, even though the levels have been unaltered since 2015. As we describe in detail below, we exploit the lending rate of banks to distinguish between supply and demand dynamics in the loan market. Hence, the interest-rate

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

[6] Other money-market and bond-market rates were largely deregulated before the start of our estimation period in 2004 (He et al., 2015).

deregulation provides insight into whether banks adjust the supply of bank loans in response to changes in monetary policy.

Finally, while the PBoC still operates in less developed financial environment than other major central banks, the loan market is the major source of funding for firms and households in China. Thus, the credit channel is likely to play a relevant role for the transmission of Chinese monetary policy. In 2016, almost 70% of new financing provided to non-bank corporate sector and households was provided in the form of bank loans.[7]

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). We estimate a factor-augmented vector autoregression (FAVAR) in the spirit of Bernanke et al. (2005), treating the latent output and inflation factors as observable variables.[8]

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. The variables appear in the same ordering in the estimation. 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

[7] 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 calculation and series codes in the CEIC Asia database are: 365867287 (CKABAVF) plus 365867297 (CKABAVG) divided by 365867277 (CKABAVE).

[8] Bernanke et al. (2005) show that treating estimated factors as data provides results consistent with estimates from Bayesian methods that consider the uncertainty involved with the estimated 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).

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.[9] The reduced-form posterior distribution (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. Therefore, we are not necessarily uninformative over the structural coefficients (Baumeister and Hamilton, 2015; Moon and Schorfheide, 2012). Applying the Bayesian (or Schwarz) information criterion, we use $p = 2$ lags in our baseline estimation.

3.2 Identification

To identify monetary policy shocks 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 the notion (consistent with a standard Taylor rule) that monetary policy responds simultaneously to changes in output and prices, but influences such variables only with a lag (Christiano et al., 1999; Ramey, 2016).[10]

To distinguish among the various dynamics of the loan market in response to policy shocks, we allow for contemporaneous effects between the policy variable and loan market variables. Thus, 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 a contractionary monetary policy shock that coincides with a decrease in the supply of loans (MP Loan Supply) and another policy shock that is linked to a decline in the demand for loans (MP Loan Demand).

Table 1 summarizes 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 linked to loan supply responses are consistent

[9]See Granziera et al. (2018) for a frequentist perspective on the sign-restriction approach.

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

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.

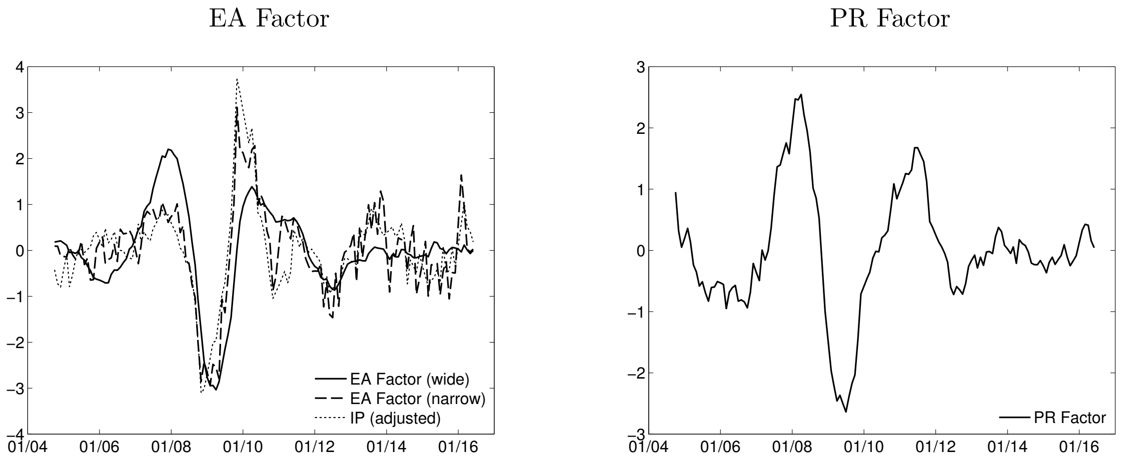
with the idea that an inward shift of the supply curve of loans implies a decline of loan volumes and an increase in the price of loans. When monetary policy shocks coincide with loan demand effects, we require that volumes and prices of loans decline simultaneously. This is consistent with an inward shift of the demand curve of loans.[11] All remaining loan-market dynamics that coincide with an increase in the policy rate are captured by the third residual shock.

Having allowed for the contemporaneous effects between the loan market variables and the policy measure, how do we distinguish between monetary policy shocks and loan market shocks? According to the empirical literature, which evaluates exogenous loan supply shocks (see e.g. Bijsterbosch and Falagiarda, 2015; Gambetti and Musso, 2017; Hristov et al., 2012), an expansionary monetary policy response is expected in the event of a contractionary loan supply shock. While loan demand shocks are typically not separately identified, they are interpreted as aggregate demand shocks. Thus, monetary policy is expected to show an expansionary response to contractionary loan demand shocks. As the policy rate increases in our identification, we can rule out that the identified monetary policy shocks are driven by exogenous loan-market dynamics. Put differently, the imposed sign restrictions imply that the identified dynamics on the loan market represent endogenous responses to policy shocks.

To implement our identification approach, we loosely follow the model selection algorithm proposed by Arias et al. (2018). The reduced form model is transformed with a random matrix Q obtained recursively such that the zero restrictions hold by construction and $QQ\prime = I$. To obtain a distribution of accepted draws, we draw 3,000 models from the reduced-form posterior

[11]Sign restrictions are widely used to distinguish between supply- and demand-side effects across various markets. Sign restrictions have been used earlier 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, 2017; Hristov et al., 2012), and distinguish between supply and demand effects in the oil market (Kilian and Murphy, 2014; Cashin et al., 2014) and the broad money market (Chadha et al., 2010). Unlike these studies, we do not identify exogenous supply or demand shocks. Instead, we identify policy shocks that coincide with endogenous changes in the demand or supply of bank loans.

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).

distribution and check a maximum of 1,000 Q-transformations for each draw.[12]

3.3 Data

We use monthly data ranging from October 2004 to June 2016 for the estimation. 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).[13] All data are taken from the CEIC China Premium Database.

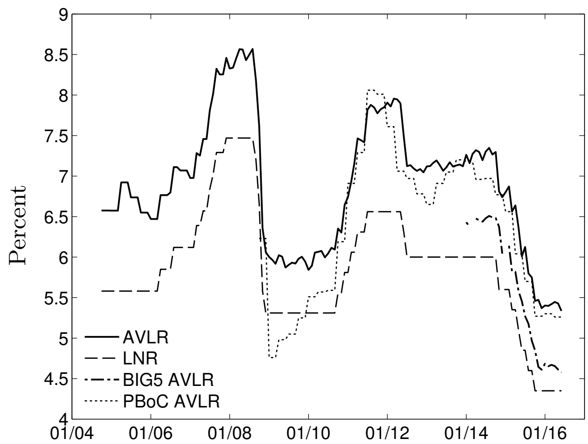
To extract the economic activity (EA) and the price (PR) factors we use a broad set of Chinese economic indicators. We use the same time series as in Fernald et al. (2014). Figure 2 shows the estimated factors and Table A.2 in Appendix A lists all variables. The wide EA factor is constructed with all economic activity measures, while the narrow EA factor is constructed with a small subset of economic activity measures. EA factors are correlated with industrial production, but not to the same extent. In the baseline, we follow the data transformation suggested in Fernald et al. (2014), i.e. we seasonally adjust the level variables, take monthly growth rates (first-log differences times 100), and remove local trends from each time-series by applying a biweight filter (see also Stock and Watson, 2012).[14]

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

[13]After 2016 the PBoC relies on a different RRR scheme, for which data is not available.

[14]In the robustness analysis, we consider different biweight parameters and unfiltered data.

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).

As policy instruments, we consider a quantity-based measurement, the average reserve requirement ratio (RRR), and two price-based measurements: the one-year lending benchmark rate (LBR) and the one-year deposit benchmark rate (DBR). As there is little variation between the two benchmark rates (see Figure 1), we only present the results for the one-year deposit benchmark rate. The results for the lending benchmark rate are quite similar and provided in Appendix B.

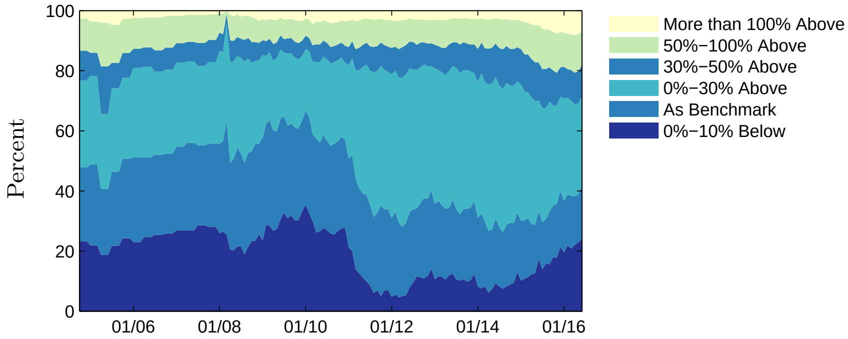
The loan volume variable is the total banking sector loan stock in domestic currency available from the PBoC monthly financial statistics. Loan growth (LNGR) is the month-on-month change in the total loan stock. As with the factor variables, we remove in our baseline local means by applying a biweight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

As the PBoC only began to report the average banking sector lending rate in late 2008 and only in quarterly frequency (see PBoC AVLR in Figure 3), we exploit monthly statistics of the share of loans priced above or below the benchmark lending rate. Specifically, we construct the average lending rate (AVLR_t) as follows:

$$\text{AVLR}_t = \text{LNR}_t \left(\sum_{i=1}^{K} (1 + \text{CHANGE}_i) \cdot \text{SHARE}_{i,t} \right)$$

where LNR_t captures the short-term benchmark lending rate (see LBR in Figure 4), CHANGE_i represents the surcharge or discount that is classified in K categories, with $i = 1, 2, \ldots, K$,

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.

and $\text{SHARE}_{i,t}$ captures the share of banks setting their lending rate according to one of the respective categories.[15] 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.[16] In Figure 3, we compare our constructed lending rate with the benchmark lending rate and the average lending rate reported by the PBoC. We also have the data on the monthly average lending rate from one of China's Big Five banks for 2014–2016 (BIG5 AVLR in Figure 3). 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

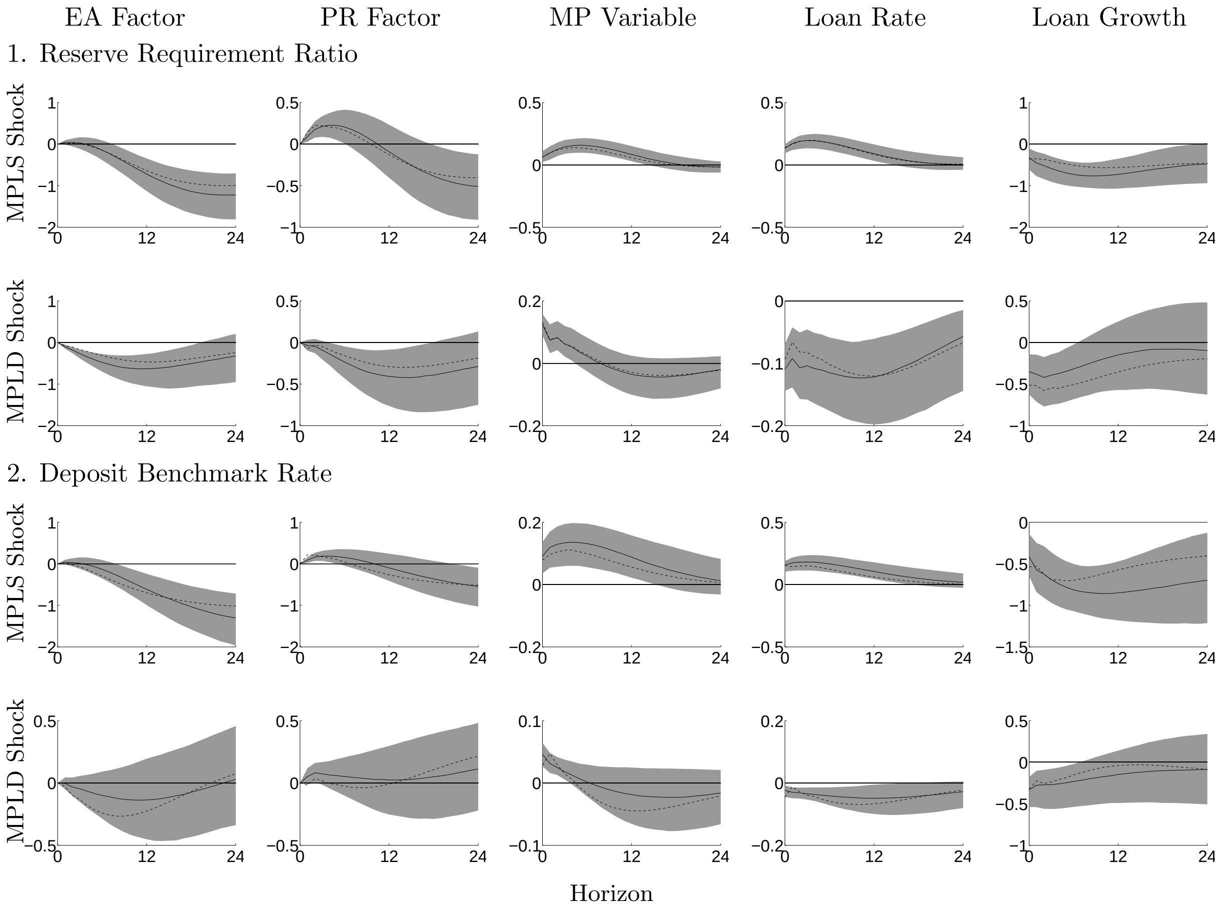
Figure 5 shows point-wise median impulses to the two identified monetary policy shocks, together with 68% of the distribution of accepted draws. In the top panel we see impulse responses from the estimation with the reserve requirement ratio as monetary policy measure and in the bottom panel monetary 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

[15]For the category with the largest surcharge, we assume a markup of 100% in the baseline estimation.

[16]In the sensitivity analysis, however, we also consider one estimation that starts in 2009M1 and our results remain robust.

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).

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 a transmission of monetary policy through loan supply. The remaining responses are restricted with the sign restrictions on impact and the first month. For policy shocks linked to loan supply effects, we see that the increase of the reserve requirement ratio coincides with an increase of the average lending rate and a decrease in the loan growth rate. For policy shocks 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 a similar 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 than through 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 (see also Kamber and Mohanty, 2018). While He et al. (2013) do not find that changes in benchmark interest rates matter for output dynamics in China, our results suggest they could matter when the policy shock is primarily transmitted through adjustments in the supply of bank loans. In other words, changes of benchmark rates affect output predominantly through the transmission of loan supply effects.

To assess 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 loan demand responses for the transmission of monetary policy? To answer this, we quantify the contributions of monetary policy shocks to the forecast error variance of economic activity according to 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 linked to loan supply and loan demand responses.[17] Table 2 presents the results for the estimation with the reserve requirement ratio as policy measure. Table 3 reports our findings related to the deposit benchmark rate. These tables further present the sum of both transmission channels, indicating the overall effect of monetary policy and 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. After two years, they account for roughly 20% of the forecast variance in the economic activity factor.[18] While these shares are exceptionally high compared to results for Western economies over similar observation periods

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

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

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.

(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 associated with loan supply effects (first column of Table 2), we see that it takes roughly a year for substantial output effects to materialize. Policy shocks linked to loan demand dynamics affect economic activity faster than supply effects. In other words, the results suggest that firms and households adjust their demand for bank loans faster than banks' supply of credit changes. After two years, however, we see higher output effects for policy shocks that correspond to loan supply responses. Specifically, monetary policy shocks associated with loan supply effects account for roughly 11% of output dynamics after two years, while policy shocks linked to loan demand effects account for 7%. The relative contributions show that the transmission effects are initially dominated by loan demand effects, but loan supply effects become more important after a year.

With the deposit benchmark rate as policy measure, Table 3 reveals generally similar patterns to the results with the reserve requirement ratio. Again, the overall effects of monetary policy increase over time and policy shocks linked to loan supply dynamics eventually display larger effects on economic activity than loan demand effects. The absolute effects on output are weaker, however. After two years, exogenous adjustments in the deposit benchmark rate account for roughly 11% of output fluctuations, compared to 17% for 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. Thus, loan supply responses represent

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.

the dominant transmission channel when monetary policy is conducted through benchmark rate adjustments. Table B.1 in Appendix B also reports results for an estimation with the lending benchmark rate as policy instrument. The relative share varies between 66% and 86% across various 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 deposit benchmark rate. Furthermore, loan supply dynamics account for at least half of policy-induced output dynamics after two years. We therefore conclude 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 FEVD analysis findings. Our sensitivity checks focus on the identification restrictions, construction of the average lending rate, the model specification, data transformations, and sample selection. All robustness checks are summarized in Table 4.[19]

Identification First, we control for a possible pass-through of interest rates. We re-estimate the baseline model using a spread between the average lending rate and the lending benchmark rate. With our baseline, we require that the average lending rate increases or decreases in the event of a policy contraction, depending on the transmission of the shock. With the spread, we require a stronger change in the lending rate than the benchmark lending rate. We also check

[19]We also perform all robustness checks on our model using the lending benchmark rate as policy instrument (see Table B.2).

estimations in which we apply a shorter sign-restriction horizon, imposing restrictions only on impact and the subsequent month.

Average Lending Rate As we have to construct an average lending rate, we check various definitions. In the baseline estimation, we include an average lending rate that is calculated using the mean values of each surcharge or discount category. We take the upper bound of each price category instead of the mean value (for the category with the largest surcharge, we assume a markup of 150%). Second, as we are primarily interested in the dynamics of an average lending rate, we use principal component analysis to summarize the dynamics in the shares of loans priced above or below the benchmark rate in a single average lending factor.

Data Transformation In the baseline, we follow Fernald et al. (2014) and filter the data with a biweight filter parameter of 36. We also consider estimations with unfiltered data and a parameter of 120. While we follow the literature in our baseline and improve data reliability by approximate economic activity with a broad set of observable indicators, we also check for similar results with a small set of economic activity indicators (see also Fernald et al., 2014).

Specification The Bayesian information criteria suggest only two lags of the endogenous variables in the FAVAR. However, due to the monthly frequency of our dataset, we further check whether our results change when twelve lags are used. Additionally, because China's economy is an open economy strongly depending on world output and commodity prices, we re-estimate the baseline model including US output and oil prices 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. Most of the stimulus funding was channeled through the banking sector. China's monetary authorities encouraged banks to provide bank loans, mainly to state-owned firms. It is likely that bank's 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

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

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	FEVD MP with		Total	Relative Effects MP with	
Checks	Loan Supply	Loan Demand		Loan Supply	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.

observation period for which we have monthly data 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 generally account for over half of the transmission effects on economic activity. The only reasonable exception is the estimation in which we exclude the recovery period after the global financial crisis. The drop in policy effects associated with loan supply responses supports 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 smaller extent. Analogously, when we re-estimate the model with the shorter sample starting in January 2008, in which the global financial crisis takes on more weight in the sample, the effects of monetary policy on economic activity appears more pronounced and the transmission of monetary policy is stronger 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, we still find the same relative importance of loan supply and loan demand effects.[21] Thus, loan supply effects in this estimation also represent an important transmission channel for Chinese monetary policy.

6 Conclusion

How important is the credit channel for the transmission of Chinese monetary policy? We applied a novel identification scheme that allowed us to evaluate monetary policy shocks linked to loan supply effects using aggregated time-series data.

We find empirical evidence that market-based policy measures over our observation period induced output effects linked to loan supply dynamics. After two years, monetary policy shocks associated with loan supply effects accounted for roughly 10% of the dynamics in economic activity. Monetary policy shocks linked to loan demand effects accounted for up to 7% of fluctuations in output over the same forecast horizon. Hence, over half of the transmission effects on output were linked to loan supply effects.

As our findings are robust to a wide range of sensitivity checks, we conclude that the credit channel represents an economically relevant transmission channel for market-based monetary policy measures in China.

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[21] Notably, when we apply a recursive identification approach, the share of monetary policy shocks in the FEVD of the narrow economic activity is also considerably smaller than the FEVD of the wide economic activity factor (see Table A.4 in Appendix A).

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Appendix A: Additional Tables and Figures

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)

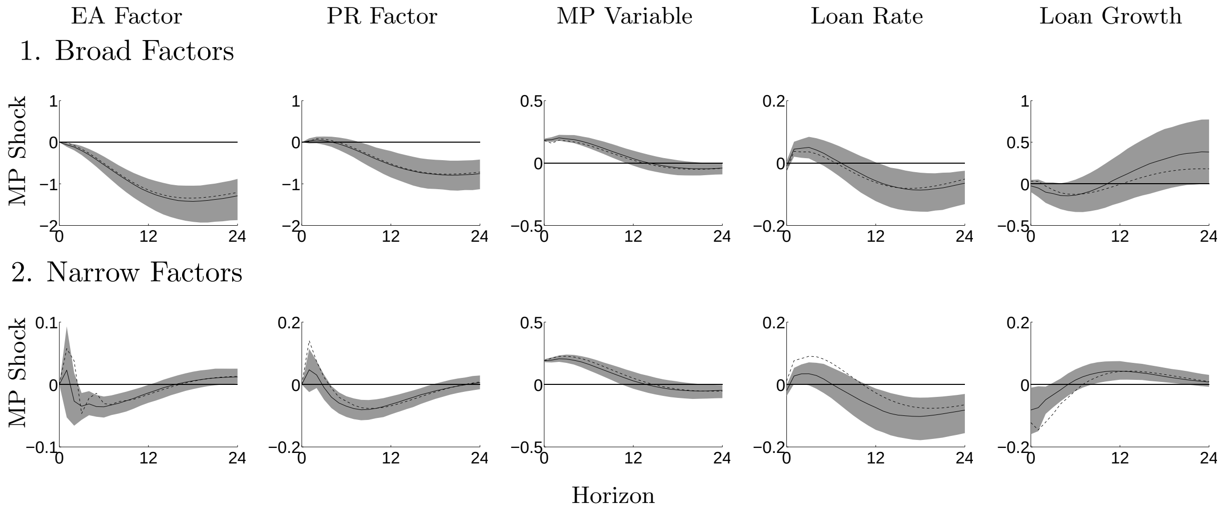
Notes: All values are reported in percent and correspond to the point-wise median values of the distribution of accepted draws. Values in parentheses represent 68% of the distribution.

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.

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.

Appendix B: Results using the lending benchmark rate as policy measure

Table B.1: 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

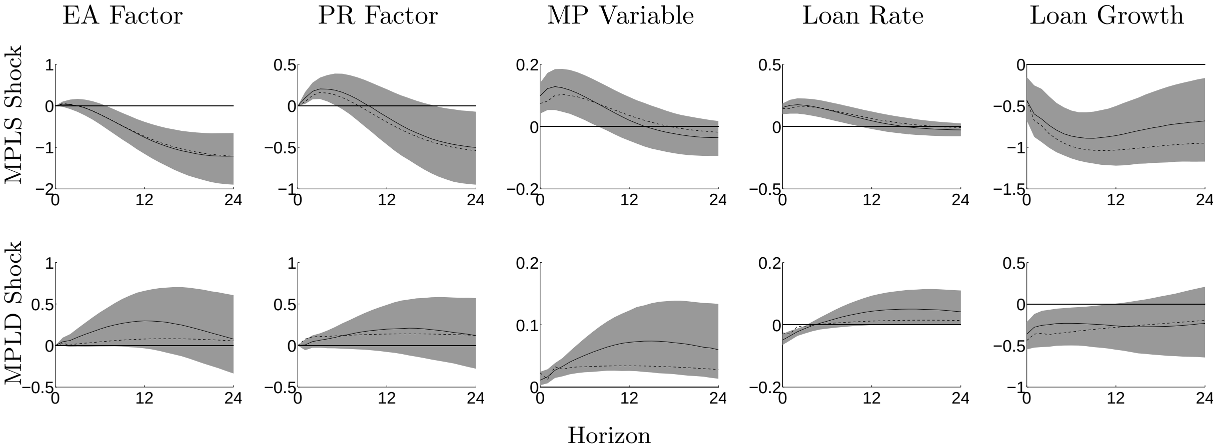
Notes: Please refer to notes of Table 2.

Table B.2: 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 B.1: 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.