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Impacts of Monetary Stimulus on Credit Allocation and the Macroeconomy:
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ABSTRACT

We construct a micro dataset that covers all newly originated bank loans by the 19 largest Chinese banks to individual firms and spans all sectors in the Chinese economy. We propose a two-stage framework comprised of a macro SVAR model and a dynamic panel model to estimate the average and aggregate effects of the 2009 monetary stimulus on the macroeconomy and credit allocation to SOEs and non-SOEs across key sectors. The two-stage framework is vital for obtaining the aggregate effects from the micro model. While credit expansion due to monetary stimulus favored the average SOE in manufacturing, non-SOEs enjoyed preferential credit treatment in real estate. There was no obvious favoritism of credit allocation toward the average SOE in infrastructure. In aggregate, non-SOEs are quantitatively as important as SOEs in understanding the dynamic effects of monetary stimulus on credit allocation. Our findings of credit allocation underlie an intertemporal tradeoff between short-term growth and long-term indebtedness in response to large monetary interventions.

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In the aftermath of the 2008 global financial crisis, central banks around the world (Federal Reserve System, European Central Bank, Bank of Japan, and People's Bank of China (PBC)) have initiated massive monetary stimulus in an attempt to combat the crisis and rescue the sagging economy. What are the consequences of such an unusual change of monetary policy on the financial system and the real economy? To answer this important question, one needs an empirical framework to assess how policy changes influence credit allocation to different types of firms as well as the dynamics of the aggregate economy.

Understanding the effects of monetary stimulus on the second largest economy gives us a general perspective of how monetary stimulus affects the banking system and the macroeconomy. During the global financial crisis, growth of China's real gross domestic product (GDP) plummeted from 13.6% in 2007Q2 to 6.4% in 2009Q1. In an attempt to stem the sharp fall of aggregate output, China's State Council in November 2008 announced a plan to invest 4 trillion RMB over the two-year period from 2009Q1 to 2010Q4. It implemented such investment plan through monetary stimulus. M2 increased by 4.2 trillion RMB in 2009Q1 alone and by a total of 11.5 trillion RMB during the 2009Q1-Q3 period. These three crucial quarters of massive monetary injections are the period identified by Chen, Ren, and Zha (2018) as a policy rule change, who measure the 2009 monetary stimulus by a combination of exogenous policy shocks and a policy rule change.

For the Chinese economy, key questions are whether such unprecedented monetary stimulus gave individual state-owned enterprises (SOEs), on average, preferential credit access and whether monetary stimulus caused disproportionate credit expansion to SOEs in aggregate during and after the 2009 stimulus period. To address these two issues, one needs a coherent empirical framework to (1) estimate the impacts of monetary stimulus on credit allocation to individual firms with proper controls for other macroeconomic shocks and (2) aggregate up, to the overall economy, the micro effects of monetary stimulus on credit allocation to individual firms. These two problems are intertwined and cannot be separated from each other. On the one hand, the adoption of proper controls for other macroeconomic shocks requires one to disentangle the component of a macro variable driven by monetary stimulus from the component of the same variable that is immune to the monetary stimulus. On the other hand, aggregation of the micro effects of monetary stimulus is necessary for properly measuring the aggregate impact of monetary stimulus. To solve these two problems simultaneously, we develop a two-stage empirical framework comprised of both a dynamic quarterly macro model and a dynamic quarter-firm panel model and we apply it to both macro and micro data in the Chinese economy.

Our paper makes several specific contributions. First, we construct a proprietary micro dataset of newly issued bank loans to individual firms. Cong, Gao, Ponticelli, and Yang (Forthcoming) is the first to exploit the same source of this loan-level data and study how credit supply shocks in 2009-2010 influenced credit allocation between SOEs and non-SOEs in the manufacturing sector. But loans to the manufacturing sector accounted for only 23% of all newly originated bank loans in 2008—an incomplete picture of the whole economy.

Rather than exclusively focusing on manufacturing as in the existing literature on China, we construct a firm-level dataset that covers all newly originated bank loans by the 19 largest Chinese banks over the entire economy, including infrastructure, real estate, and others such as education, public administration, and environment. We show that sectors other than manufacturing make up a majority of loan increases during the stimulus period and have different characteristics of how credit is allocated to SOEs versus non-SOEs.

Second, our paper estimates the dynamic impacts of monetary stimulus beyond the manufacturing sector and shows that the effects of monetary stimulus on credit allocation to SOEs and non-SOEs, on average, are heterogeneous across sectors: while an average SOE in the manufacturing sector enjoys favored access to bank credit, the opposite is true for the real estate sector, and there is no clear pattern of preferential credit allocation in the infrastructure sector. Unlike the static stimulus effects as often estimated in the literature, our estimated dynamic impacts on SOEs and non-SOEs across different sectors are necessary for quantifying how the effects changed during and after the stimulus period. We find that all the dynamic responses of bank loans to SOEs and non-SOEs are hump-shaped and that the peak responses in real estate lag two quarters behind those in manufacturing, infrastructure, and others.

Third, our paper makes a clear distinction between average (micro) and aggregate (macro) effects of monetary stimulus on bank credit allocation. While monetary stimulus, *on average*, leads to more bank loans to SOEs in the manufacturing sector, we find that its aggregate impacts on credit allocation to manufacturing non-SOEs were quantitatively more important than loans to manufacturing SOEs because non-SOEs with positive newly originated loans dominated in number (the extensive margin) during and after the 2009 monetary stimulus period. We find the similar aggregate effects of monetary stimulus in real estate. That is, more loans were allocated to non-SOEs than to SOEs during and after the 2009Q1-Q3 monetary stimulus period. In infrastructure and others, however, more loans were allocated to SOEs than to non-SOEs. Aggregating the stimulus effects on loans in all four sectors, we find that credit allocation to non-SOEs rose at least as much as loans allocated to SOEs during and after the 2009 stimulus period. This finding is crucial for understanding the transmission mechanism of monetary stimulus on aggregate output via investment in which non-SOEs have a large share.

Fourth, we estimate a structural vector autoregression (SVAR) model with key macroeconomic variables to assess the macroeconomic impacts of monetary stimulus. In our SVAR findings, the monetary policy shock contributes to as much as 45% of the GDP fluctuation in the shortfall state, in contrast to only one fifth in the normal state. We study a counterfactual economy in which monetary policy had not switched to a new regime so that M2 growth had remained at 16% instead of shooting up to 25% in 2009Q1-Q3. Comparing the counterfactual and actual economies, we find that this unprecedented expansion of M2 growth boosted annual GDP growth by as high as 3.1% by the end of 2009, accounting for over 65% of the annual growth rate of GDP between 2008Q4 and 2009Q4. And monetary policy exerts a far larger impact on investment than consumption through bank loans. As a result, while the effect of the 2009 monetary stimulus on GDP growth was short lived (about two years), its effects on the investment-to-GDP and debt-to-GDP ratios were much more persistent and lasted for a longer period. The rise of the debt-to-GDP ratio caused by the 2009 monetary stimulus is consistent with the increase of credit allocation to both SOEs and non-SOEs when the stimulus impacts on loans are aggregated from the impacts on credit allocation to individual firms.

Our paper also makes two specific methodological contributions. The two-stage empirical framework is a synthesis of the aggregate SVAR analysis and the firm-level dynamic panel analysis. The SVAR model is used to control for the effects on output growth and inflation of aggregate shocks other than monetary policy changes when we use firm-quarter dynamic panel regressions to analyze the stimulus effects on credit allocation to different types of firms across sectors.[1] The firm-quarter dynamic panel regressions allow us to estimate the micro effects of monetary policy changes for different types of firms, which we add up to obtain the aggregate effects of monetary stimulus. The two-stage empirical framework is broad enough for other researchers to utilize the micro data for studying the macro effects of aggregate shocks or policy changes.

The second methodological contribution is the novel result that the dynamic impacts of monetary policy changes on credit allocation and the aggregate economy are uniquely determined in our multivariate and panel models without any restrictions on equations other than the monetary policy equation. In the existing SVAR literature, the system is customarily identified by strong assumptions such as the Choleski ordering or sign restrictions (Leeper, Sims, and Zha, 1996; Christiano, Eichenbaum, and Evans, 1999; Uhlig, 2005; Cogley and Sargent, 2005). One persistent criticism is that such restrictions are often too strong to be credible for many applications (Baumeister and Hamilton, 2015, 2018). Our new methodology advances the existing approach by allowing no restrictions on all the equations other than the monetary policy equation, which avoids what Sims (1980) calls "incredible restrictions." Our empirical methodology enables us to disentangle how much of the economic stimulus attributable to monetary policy changes from how much of the effect such changes may exert. It helps quantify both the micro and macro variations that were caused by monetary stimulus—the stimulus initiated by massive monetary injections. The methodology is valid whether the stimulus effects are triggered by an exogenous shock or by an endogenous policy change.

Our work is related to several papers in the empirical literature on China's stimulus program. Ouyang and Peng (2015) estimate the impact of China's stimulus on GDP to be 3.2%. Their approach is similar to the difference-in-difference approach without identifying specific shocks during the stimulus period. By contrast, we assess how *identified* monetary policy

[1] All other aggregate shocks, such as those to the bank-entry deregulation as recently explored by Gao, Ru, Townsend, and Yang (2019), fiscal shocks, and technology shocks, are accounted for in our VAR framework, even though these shocks are not explicitly identified.

changes affect GDP and other aggregate variables. Cong, Gao, Ponticelli, and Yang (Forthcoming) use loan-level data to explore the average stimulus effect on bank credit allocation. Their study focuses on manufacturing only and is silent on the aggregate stimulus effect on credit allocation. Our analysis encompasses manufacturing and all other sectors, highlights the cross-sector heterogeneity in credit allocation to SOEs versus non-SOEs (the average effect), and shows the importance of non-SOEs in receiving bank loans at the aggregate level (the aggregate effect). To our knowledge, this is a first paper that quantifies how important SOEs versus non-SOEs are in credit allocation at the aggregate level across sectors as well as over the whole economy.[2]

Bai, Hsieh, and Song (2016) study how the booming of local government financing vehicles (LGFVs) posed a threat to long-term GDP growth, using the official time-series data of bonds issued by LGFVs from the National Audit Office and WIND database and the anecdotal information of bank loans allocated to LGFVs during the stimulus period. Huang, Pagano, and Panizza (2016) use firm-level data of investment and city-level data of local government debt to explore the crowding-out effects of local government debts on financial lending to private investment. Our micro data includes every newly issued bank loan to each LGFV, which allows us to assess the importance of bank loans to LGFVs across various sectors.

The important role of investment in promoting China's GDP growth is discussed in Chang, Chen, Waggoner, and Zha (2016) and Zilibotti (2017). Zilibotti (2017) argues that the economic stimulus benefited the infrastructure sector financially and prolonged the longevity of the investment-driven economy, but at the cost of an inevitable slowdown of China's long-term output growth. We show that large interventions by monetary authorities, like China's 2009 monetary stimulus, may help stem the steep fall of GDP growth but at the cost of exacerbating the debt problem in the long-run. Therefore, monetary stimulus faces an intertemporal tradeoff between temporarily high GDP growth and long-term indebtedness.

The rest of the paper is organized as follows. Section I discusses both macro and micro data and provides relevant summary statistics. Section II proposes a new estimation framework comprised of the macro and micro models. Section III estimates the macro SVAR model and provides the macroeconomic impacts of monetary stimulation. Section IV estimates the micro panel model and uses a bottom-up approach to quantifying the dynamic impacts of the 2009 monetary stimulus on credit allocation. Section V concludes.

[2]In the 1 November 2018 Symposium on Private Enterprises, Chinese President Xi Jinping remarked that "by the end of 2017, the private sector of the economy, which contains more than 27 millions of private enterprises and owns 16.5 trillion RMB of registered capital, has contributed to more than 60 percent of China's GDP, more than 70 percent of technological innovations, more than 80 percent of job positions, and *more than 90 percent of the number of total enterprises in China* [the emphasis added by the authors]." See the link `http://www.xinhuanet.com//politics/2018-11/01/c_1123649488.htm`.

I. Data and summary statistics

In this section, we discuss the macro time series, construct the micro loan data at the firm level, and provide summary statistics at both macro and micro levels.

I.1. **Macro time series.** The sample period for estimation is from 1999Q1 to 2016Q2, including the initial four lags in our dynamic system. This is a period in which the PBC has made M2 growth an explicit policy instrument and the PBC's official Monetary Policy Reports (MPRs) have been made available to the public since 2001Q1.[3] The sample length for our quarterly data is over 17 years, comparable to the sample length often used for studying U.S. monetary policy during its inflation-targeting period of 16 years prior to the 2008 financial crisis (1992-2007).

When assessing how a change in monetary policy is transmitted to the real economy, it is necessary to control for macroeconomic variables other than M2 stock. Our benchmark SVAR model consists of 11 variables with the following 10 variables besides M2 supply: GDP, consumer price index (CPI), the excess reserve ratio (ERR), the actual reserve ratio (ARR), total bank loans, short-term (ST) bank loans, the 7-day repo rate (Repo), the bank lending rate (LR), the bank deposit rate (DR), and foreign exchange reserves (FXR).[4] We denote these variables by y_t, an $n \times 1$ vector with $n = 10$ for the benchmark model. As in the SVAR literature, we express all the variables in natural log except for interest rates and ratio variables, which are expressed in level as a fraction. We follow Bianchi and Bigio (2014) and include both ERR and ARR in the system to isolate the effect on ERR by controlling for ARR. Similarly, we control for LR and DR to isolate the effect on the market interest rate (Repo). These variables would be potentially important for the monetary transmission mechanism.

One may question the quality of China's official macroeconomic data, especially the GDP and CPI series. For example, Nakamura, Steinsson, and Liu (2016) argue that the official CPI data underestimate the volatility of CPI inflation since 1995.[5] Despite the unsettled debates on this issue, the official CPI series is the headline price series the PBC and other central government units have routinely relied on *when making monetary policy decisions*. For this reason, we should use the official series for the monetary policy equation. A similar

[3]The only official release of how the PBC conducts its monetary policy each quarter is a published quarterly MPR. The first publication of the MPR was issued in 2001Q1. Opinions expressed in the monetary policy committee (MPC)'s meetings are recorded in the form of "meeting minutes." The minutes, if approved by more than two thirds of the MPC members, are attached as an annex to the PBC's proposal on money supply, interest rates, exchange rates, and other monetary variables. The proposal is then sent to the State Council for approval. Once approved, the MPR provides an executive summary of the state of the economy along with additional descriptions of how the PBC adjusts its monetary policy actions, mainly M2 growth rates, in response to the state of the economy.

[4]See Appendix A for a detailed description of the data.

[5]Ideally we would like to use their series to verify the robustness of our results, but unfortunately their series is only available at annual frequency. Nonetheless, their CPI series is likely to make the CPI response to a monetary policy shock stronger because their series tends to be more volatile than the official series.

argument applies to the GDP series. One should *not* abandon the official GDP figures because they are precisely the most important series targeted by the central government when formulating monetary policy.[6]

I.2. **Micro firm-quarter loan data.** Our micro loan dataset, provided by the China Banking Regulatory Commission (CBRC), covers all the newly issued bank loans to the borrowers with an annual credit line over 50 million RMB (approximately 8 million USD) from January 2007 to June 2013. The coverage is comprehensive: the CBRC data accounts for over 80% of the total bank credit in China during this sample period. It consists of over 7 million individual loan contracts granted by the 19 largest Chinese banks to more than 160,000 unique firms with a specific identifier (i.e. the 9-digit corporate organization code). The borrowers are located in all 31 provinces and autonomous regions and over 90 two-digit industries according to the Economic Industrial Classification Code. We sum up all individual loans for a particular firm at a given quarter to create the firm-quarter data from 2007Q1 to 2013Q2.

The loan variable used throughout the paper is the amount of newly issued loans with maturity greater than three years in each firm-quarter. Bank loans to the infrastructure sector are the largest among the loans to the four different sectors during the stimulus period: manufacturing, infrastructure, real estate, and the remaining sector ("others"). Most of these loans have a maturity greater than five years for investment purposes. The aggregate time series of bank loans to fixed asset investment (FAI) are obtained from the CEIC. Our micro data on newly issued loans with maturity greater than three years is comparable to the CEIC aggregate FAI loan series. There are, however, two main differences between our constructed dataset and the CEIC data. One difference is that the CBRC micro data excludes bank loans with the size less than 50 million RMB while the CEIC macro data includes all investment loans. In that case, the aggregated loans to infrastructure from our micro data source are less than those from the macro data source. In 2010, for example, infrastructure loans as a percent of GDP is 4.59% from our micro data source and 4.75% from the macro data source. On the other hand, loans to FAI from the CEIC macro data source are calculated as an increase of outstanding loans from the balance in the previous year while our micro data source provides newly issued bank loans. Since some existing loans may be retired at any given time, the aggregated loans from our micro data source can be larger than those from the macro data source. In 2009, for instance, infrastructure loans as a percent of GDP is 6.21% from the micro data source and 4.73% from the macro data source.

[6] In a recent paper, Nie (2016) argues that "official GDP figures remain a useful and valid measure of Chinese economic growth." There is widespread suspicion that the GDP growth rates published by the National Bureau of Statistics of China have overstated actual growth in China, especially for the last several years. New research by Clark, Pinkovskiy, and Sala-i-Martin (2017), however, argue that China's GDP growth may be understated. All these debates imply that one should not simply abandon official GDP statistics without viable and authoritative alternatives, especially when monetary policy decisions explicitly rely on the officially published GDP series.

We first categorize our micro loan data into two groups: loans to SOEs and those to non-SOEs. Two approaches coexist in the literature to define the ownership type. The first approach uses information of the registration type of an individual firm (Brandt, Van Biesebroeck, and Zhang, 2012); the second approach uses a firm's shareholder information (Hsieh and Song, 2015). The challenge to identify SOEs is how to use publicly available information to determine the state ownership of unlisted firms as these firms are not required to disclose the ownership information. A great many non-SOEs are private firms whose information is almost impossible to obtain. In particular, although the Chinese Industry Census (CIC) provides shareholders' information for unlisted firms, such information is unavailable for unlisted firms beyond the industrial/manufacturing sector. Therefore, our baseline approach to define a firm's ownership type uses its official registration status.[7] To avoid the possible bias of identifying SOEs with the legal registration type, in Appendix S1 we use a subsample consisting of only manufacturing firms to check the robustness of our results with both approaches. With manufacturing firms detailed ownership information, we follow Hsieh and Song (2015) and Cong, Gao, Ponticelli, and Yang (Forthcoming) to construct the share owned by the government and define a firm as an SOE when the government's share exceeds or equals 50% or when the state is reported as the controlling shareholder.

To obtain information on a firm's registration type, we first merge the CBRC data with the firm-level panel data from the Chinese Industry Census (CIC) between 1998 and 2013. The CIC database includes all SOEs and all non-SOEs with gross sales exceeding five million RMB (this standard was increased to 20 million RMB in 2011) in the industrial sector (i.e. manufacturing, mining, and utilities). We use firms' registration information from the CIC database to identify the registration type of a firm belonging to the industrial sector.

Although the CIC database has comprehensive coverage of China's industrial firms, it does not cover firms outside the industrial sector. To obtain the registration information for non-industrial sectors, we merge the CBRC data with the information provided by the National Enterprise Credit Information Publicity System (NECIPS), another national economic census conducted in 2008. For each firm in the CBRC dataset, we manually search for the firms registration type on the NECIPS website. For unlisted firms, these merged datasets enable us to determine whether an unlisted firm is an SOE or not. For listed firms, in addition to the merged information, we also use the ultimate controller information. Taken together, a listed firm is an SOE if the firms ultimate controller is central government or local government or the firms registration type equals "110" (i.e. state-controlled enterprises) or "151" (i.e. solely state-owned enterprise).

Within the category of SOEs, we further categorize loans into two subgroups: loans to LGFVs and those to non-LGFVs. The 1994 tax reform was implemented to redistribute fiscal revenues between the central and local governments, which led to a significant disparity

[7] See also Yu (2015), Ma, Qiao, and Xu (2015), Wang and Wang (2015), Bai, Lu, and Tian (2016), Berkowitz, Ma, and Nishioka (2017), Wu (2018) for using information of a firm's registration type to define SOEs.

between local government revenues and expenditure commitments and thus to a large extent explained the increasing fiscal deficit. Under the 1994 Budget Law (i.e. the "Old Budget Law" until January 1, 2015), the local government was prohibited from any borrowing from outside (e.g. bank loans and municipal bonds). To satisfy the huge demand for financing investment in local infrastructure, local governments set up LGFVs backed by land revenues and public assets, especially during the "Four Trillion" stimulus period (Gao, Ru, and Tang, 2018; Chen, He, and liu, 2018; Mo, 2018). According to (Gao, Ru, and Tang, 2018), more than 90% of newly issued LGFV debt came from bank loans, while less than 10% came from new issuance of urban construction and investment bonds ("Chengtou bonds"). The official list of LGFVs is in the CBRC dataset. We manually cross-check each firm's business type or scope in the NECIPS and identify LGFVs whose firm names match their 9-digit corporate organization codes.

I.3. **Summary statistics.** We first provide key macroeconomic facts around the stimulus period. Figure 1 displays several key facets of China's macroeconomy. During the global financial crisis, growth of China's real gross domestic product (GDP) plummeted from 13.6% in 2007Q2 to 6.4% in 2009Q1 (top left graph of Figure 1). In November 2008, China's State Council announced a plan to invest 4 trillion RMB over the two-year period from 2009Q1 to 2010Q4 in an attempt to stem the sharp fall of aggregate output (the four trillion RMB investment plan). The rectangular box in each graph marks this plan period. This stimulus plan resulted in a 25% growth rate of M2 supply and a 30% growth rate of bank loans in 2009 (top right graph of Figure 1). While GDP growth bounced back in 2009Q1 and peaked at 11.6% in 2010Q1, both the investment-to-GDP ratio and the loans-to-GDP ratio surged during the stimulus to 48% and 110% and persisted at high levels long after the stimulus was over (bottom two graphs of Figure 1).[8]

We now provide key aggregate patterns of credit allocation to SOEs and non-SOEs across time and across sectors from the micro loan data as constructed in the previous section. A description of such data patterns is a first step for researchers to understand the role of non-SOEs in credit allocation before, during, and after the 2009 stimulus period. Figure 2 displays the ratio of aggregated newly issued bank loans to GDP. This ratio was on average 5.65% during 2007-2008. During the 2009 monetary stimulus, it increased sharply to 17.24% in 2009Q2 before it declined afterwards. The increase of newly issued loans was concentrated in the first three quarters of 2009, a period identified by Chen, Ren, and Zha (2018) as monetary stimulus. The quarterly net increase of newly issued loans from the average 2008Q1-2008Q4 level is on average 7.81% (5.42%) of GDP during 2009Q1-Q3 (2009Q4-2010Q4). Thus, the net increase of total newly issued loans during 2009Q1-2010Q4 is 4.97 trillion RMB, consistent with the Chinese government's four trillion RMB investment plan.

Most of the existing literature on China focuses exclusively on the manufacturing sector. To be consistent with the macro time series, one must analyze the micro loan data beyond

[8]In 2009-2010, bank credit accounted for at least 75% of the overall debt-to-GDP ratio.

the manufacturing sector. We group all industries into four major sectors: manufacturing, infrastructure, real estate, and others. Infrastructure and real estate are arguably the two most important sectors in the government's four trillion RMB investment plan and the fourth sector is the rest of the economy and we call it "others," which include health, public administrations, education, and environment.[9] Figure 3 displays the share of newly issued bank loans across all four sectors. Bank loans to infrastructure took up half of all newly issued loans throughout 2007-2013, while loans to manufacturing were one fourth. The share of loans to the real estate sector was 12%-13%, whereas the remaining 12% of loans was allocated to others.

In comparison with the aggregated bank loans reported by Figure 2, Figure 4 displays the time series of bank loans as a fraction of GDP for the four sectors. All these sectors experienced a significant increase of bank loans during and after the stimulus period, with loans allocated to infrastructure having the largest increase (from an average of 2.93% in 2007Q1-2008Q4 to 8.79% in 2009Q2). In 2009Q1-2010Q4, the increase of bank loans to infrastructure from the average 2008Q1-2008Q4 level was 2.28 trillion RMB or 45.9% (2.28/4.97) of the total increase of bank loans to all sectors, consistent with the share of infrastructure investment in the four trillion RMB investment plan.[10] Except for real estate, bank loans to all other sectors as a percent of GDP returned to their pre-stimulus levels by 2011.

In 2009, LGFVs were created to allow local governments to fund the stimulus investment. Figure 5 displays the share of newly issued bank loans to LGFVs as a percentage of GDP. Prior to the monetary stimulus, this share was on average than 1%. It rose sharply to more than 5% in 2009Q1. As we will show in Section IV.2, most LGFV loans were allocated to the infrastructure sector. The total amount of LGFV loans in 2009 was around 1.58 trillion RMB.[11]

Table 1 reports the share of bank loans to SOEs across different periods in our data sample. Throughout these periods, the shares of SOE loans in manufacturing and real estate were less than 50% while the SOE shares in infrastructure and others were more than 50%.[12] During the monetary stimulus period, the share of SOE loans increased across all sectors to an average of 55.0% in 2009Q1-Q3 from an average of 50.6% in 2008Q1-Q4. This 4.4% increase in the SOE loan share does not necessarily imply that the monetary stimulus would

[9]The four trillion RMB investment plan includes housing, infrastructure, railways, roads, airports, water conservancy, urban power grids, health, education, and culture, and environmental protection.

[10]Investment in infrastructure was planned to be 1.87 billion RMB or 46.8% of the planned four trillion RMB investment.

[11]In 2009, total LGFV loans, including both short-term and long-term loan, in our data sample were 3.17 trillion RMB, consistent with the number from the informal source reported by Bai, Hsieh, and Song (2016).

[12]Other sectors include education, health, social security and welfare, culture, sports and entertainment, public management and social organizations, and scientific research. Although loans to these sectors were only 15% of the total bank loans newly issued during 2008Q1-2008Q4, the SOE loan share within these sectors was high because most firms were public institutions with large state-owned assets. An exception is hotel and catering services, whose SOE loan share was only 13.7%.

lead to more credit allocation to SOEs than to non-SOEs. To understand this point, consider an illustrative example in which loans to SOEs are worth 1 billion RMB and loans to non-SOEs are worth 3 billion RMB at the beginning. The SOE loan share is thus $25\% = \frac{1}{4}$. Now suppose that a monetary stimulus leads to additional 2 billion RMB loans allocated to non-SOEs and additional 1 billion RMB loans allocated to SOEs. As a result, the SOE loan share increases from 25% to $28.57\% = \frac{1+1}{4+(2+1)}$. Despite this 3.57% increase in the SOE loan share, however, more credits are allocated to non-SOEs than those to SOEs. This example illustrates a powerful point that one must study how *additional* loans are allocated to SOEs and non-SOEs sector by sector to understand the effects of monetary stimulus.

Table 2 reports additional loans allocated to SOEs and non-SOEs in the stimulus period (2009Q1-Q3) and the post-stimulus period (2009Q4-2010Q4), where additional loans are calculated as net increases from the 2008Q1-2008Q4 averages. For the manufacturing and real estate sector, additional newly issued bank loans to non-SOEs were larger than those to SOEs for both periods while the reverse was true for the infrastructure and others. In aggregate, SOEs received more additional loans than non-SOEs in the stimulus period while the reverse was true in the post-stimulus period (see the last column of Table 2).

Table 3 reports the percent of the number of SOEs in the total number of firms with positive newly originated bank loans across time and across sectors. The two sectors in which non-SOEs are a majority of firms with positive newly issued loans are manufacturing and real estate. In infrastructure and others, by contrast, SOEs form a majority of firms with positive newly originated bank loans. In aggregate, non-SOEs are a majority of firms (at least 57% of all firms). As we will show in Section IV.2, these extensive margins play a crucial role in understanding the aggregate effects of monetary stimulus on credit allocation to each type of firms.

In summary, Figures 2 and 4 and Table 2 establish the basic facts about the importance of credit allocation to not only SOEs but non-SOEs as well during and after the monetary stimulus; and Figure 5 shows the rise of LGFV loans during these periods. In our empirical analysis, we estimate how much of these additional loan allocations to SOEs versus non-SOEs across time and across sectors was attributed to the effects of the 2009 monetary stimulus and quantify the importance of credit allocation to LGFVs within SOE loans across different sectors.

II. The dynamic empirical framework

We propose a two-stage framework that is general enough to link the micro dynamic panel model with the macro SVAR model. This linkage is essential for estimating the stimulus effects on credit allocation and the aggregate economy. In particular, the micro model in the second stage requires proper controls for aggregate shocks other than monetary policy changes. These controlled macro variables are obtained in the first stage by the estimated macro model.

II.1. **The macro model.** Our macro SVAR model includes the log M2 variable (M_t) and the other $n = 10$ variables, including log CPI (P_t) and log real GDP (x_t). One key equation in this model, following Chen, Ren, and Zha (2018) and Chang, Liu, Spiegel, and Zhang (Forthcoming), is the monetary policy equation in which monetary policy switches between two regimes, depending on whether the gap between GDP growth and its target is positive or not. For the Chinese government, M2 growth has been used as the primary policy instrument. Use of M2 growth in the monetary policy equation captures China's quantity-based policy that differs from the interest-rate based policy widely used for developed economies.

Chen, Ren, and Zha (2018)'s regime-switching monetary policy equation is specified as

$$g_{m,t} = \gamma_0 + \gamma_m g_{m,t-1} + \gamma_\pi (\pi_{t-1} - \pi^*) + \gamma_{x,t} \left(g_{x,t-1} - g^*_{x,t-1}\right) + \sigma_{m,t}\eta_{m,t}, \tag{1}$$

where $\eta_{m,t}$ is a serially independent monetary policy shock with the standard normal distribution, $g_{m,t} = \Delta M_t$, $\pi_t = \Delta P_t$, $g_{x,t} = \Delta x_t$, and $g^*_{x,t} = x^*_t - x_{t-1}$. The (log) GDP level target is x^*_t and thus $g^*_{x,t}$ measures the targeted GDP growth. In estimation, we take π^* and $g^*_{x,t}$ as given.[13] The time-varying coefficients take the form of

$$\gamma_{x,t} = \begin{cases} \gamma_{x,a} & \text{if } g_{x,t-1} - g^*_{x,t-1} \geq 0 \\ \gamma_{x,b} & \text{if } g_{x,t-1} - g^*_{x,t-1} < 0 \end{cases}, \quad \sigma_{m,t} = \begin{cases} \sigma_{m,a} & \text{if } g_{x,t-1} - g^*_{x,t-1} \geq 0 \\ \sigma_{m,b} & \text{if } g_{x,t-1} - g^*_{x,t-1} < 0 \end{cases}.$$

The subscript "a" stands for "above the target" and "b" for "below the target". There are two parts associated with a change in monetary policy: an exogenous shock and a regime switch of monetary policy from the normal regime to a more aggressive regime. The time-varying coefficients, $\gamma_{x,t}$ and $\sigma_{m,t}$, capture two policy regimes in response to output growth: (a) the normal state when actual GDP growth meets the target set by the government *as a lower bound* and supported by monetary expansion and (b) the shortfall state when actual GDP growth falls short of its target. The Chinese government's GDP growth target, by weighing social and political considerations heavily, is politically mandated and takes precedence over all other economic objectives.

To quantify how monetary policy affects M_t as well as other macroeconomic variables y_t, we postulate the dynamics of y_t in a general system of simultaneous equations

$$A_0 y_t + b_0 M_t = c + \sum_{\ell=1}^{4} A_\ell y_{t-\ell} + \sum_{\ell=1}^{4} b_\ell M_{t-\ell} + \xi_t, \tag{2}$$

where $y_{t-\ell}$ is an $n \times 1$ vector of endogenous variables, c is an $n \times 1$ vector of constant terms, ξ_t is an $n \times 1$ vector of shocks orthogonal to the monetary policy shock $\varepsilon_{m,t}$, which have mean zero and covariance identity matrix, b_ℓ is an $n \times 1$ coefficient vector, and A_ℓ is an $n \times n$ coefficient matrix. The variable vector y_t includes π_t and x_t as well as other variables; for the analysis in the rest of this paper, we order the elements of y_t such that the first two elements of y_t are π_t and x_t.

[13]The government specifies the CPI inflation target between 3% and 4%. The value of π^* is set at 3.5%.

In the existing literature (Christiano, Eichenbaum, and Evans, 1999; Sims and Zha, 2006), strong identifying restrictions are imposed on A_0 to identify system (2). To maintain the principle of minimal restrictions on identification (Sims, 1980), we impose no restrictions on A_ℓ and b_ℓ (including the contemporaneous coefficient vector b_0 and the contemporaneous coefficient matrix A_0). The principle of minimal restrictions is especially relevant to the Chinese economy because the relationships among its key macroeconomic variables remain largely unknown to the research community.

Without any restrictions, system (2) is unidentified because the transformed system

$$(QA_0)y_t + (Qb_0)M_t = (Qc) + \sum_{\ell=1}^{4}(QA_\ell)y_{t-\ell} + \sum_{\ell=1}^{4}(Qb_\ell)M_{t-\ell} + Q\xi_t$$

obtained by multiplying any orthogonal matrix Q generates the same dynamics of y_t as does the original system.[14] Because the policy variable M_t is contemporaneously correlated with the rest of the variables (y_t), the identification question arises as to whether monetary policy equation (1) is identified and whether the effect of a monetary policy shock $\eta_{m,t}$ on the economy indexed by y_t depends on the rotation matrix Q, when equation (1) is estimated *jointly* with subsystem (2). The following proposition answers this question by establishing the identification of monetary policy in the dynamic system.

Proposition 1. When the system represented by (1) and (2) is jointly estimated, the following two results hold.

- Monetary policy equation (1) is identified, even though subsystem (2) is unidentified.
- Impulse responses of y_t to $\varepsilon_{m,t}$ are invariant to the rotation matrix Q.

Proof. See Appendix B. □

The intuition for identification of the monetary policy equation is that M_t is determined before all other variables are determined at time t. In the SVAR literature, it is required that the rest of the system has a recursive structure as well—an incredibly strong assumption. What is new in Proposition 1 is that this additional assumption is unnecessary and moreover the responses of all variables in the system to a monetary policy shock can be *uniquely* determined.

To assess the effect of monetary policy, one must be able to estimate the impulse responses to a monetary policy shock. The following proposition shows that the impulse responses are nonlinear and regime-dependent.

[14]Note that $Q\xi_t$ and ξ_t have exactly the same probability distribution: a normal probability distribution with mean zero and variance identity matrix.

Proposition 2. The impulse responses to a monetary policy shock, $\varepsilon_{m,t}$, can be computed from the following regime-dependent system:

$$\begin{bmatrix} M_t \\ y_t \end{bmatrix} = \tilde{b}_t + \sum_{\ell=1}^{4} \underbrace{\begin{bmatrix} \widetilde{B}^{11}_{\ell,t} & \widetilde{B}^{12}_{\ell,t} \\ \widetilde{B}^{21}_{\ell,t} & \widetilde{B}^{22}_{\ell,t} \end{bmatrix}}_{\widetilde{B}_{\ell,t}} \begin{bmatrix} M_{t-\ell} \\ y_{t-\ell} \end{bmatrix} + \widetilde{D}_t \begin{bmatrix} \varepsilon_{m,t} \\ \xi_t \end{bmatrix}, \tag{3}$$

where $\widetilde{B}^{12}_{1,t}$ is a function of $\gamma_{x,t}$ and γ_π and $\widetilde{B}^{22}_{1,t}$ is a function of $\gamma_{x,t}$, γ_π, b_0, and A_0.

To prove Proposition 2, consider the complete system composed of (1) and (2), which can be written in the SVAR form of

$$\underbrace{\begin{bmatrix} \frac{1}{\sigma_{m,t}} & \underset{1\times n}{0} \\ b_0 & A_0 \end{bmatrix}}_{\widetilde{A}_{0,t}} \begin{bmatrix} M_t \\ y_t \end{bmatrix} = \underbrace{\begin{bmatrix} \frac{\gamma_0 - \gamma_\pi \pi^* - \gamma_{x,t} x^*_{t-1}}{\sigma_{m,t}} \\ c \end{bmatrix}}_{\tilde{c}_t} + \underbrace{\begin{bmatrix} \frac{1+\gamma_m}{\sigma_{m,t}} & \begin{bmatrix} \frac{\gamma_\pi}{\sigma_{m,t}} & \frac{\gamma_{x,t}}{\sigma_{m,t}} & \underset{1\times(n-2)}{0} \end{bmatrix} \\ b_1 & A_1 \end{bmatrix}}_{\widetilde{A}_{1,t}} \begin{bmatrix} M_{t-1} \\ y_{t-1} \end{bmatrix}$$

$$+ \underbrace{\begin{bmatrix} -\frac{\gamma_m}{\sigma_{m,t}} & \underset{1\times n}{0} \\ b_2 & A_2 \end{bmatrix}}_{\widetilde{A}_{2,t}} \begin{bmatrix} M_{t-2} \\ y_{t-2} \end{bmatrix} + \underbrace{\begin{bmatrix} 0 & \underset{1\times n}{0} \\ b_3 & A_3 \end{bmatrix}}_{\widetilde{A}_3} \begin{bmatrix} M_{t-3} \\ y_{t-3} \end{bmatrix} + \underbrace{\begin{bmatrix} 0 & \underset{1\times n}{0} \\ b_4 & A_4 \end{bmatrix}}_{\widetilde{A}_4} \begin{bmatrix} M_{t-4} \\ y_{t-4} \end{bmatrix} + \begin{bmatrix} \varepsilon_{m,t} \\ \xi_t \end{bmatrix}. \tag{4}$$

It follows that $\tilde{b}_t = \widetilde{A}^{-1}_{0,t} \tilde{c}_t$, $\widetilde{B}_{\ell,t} = \widetilde{A}^{-1}_{0,t} \widetilde{A}_{\ell,t}$, and $\widetilde{D}_t = \widetilde{A}^{-1}_{0,t}$, where

$$\widetilde{A}^{-1}_{0,t} = \begin{bmatrix} \sigma_{m,t} & \underset{1\times n}{0} \\ -\sigma_{m,t} A_0^{-1} b_0 & A_0^{-1} \end{bmatrix}.$$

It is straightforward to see that $\widetilde{B}_{1,t}$ and $\widetilde{B}_{2,t}$ embody cross-equation restrictions (i.e., restrictions across the first equation and the rest of the equations). One can also see that $\widetilde{B}^{12}_{1,t}$ depends on $\gamma_{x,t}$ and γ_π and $\widetilde{B}^{22}_{1,t}$ depends on $\gamma_{x,t}$, γ_π, b_0, and A_0. The dependence of the reduced-form coefficient $\widetilde{B}^{22}_{1,t}$ on $\gamma_{x,t}$ implies that the impulse responses in the shortfall state are different from those in the normal state, as will be demonstrated in Section III.2.

The regime dependence and cross-equation restrictions make estimation of impulse responses an extremely difficult task in two aspects. First, both output coefficient and shock volatility in monetary policy equation (1) depend on the state of the economy. These endogenous-switching parameters make it computationally challenging to estimate the medium-sized nonlinear system (3). Second, although the first equation in system (3) is exactly the same as the monetary policy equation represented by (1), the parameters in the other equations of system (3) are functions of $\sigma_{m,t}$ and $\gamma_{x,t}$. In principle, therefore, estimating the monetary policy equation *jointly* with the rest of system (3) may not yield the same results as does estimation of equation (1) alone.

To overcome these difficulties, we propose a new estimation method stated in the following proposition.

Proposition 3. Statistical estimation and inference of nonlinear system (3) are equivalent to two separate estimation procedures such that nonlinear monetary policy equation (1) and linear system (2) can be estimated independently. That is, estimation and inference of system (2) do not depend on the coefficients of equation (1).

Proof. See Appendix C. □

Corollary 1. The reduced form of system (2) is

$$y_t = d + \sum_{\ell=1}^{4} B_\ell y_{t-\ell} + \sum_{\ell=0}^{4} h_\ell M_{t-\ell} + u_t, \tag{5}$$

where $d = A_0^{-1}c$, $B_\ell = A_0^{-1}A_\ell$, $h_\ell = A_0^{-1}b_\ell$, and $u_t = A_0^{-1}\xi_t$. This reduced-form linear system can be estimated independently of monetary policy equation (1). That is, a regime shift in monetary policy does not affect estimation of the reduced-form system represented by (5).

Although y_t depends on M_t in equation (5), the separation property in Proposition 3 or Corollary 1 still holds because M_t is predetermined by the monetary policy equation alone. The customary SVAR representation is the reduced-form system represented by (3). This representation facilitates a clear way of understanding how variables respond to a structural shock dynamically (in our case, the monetary policy shock $\varepsilon_{m,t}$). Direct estimation of this nonlinear system, however, is computationally expensive and conceptually difficult for the general researcher to handle. Working with the alternative form represented by (1) and (5) enables one to avoid the needless cost of dealing with the nonlinear system represented by (3).

Equivalent to the system represented by (1) and (5) is the one represented by (1) and (2). There are two advantages of working directly on (1) and (2). First, one can use the standard Bayesian prior of Sims and Zha (1998), which is imposed directly on the structural form.[15] Second, once estimation of the contemporaneous coefficient matrix A_0 is obtained, one can proceed to estimate, equation by equation, system (2) (see Appendix C for the proof). Although the monetary policy equation represented by (1) is nonlinear, its estimation entails little computational cost on estimation of the rest of the system.[16]

In summary, Propositions 1 and 3, together with Corollary 1, provide a general framework in which one is able to quantify how a regime change in monetary policy affects the aggregate economy without violating the Lucas critique (Leeper and Zha, 2003; Sims and Zha, 2006). As shown in Section II.2, moreover, the macro model is necessary for computing the counterfactual paths of CPI inflation and GDP growth driven by aggregate shocks other than the monetary policy stimulation. These paths are essential for estimating the firm-level model by controlling for aggregate shocks other than those of monetary policy changes.

[15]The hyperparameters for the prior, in the notation of Sims and Zha (1998), are $\lambda_i = 1$ for $i = 0, 1, 2, 4$, $\lambda_3 = 4$, $\mu_5 = \mu_6 = 1$. Except for the hyperparameter λ_3, the prior setting is standard. The large decay value for λ_3 is necessary for the Chinese data as it helps produce a superior out-of-sample forecasting performance documented by Higgins, Zha, and Zhong (2016) and Li (2016).

[16]All the coefficients in equation (1) are very tightly estimated (including those in the shortfall state) and the estimates are $\gamma_m = 0.391, \gamma_\pi = -0.397, \gamma_{x,a} = 0.183, \gamma_{x,b} = -1.299, \sigma_{m,a} = 0.005, \sigma_{m,b} = 0.010$. Note that there are a total of 15 shortfall periods, including the three quarters of 2009Q1-Q3.

II.2. **The dynamic panel model for the firm-quarter data.** With the micro loan data we construct, we develop and estimate a micro model to quantify the effects of monetary stimulus on bank loans allocated to SOEs and non-SOEs in various sectors.

As discussed in the previous section, the total measure of monetary policy changes consists of three components:

$$\varepsilon_{m,t} = \varepsilon_{m,t}^{\text{Norm}} + \varepsilon_{m,t}^{\text{Extra}} + \varepsilon_{m,t}^{\text{RuleCh}},$$

where $\varepsilon_{m,t}^{\text{Norm}}$ is the normal monetary policy shock that does not contain the extra stimulus shock (the business-as-usual monetary policy shock), $\varepsilon_{m,t}^{\text{Extra}}$ is the extra stimulus shock, above $\varepsilon_{m,t}^{\text{Norm}}$, that occurred during the 2009Q1-Q3 period, and $\varepsilon_{m,t}^{\text{RuleCh}}$ is the stimulus attributable to the policy rule change. The magnitude of $\varepsilon_{m,t}^{\text{RuleCh}}$ is calculated as the difference between the actual M2 growth and the counterfactual M2 growth when monetary policy were kept the same as in the normal state, even when output growth is short of the target. That is, we set $\gamma_{x,t}$ to $\gamma_{x,a}$ even when $g_{x,t-1} < g_{x,t-1}^*$ for the 2009Q1-Q3 period. By construction, $\varepsilon_{m,t}^{\text{Extra}} = 0$ and $\varepsilon_{m,t}^{\text{RuleCh}} = 0$ for the period prior to 2009Q1. Although the trigger for monetary policy to change its rule is endogenous, the magnitude of this change, measured by $\varepsilon_{m,t}^{\text{RuleCh}}$, is exogenous because the coefficient $\gamma_{x,t}$ is not a function of any endogenous variable. Within our general dynamic framework, we construct the counterfactual paths of output growth and inflation by excluding all monetary policy changes (exogenous shocks and a rule change) and we denote these two counterfactual variables by $\tilde{x}_t$ and $\tilde{\pi}_t$.

Let i denote the i^{th} firm within a particular sector (i.e., manufacturing, infrastructure, real estate, and others) and $\mathcal{B}_{i,t} = \frac{L_{i,t}}{N_{i,t-1}}$ denote the firm's borrowings $L_{i,t}$ divided by the firm's total nominal assets $N_{i,t-1}$, where $i = 1, \ldots, N^j$, N^j is the number of firms within the j^{th} sector, and j belongs to manufacturing, infrastructure, real estate, or others. We seasonally adjust both firm-level new borrowing and firm-level assets.[17] We adopt the method of Romer and Romer (2004) and estimate a *quarterly* dynamic panel regression within each sector as follows.

$$\mathcal{B}_{i,t} = c^i + \sum_{k=1}^{\ell} a_k^i \mathcal{B}_{i,t-k} + \sum_{k=0}^{\ell} c_k^i \varepsilon_{m,t-k} + c_x^i \tilde{x}_{t-1} + c_\pi^i \tilde{\pi}_{t-1} + \eta_{i,t}, \tag{6}$$

where c^i represents an individual (firm-level) fixed effect, $\varepsilon_{m,t}$ is the total monetary policy change estimated by Chen, Ren, and Zha (2018), $\eta_{i,t}$ is an iid random variable with mean

[17]For each sector and each type of firm (e.g., a manufacturing-SOE combination), we seasonally adjust aggregated new loans and total assets. We then multiply each firm-level variable by the ratio of the seasonally adjusted aggregate to the non-seasonally adjusted aggregate. This method allows us to obtain seasonally adjusted firm-level data. Because the sample is short in the time dimension, we use a seasonal ARIMA$(0,1,1)(0,1,1)_4$ model to perform seasonal adjustments. This model is similar to the seasonal ARIMA$(0,1,1)(0,1,1)_{12}$ model, known as the airline model, that Box, Jenkins, Reinsel, and Ljung (2015) used to seasonally adjust monthly airline passenger data. Results without seasonal adjustments are similar to those with seasonal adjustments (see Appendix S2).

zero and variance σ^i, and

$$a_k^i, c_k^i, \sigma^i = \begin{cases} a_k^s, c_k^s, \sigma^s & \text{if } i \in \text{SOE} \\ a_k^{ns}, c_k^{ns}, \sigma^{ns} & \text{if } i \in \text{NSOE} \end{cases}.$$

The superscript "s" stands for SOE and "ns" stands for NSOE (non-SOE).

The terms involving $\tilde{x}_{t-1}$ and $\tilde{\pi}_{t-1}$ in equation (6) control for aggregate shocks other than those of monetary policy changes. The challenge is that most macro variables are endogenous to both monetary policy shocks and other aggregate shocks. Therefore, we first use the macro model to construct the counterfactual paths of GDP growth and CPI inflation from 2009Q1 on by excluding $\varepsilon_{m,t}^{\text{Extra}}$ and $\varepsilon_{m,t}^{\text{RuleCh}}$, conditional on actual data prior to 2009Q1. We denote these post-2008Q4 counterfactual paths by x_t^{ctf} and π_t^{ctf}. Thus, x_t^{ctf} and π_t^{ctf} are driven by all aggregate shocks other than the 2009 monetary stimulation.

To keep the notation manageable, we omit the superscript or subscript j in the rest of the paper, with the understanding that all the variables, coefficients, and shocks related to firm i are also related to a particular sector j. Using the quarter-firm data described in Section I.2 with the number of lags ℓ set to four quarters as in the SVAR literature, we estimate equation (6) sector by sector similar to the approach of Cloyne, Ferreira, and Surico (Forthcoming), as one does not expect loans to an individual firm in one sector to *directly* affect loans to an individual firm that belongs to another sector. In Section IV, we estimate the heterogeneous effects of aggregate monetary stimulus on credit allocation across the types of firms as well as across the four key sectors. Baseline model (6) takes into account the firm's assets as well as the firm fixed effect. Our empirical results are insensitive to an inclusion of additional firm-specific characteristics.[18]

As in the macro model, we take the position that all the coefficients in model (6) are time-invariant. This assumption is consistent with the standard practice in the existing literature. What differs from the existing literature is that we allow for time-varying coefficients in the monetary policy rule represented by (1). As a result, $\varepsilon_{m,t}^{\text{RuleCh}}$ captures the monetary stimulation initiated by a change in the monetary policy rule. Let $\hat{c}^i$, $\hat{a}_k^i$, $\hat{c}_k^i$, $\hat{c}_x^i$, $\hat{c}_\pi^i$, and $\hat{\eta}_{i,t}$ be the estimated coefficients and firm-specific idiosyncratic shock. We construct firm-level dynamic response functions by feeding three consecutive shocks $\varepsilon_{m,t} = \varepsilon_{m,\text{2009Q1}}^{\text{Extra}} + \varepsilon_{m,\text{2009Q1}}^{\text{RuleCh}}$, $\varepsilon_{m,t+1} = \varepsilon_{m,\text{2009Q2}}^{\text{Extra}} + \varepsilon_{m,\text{2009Q2}}^{\text{RuleCh}}$, and $\varepsilon_{m,t+2} = \varepsilon_{m,\text{2009Q3}}^{\text{Extra}} + \varepsilon_{m,\text{2009Q3}}^{\text{RuleCh}}$ during the stimulus period into the equation

$$\mathcal{B}_{i,t} = \hat{c}^i + \sum_{k=1}^{\ell} \hat{a}_k^i \mathcal{B}_{i,t-k} + \sum_{k=0}^{\ell} \hat{c}_k^i \varepsilon_{m,t-k} + \hat{c}_x^i \tilde{x}_{t-1} + \hat{c}_\pi^i \tilde{\pi}_{t-1} \tag{7}$$

at time t with $\mathcal{B}_{i,t-k} = 0$ for $k > 0$, $\varepsilon_{m,t+k} = 0$ for $k > 2$, and $\varepsilon_{m,t-k} = 0$ for $k > 0$.[19] The firm-level dynamic responses (the intensive margin) measures the *average* firm-level impact

[18] See Supplemental Appendices S1-S3 for various robust results.

[19] The dynamic responses do not depend on t, $\mathcal{B}_{i,t-k}$ $(k > 0)$, $\hat{c}^i$, or $\hat{\eta}_{i,t}$. By construction, $\tilde{x}_{t-1}$ and $\tilde{\pi}_{t-1}$ are not affected by monetary policy changes.

of monetary stimulus during the 2009Q1-Q3 period and are expressed as percentage changes of newly issued loans over assets and denoted by $f(t,i)$ for $i \in \{\text{SOE}, \text{non-SOE}\}$.

To generate probability bands for dynamic responses, we group the regression coefficients in equation (6) into the vector

$$\Phi^i = \begin{bmatrix} c^i & a_1^i & \cdots & a_\ell^i & c_0^i & \cdots & c_\ell^i & \sigma^i & c_x^i & c_\pi^i \end{bmatrix}',$$

where $i \in \{\text{SOE}, \text{non-SOE}\}$. We collect the corresponding regressors in matrix X^i for firm i, where the t^{th} row of X^i is the vector

$$\Big[\tau_i \; \mathcal{B}_{i,2007\text{Q}2+(t-1)+(\ell-1)} \; \cdots \; \mathcal{B}_{i,2007\text{Q}2+(t-1)} \; \varepsilon_{i,2007\text{Q}2+(t-1)+\ell} \\ \cdots \; \varepsilon_{i,2007\text{Q}2+(t-1)} \; x_{2007\text{Q}2+(t-1)} \; \pi_{2007\text{Q}2+(t-1)}\Big].$$

Note that τ_i is a $1 \times N$ row vector with 1 in the i^{th} position and 0 in the remaining positions. We stack firm-specific residuals in equation (6) into the $T \times 1$ ($T = N(21-\ell)$) vector

$$\boldsymbol{\eta} = \begin{bmatrix} \eta_{1,2007\text{Q}2+\ell+1} & \cdots & \eta_{1,2013\text{Q}2} & \cdots & \eta_{N,2007\text{Q}2+\ell+1} & \cdots & \eta_{N,2013\text{Q}2} \end{bmatrix}'.$$

We define $\boldsymbol{\Omega} = \boldsymbol{\eta}'\boldsymbol{\eta}$, denote the $\mathfrak{h}^{\text{th}}$ random draw from the inverse Wishart (IW) distribution $\text{IW}(\boldsymbol{\Omega}, T+2-(N+2\ell+1))$ by $\boldsymbol{\Psi}^{(\mathfrak{h})}$, and define the $\mathfrak{h}^{\text{th}}$ draw $\hat{\Phi}^{i,(\mathfrak{h})} = \Phi^i + \boldsymbol{\nu}^{(\mathfrak{h})\prime}\,\text{chol}(\boldsymbol{\Psi}^{(\mathfrak{h})}(X'X)^{-1})$, where chol represent the Choleski decomposition of the enclosed matrix, $X = \left[X^{1\prime}, \ldots, X^{N\prime}\right]'$, and $\boldsymbol{\nu}^{(\mathfrak{h})}$ is an $(N+2\ell+1) \times 1$ vector randomly drawn from the iid Gaussian distribution $N(\mathbf{0}, \boldsymbol{I}_{N+2\ell+1})$ (see Bańbura, Giannone, and Reichlin (2010) for details). We substitute the randomly drawn coefficients, represented by the vector $\hat{\Phi}^{i,(\mathfrak{h})}$, for $1 \le \mathfrak{h} \le \mathcal{H}$, into equation (7) and generate a draw of the dynamic response function $\boldsymbol{f}^{(\mathfrak{h})} = [f^{(\mathfrak{h})}(0,i), \ldots, f^{(\mathfrak{h})}(12,i)]'$ for $i \in \{\text{SOE}, \text{non-SOE}\}$ by feeding in three consecutive shocks $\varepsilon_{m,t} = \varepsilon^{\text{Extra}}_{m,2009\text{Q}1} + \varepsilon^{\text{RuleCh}}_{m,2009\text{Q}1}$, $\varepsilon_{m,t+1} = \varepsilon^{\text{Extra}}_{m,2009\text{Q}2} + \varepsilon^{\text{RuleCh}}_{m,2009\text{Q}2}$, and $\varepsilon_{m,t+2} = \varepsilon^{\text{Extra}}_{m,2009\text{Q}3} + \varepsilon^{\text{RuleCh}}_{m,2009\text{Q}3}$ at time t with $\mathcal{B}_{i,t-k} = 0$ for $k > 1$. The 5^{th} and 95^{th} percentiles of the set $\{f^{\mathfrak{h}}(t,i)\}_{\mathfrak{h}=1}^{\mathcal{H}}$ deliver the .90 probability bands of dynamic responses at time t.[20]

The estimated average (micro) impact of monetary policy changes on credit allocation to each type of firm does not automatically imply the aggregate (macro) effect. To obtain the aggregate effect, we construct the following two counterfactuals for newly issued loans by feeding an alternative sequence of policy stimulation $\varepsilon^{\text{Alt}}_{m,t}$ in place of $\varepsilon_{m,t}$ in equation (6).

- Counterfactual path $\mathcal{B}^{\text{Alt}}_{i,t}$ under scenario A. Conditional on the initial condition $\mathcal{B}^{\text{Alt}}_{i,t} = \mathcal{B}_{i,t}$ for $t = 2008\text{Q}1, \ldots, 2008\text{Q}4$, actual GDP growth in 2008Q4, actual CPI inflation in 2008Q4, $\tilde{x}_t = x^{\text{ctf}}_t$ from 2009Q1 on, $\tilde{\pi}_t = \pi^{\text{ctf}}_t$ from 2009Q1 on, and the estimated values $\hat{c}^i$, $\hat{a}^i_k$, $\hat{c}^i_k$, $\hat{c}^i_x$, and $\hat{c}^i_\pi$, we simulate the path of $\mathcal{B}_{i,t}$ through equation (6) by setting $\varepsilon^{\text{Alt}}_{m,t} = \varepsilon^{\text{Norm}}_{m,t}$ throughout the sample.

[20] We set $\mathcal{H} = 1500$. Since all the random draws are iid, 1500 draws are more than sufficient for achieving accuracy. The dynamic response results do not depend on a particular value of t.

- Counterfactual path $\mathcal{B}_{i,t}^{\text{Alt}}$ under scenario B. Conditional on the initial condition $\mathcal{B}_{i,t}^{\text{Alt}} = \mathcal{B}_{i,t}$ for $t = 2008\text{Q1}, \ldots, 2008\text{Q4}$, actual GDP growth in 2008Q4, actual CPI inflation in 2008Q4, $\tilde{x}_t = x_t^{\text{ctf}}$ from 2009Q1 on, $\tilde{\pi}_t = \pi_t^{\text{ctf}}$ from 2009Q1 on, and the estimated values $\hat{c}^i + \hat{\eta}_{i,t}$, $\hat{a}_k^i$, $\hat{c}_k^i$, $\hat{c}_x^i$, and $\hat{c}_\pi^i$, we simulate the path of $\mathcal{B}_{i,t}$ through equation (6) by setting $\varepsilon_{m,t}^{\text{Alt}} = \varepsilon_{m,t}^{\text{Norm}} + \varepsilon_{m,t}^{\text{Extra}}$ in 2009Q1-Q3 and $\varepsilon_{m,t}^{\text{Alt}} = \varepsilon_{m,t}^{\text{Norm}}$ for the remaining quarters.

We multiply the counterfactual path $\mathcal{B}_{i,t}^{\text{Alt}}$ under each scenario by $\frac{N_{i,t-1}}{GDP_t}$ and aggregate across firms of the same type in the same sector. The aggregation includes all the firms in our sample. We then subtract the GDP-scaled aggregated counterfactual path under scenario A from the aggregated loans to GDP for the particular combination of firm type and sector (e.g., SOEs in manufacturing), which yields the total stimulus effects due to the monetary policy stimulation in 2009Q1-Q3. If we subtract the GDP-scaled aggregated counterfactual path under scenario B from the aggregated loans to GDP for the particular combination of firm type and sector, we obtain the stimulus effects due to only the change of the monetary policy rule in 2009Q1-Q3.[21]

III. The macroeconomic impact of the 2009 monetary stimulus

This section presents the dynamic impacts of the 2009 monetary stimulus on the macroeconomy. In the macro model, an analysis of impulse responses in the normal and shortfall states provides a foundation for quantifying aggregate impacts. We begin with this analysis and then estimate the dynamic impacts of monetary stimulus on the banking system and the real economy.

III.1. **Impulse responses in the normal state.** In normal times when GDP growth is above the government's target, what is the impact of monetary policy on aggregate output? Figure 6 displays the impulse response of GDP to a monetary policy shock along with probability bands. The impulse responses of other macroeconomic variables for the benchmark SVAR model with 11 variables are displayed in Figure 7. From Figures 6 and 7 one can see that a positive one-standard-deviation shock to monetary policy raises M2 by 0.9% and GDP by 0.37% at their peak values.[22] The output response is hump-shaped, while the M2 response is much more persistent. Both responses are highly significant both economically and statistically. The CPI response displays little price puzzle, further supporting our argument that the estimated monetary policy shock does not contain endogenous responses to

[21]Because the micro model is linear, it is equivalent to obtain aggregate effects by feeding in only monetary policy changes during 2009Q1-Q3 while setting $\varepsilon_{m,t}^{\text{Norm}} = 0$ and using the same initial conditions discussed for scenarios A and B.

[22]As Appendices D and E show, this result is robust to alternative SVAR specifications when we remove the three interest rates or foreign exchange reserves from the list of variables.

other macroeconomic variables.[23] The correct sign of a price response is one of the building foundations for the SVAR literature (Sims, 1992; Uhlig, 2005). In response to an expansionary monetary policy shock, the excess reserve ratio and the Repo rate fall in the initial periods.[24] These responses are consistent with most theoretical predictions of the effect of a monetary policy shock.

The response of total (real) bank loans has a pattern very similar to the M2 response (top left panel of Figure 8), indicating that monetary expansion increases output through an increase of bank lending. As shown in our micro dynamic model (Section IV.2), a majority of such bank loans were allocated to infrastructure, real estate, and other supporting industries during and after the stimulus period. Since these loans are typically not of short term, our estimation reveals that the response of short-term bank loans is much smaller in magnitude than that of total bank loans and its wide probability bands further indicate weak statistical significance (top right panel of Figure 8).

The finding about bank lending is reinforced by how investment and consumption respond to expansionary monetary policy. The bottom panel of Figure 8 shows that investment responds strongly to an expansionary monetary policy shock (hump-shaped response) while the response of consumption (no hump shape) is small in magnitude and its statistical significance, according to the probability bands, is very weak.[25] In sharp contrast to the finding of Christiano, Eichenbaum, and Evans (2005) for the U.S. economy that the response of consumption to an expansionary monetary policy shock is hump-shaped, strong, and sizable, this result indicates that bank lending in China is mainly used for investment and that investment rather than consumption is a driving force behind the output fluctuation.

Certain key variance decompositions attributable to the monetary policy shock relative to other aggregate shocks are reported in Table 4. The monetary policy shock explains one fifth of the GDP variation at the peak value. This result is robust across various model specifications. The contribution to the investment fluctuation reaches 16% at its peak; the contribution to the bank-loan fluctuation is over 23% for the five-year horizon. By contrast, the contribution to the fluctuation in short-term bank loans is small ($3-6\%$), the contribution to the price fluctuation is also small ($0.5 - 7\%$), and the contribution to the consumption fluctuation is even smaller (under 3.1% for the first four years). These results reinforce our argument that monetary policy affects the macroeconomy mainly through bank credit to investment rather than consumption, consistent with the investment-driven feature of the Chinese economy.

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[23]A price puzzle emerges if the identified monetary shock is contaminated by the endogenous component such that prices do not fall in response to contractionary monetary policy. This point is made forcibly by Sims (1992).

[24]The lending and deposit rates respond in a similar fashion.

[25]This result is generated by a larger model that expands the benchmark model to inclusion of the investment and consumption series.

III.2. **Impulse responses in the shortfall state.** The estimated impulse responses in the shortfall state differ from those in the normal state in both timing and magnitude. Figure 9 plots the estimated impulse responses in the shortfall state. Our subsequent analysis focuses on the one year horizon in which the impulse responses differ most from those in the normal state. While informative in theory, impulse responses over longer horizons are not particularly realistic because the shortfall state lasted for only three quarters.

As a direct result of aggressive monetary policy to stem the shortfall of GDP growth, the M2 response peaks within 2 quarters, faster than the response in the normal state, and the GDP response peaks within 3 quarters as compared to a much delayed peak (9 quarters) in the normal state. According to our estimates, the volatility of a monetary policy shock in the shortfall state is twice as high as in the normal state (0.10 vs 0.005), which leads to a stronger response of M2 supply on impact (a 1% increase in the shortfall state versus a 0.5% increase in the normal state). The response is immediately translated to the banking system with the initial response of bank lending to a monetary policy shock in the shortfall state almost doubling the initial response in the normal state (1% vs. 0.55%). By contrast, short-term bank loans rise only 0.5% for the first year.

In the shortfall state, because most of the new bank credit is allocated to financing investment, the response of consumption is almost the same as that in the normal state (comparing Figures 8 and 9). By contrast, the peak response of investment in the shortfall state, occurring two quarters earlier, is significantly higher than in the normal state (1.5% vs. 1.1% by comparing Figures 8 and 9). Thus, the early GDP responses rely on investment rather than on consumption.

The asymmetric responses of bank credit across the two states lead to the asymmetry of monetary policy's impacts on the real economy. Table 4 reports the asymmetric importance of the monetary policy shock in driving the GDP fluctuation. In the shortfall state, the GDP variation attributed to the monetary policy shock is as high as 45%, more than twice as much as the counterpart in the normal state. Relative to all other shocks in the economy, monetary policy plays a far more important role in stimulating the aggregate economy in the shortfall state than in the normal state.

III.3. **Impacts on the macroeconomy.** Because the effects of monetary policy are uniquely determined in our empirical framework and the rest of the system is not affected by a switch in the monetary policy rule, we are able to use the posterior estimates to simulate a counterfactual economy in which we assume that monetary policy regime had not changed in 2009Q1-Q3 from monetary policy in the normal state (the pre-stimulus and post-stimulus periods) and there were no extra stimulative monetary policy shocks in 2009Q1-Q3. Following Sims and Zha (2006), we back out the monetary policy shock sequence $\eta_{m,t}$ and all the other aggregate shock sequences u_t. We keep these shocks intact in our counterfactual simulations except for monetary policy shocks in 2009Q1-Q3. The difference between the actual and counterfactual paths measures the impact of the unprecedented monetary stimulation (both exogenous and endogenous) during the first three quarters of 2009.

Using our macro model we show that the rule change in monetary policy played the most conspicuous role in implementing the government's stimulus package by separating a change in monetary policy from the effect of this change. The shortfall state lasted for only three quarters from 2009Q1 to 2009Q3 in which monetary policy switched to be much more expansionary. By the third quarter of 2009, M2 growth sprang up to over 25% from the average of 16% in normal times. Figure 10 shows the effect of this policy switch on M2 growth. The shaded bar marks the period 2009Q1-Q3 in which the monetary policy rule changed. High M2 growth in the period after 2009Q3 was the *consequence* of this policy change, not the stimulus itself. If the PBC had not changed its policy by increasing M2 supply drastically, M2 growth would have been hovering around 16% for the next two years (the circle line in Figure 10).

Such a monetary stimulus had a significant impact on GDP growth. The left panel of Figure 11 indicates that as high as 66% of actual GDP growth in 2009-2010 was attributable to the stimulus. By the end of 2009, GDP growth reached 11.59% with an increase of 4.68% above the 6.91% growth rate in 2008Q4. The portion attributable to the stimulus, measured by the difference between actual and counterfactual paths (right panel of Figure 11), reached 3.1% in 2009Q4, which accounted for 66.24% of the 4.68% increase.

Without the stimulus, actual GDP growth would have been below its official 8% target in 2009 (left panel of Figure 11) and would have been lower by as much as 3.1% during the next two years (right panel of Figure 11). As also shown in the right panel of Figure 11, almost all of the impact was driven by the change in the monetary policy rule in response to the shortfall of GDP growth, not by a change in shock volatility or by a monetary policy shock itself. Thus, it is the policy rule change that offers the key to understanding the stimulus effect on GDP growth. Despite its economic significance, however, the effect of this monetary stimulus on GDP growth was transitory. The gap between the actual and counterfactual paths began to narrow in 2010 and became negligible by the end of 2011.

The effect of monetary stimulus on the macroeconomy through bank credit is particularly specific to China. The top left panel of Figure 12 shows that the 2009 monetary stimulus increased the growth of *real* bank loans by as high as 7% (the difference between actual and counterfactual paths), which has a magnitude close to its impact on M2 growth. Most of the increase in M2 growth is channeled to the macroeconomy through long-term bank loans. As one can see from the top right panel of Figure 12, the 2009 monetary stimulus had a considerably smaller effect on the growth of short-term loans.

Long-term loans are mainly used to finance investment in physical capital. According to the 2010Q1 MPR and Table 2, most of newly issued bank loans were allocated to infrastructure, real estate, and other supporting industries such as steel, cement, and public public management and administration. Unlike many developed economies such as the U.S., the effect of China's monetary stimulus on GDP growth is through investment, rather than through consumption (which includes consumer durable goods). The bottom row of Figure 12 displays the sharp contrast between the impacts on investment and consumption. The regime switch to extraordinarily expansionary monetary policy in 2009Q1-Q3 had a negligible effect on consumption growth, but it increased investment growth by as much as 13% (the difference between the actual and counterfactual paths). With the 40% investment-to-GDP ratio at the end of 2008, a 13% increase in investment growth should contribute to over a 4% increase in GDP growth by accounting, which is perfectly in line with the magnitude of the stimulus effect on GDP growth.

For our macro model as well as the micro model, the actual paths can be below the counterfactual paths after the monetary stimulus as shown in Figures 10 and 12 for growth rates of M2 supply, bank loans, and investment. To understand this point, consider the following illustrative example:

$$z_t = B_t z_{t-1} + \epsilon_t,$$

where z_t is an $(n+1) \times 1$ vector with the first element being M2 and the first element of the shock vector ϵ_t is an exogenous monetary policy shock. The time-varying coefficient is defined as $B_t = B_n$ in normal times and $B_t = B_s$ in the shortfall state. At time 1, the economy enters the shortfall state; at time 4, the economy returns to the normal state. The dynamics of z_t can be traced out recursively:

$$\begin{aligned} z_1 &= B_s z_0 + \epsilon_1, \\ z_2 &= B_s^2 z_0 + B_s \epsilon_1 + \epsilon_2, \\ z_3 &= B_s^3 z_0 + B_s^2 \epsilon_1 + B_s \epsilon_2 + \epsilon_3, \\ z_4 &= B_n B_s^3 z_0 + B_n B_s^2 \epsilon_1 + B_n B_s \epsilon_2 + B_n \epsilon_3 + \epsilon_4, \\ &\vdots \end{aligned}$$

For the first term on the right hand side of the equation, for example, the effect due to endogenous switching from the normal state to the shortfall state can be measured by $(B_s - B_n)z_0$ for the first quarter and $(B_n B_s^3 - B_n^4)z_0$ for the fourth quarter. Clearly, although the shortfall state lasts for only three quarters, the coefficient B_s influences the dynamics of z_t beyond the third period. The time series displayed in Figures 1 and 10 shows that M2 growth rose sharply in 2009Q1-Q3 but fell sharply as well after 2009. When we fit the model to the data, the coefficients B_s and B_n are jointly estimated to reflect this sharp rise and fall pattern. Consequently, even though our hypothetical length of the shortfall state for impulse responses lasts more than three quarters, they tend to fall at a speed faster than those in the normal state after the initial four quarters.

For comparison across the two states, we assemble the impulse responses of M2 and total bank loans in Figure 13. All these impulse responses exhibit similar patterns across the two states: the responses in the shortfall state are stronger than those in the normal state for the first four quarters, but decline at a faster speed since that, and eventually fall below their counterparts in the normal state. The sharper fall of M2 growth originated from the transitory surge in M2 growth during the shortfall state, which translates into the temporary surge in bank loans. This transitory stimulation, however, generated lasting consequences on the macroeconomy. Unlike the temporary effects on M2 growth and real GDP growth, the 2009 monetary stimulus had persistent impacts on both the investment-to-GDP ratio and the debt-to-GDP ratio (Figure 14), where accumulated longer-term loans were allocated to investment despite an already high investment rate at the end of 2008.

IV. Credit allocation and aggregate effects

The existing literature emphasizes the stimulus effect on economic growth by establishing evidence in the manufacturing sector that on average SOEs received more bank loans than non-SOEs in 2009-2010 through the channel of credit misallocation. While credit misallocation may be important, this paper focuses on another channel: the 2009 monetary stimulus promoted GDP growth through bank loans to finance investment. For this channel to be important for the overall economy, bank loans to non-SOEs should be significant in manufacturing as well as in other sectors. In this section, we estimate the micro dynamic model discussed in Section II.2 and provide empirical evidence on the dynamic impacts of the 2009 monetary stimulus on credit allocation to SOEs versus non-SOEs beyond the manufacturing sector. The estimation requires us to control for the effects of aggregate shocks other than changes in monetary policy. The controlled aggregate variables, produced by the macro model, are the counterfactual variables of inflation and GDP growth driven by aggregate shocks other than monetary policy shocks or changes in the monetary policy rule.

IV.1. **Average effects.** We first examine whether SOEs, on average, have easier access to bank loans than non-SOEs when monetary policy stimulates the economy. This question is at the center of discussions of stimulus effects and is related to the issue of allocative efficiency of bank credit. The average stimulus effects can be measured by calculating the dynamic responses of loans allocated to SOEs verus non-SOEs to monetary policy changes as detailed in Section II.2. That is, by setting the model coefficients to the estimated values, we feed $\varepsilon_{m,t}^{\text{Extra}} + \varepsilon_{m,t}^{\text{RuleCh}}$ for $t =$ 2009Q1, 2009Q2, and 2009Q3 into model (7). These dynamic responses to monetary stimulation are measured by the percentage changes in loans allocated to the average firm, relative to its level in the normal state.

Figure 15 reports the dynamic responses of bank loans allocated to SOEs and non-SOEs at the firm level across various key sectors, along with .90 probability bands. These bands indicate that the dynamic responses are tightly estimated because of the large sample at the firm level. All the responses are hump-shaped, peaking at the second quater and dying out at the eighth quarter. The hump-shape response implies that it takes time for monetary expansion to exert the full effect and both the peak and tough are consistent with the aggregated data from the micro loan data for each sector (Figure 4).

In manufacturing, on average, the monetary stimulus leads to a larger increase in bank loans (relative to the firm's assets) to an individual SOE than bank loans allocated to an individual non-SOE for the first three quarters (top left panel of Figure 15). This finding, consistent with the static regression result on manufacturing firms in Cong, Gao, Ponticelli, and Yang (Forthcoming), suggests a favoritism of bank credit toward SOEs at the individual firm level. This preferential credit access by SOEs, however, is not found in the infrastructure and real estate sectors. In infrastructure, the dynamic responses of bank loans advanced to an individual SOE have a similar magnitude to those loans advanced to an individual non-SOE (top right panel of Figure 15). In real estate, bank loans advanced to an individual non-SOE increase more than those to an individual SOE. In particular, while the loan response for an individual SOE declines to essentially zero after four quarters, the loan response for an individual non-SOE is still positive until after the seventh quarter. The results for the remaining (other) sectors are similar to those for manufacturing: the loan response for an individual SOE, on average, is larger than that for an individual non-SOE. In sum, we find that the effects of monetary stimulation on credit allocation to an individual SOE versus non-SOE are heterogeneous across different sectors.

Why do these heterogeneous effects exist? In particular, why do non-SOEs in infrastructure and real estate sectors have easy access to bank loans? Answers to these questions require an understanding of China's institutional facts. One important fact is that both infrastructure and real estate belong to the government's *strategic* industries. Since the late 1990s, the government has viewed most industries in the heavy sector as strategically important and supported them with preferential credit.[26] In March 1996, the Eighth National People's Congress passed the National Economic and Social Development and Ninth Five-Year Program called "Vision and Goals for 2010." This program was prepared by the State Council and specifically urged continuation of strengthening infrastructure, real estate, and other strategic industries.

The stimulus plan announced in November 2008 by the Chinese government called for massive investment in seven areas of Chinese economy to promote GDP growth in the face of the 2008 global financial crisis. Among these areas, the Chinese government placed a more emphasis on infrastructure and real estate than any other sector, whether firms within the infrastructure and real estate sectors are SOEs or non-SOEs. In fact, non-SOEs were encouraged to participate actively in investment. In its No. 13 decree announced in May 2010, for example, the State Council explicitly expressed its support for allocating private capital into infrastructure, including roads, waterway, port terminals, civil airports, general aviation facilities, and other projects through sole proprietorship, holding, and shareholding.[27] With such implicit government guarantees supported by the State Council, the average non-SOE

[26]Since most of these strategic industries are capital intensive, Chang, Chen, Waggoner, and Zha (2016) group all these strategic industries into one large sector often called the "heavy sector." See also the IMF 2016 Country Report No. 16/270 and 2017 Country Report No. 17/247 for the terminology of heavy industries or heavy sector.

[27]See the link `http://www.gov.cn/zhengce/content/2010-05/13/content_3569.htm` for details of the No. 13 [2010] degree of State Council, named "Several Opinions of the State Council on Encouraging and Guiding the Healthy Development of Private Investment" and announced on 7 May 2010.

in infrastructure and real estate tend to receive credit treatments similar to their SOE counterparts during the stimulus period.[28]

Many non-SOEs in manufacturing and others, however, do not belong to the government's strategic industries. In manufacturing, the government's program "Grasp the large and let go the small" was designed to allow SOEs to exit non-strategic light industries and become non-SOEs (Song, Storesletten, and Zilibotti, 2011). In others (i.e., the remaining sector), such as education, health, social security and social welfare, culture, public management and social organizations, technical services, and scientific research, a majority of firms are public institutions with state-owned assets. Most of the bank credit to these sectors was allocated to SOEs; non-SOEs do not enjoy favored credit treatment.

To summarize, we find heterogeneous impacts of monetary stimulus on bank lending to SOEs verus non-SOEs across different sectors. While manufacturing SOEs gain easier access to bank loans than non-SOEs when monetary policy stimulates the economy, this is not the case for the infrastructure and real estate sectors. The infrastructure sector exhibits no clear favoritism towards either the average SOE or non-SOE in receiving bank credit; non-SOEs in the real estate sector, on average, have easier access to bank credit than SOEs. Our empirical results indicate that findings based on the manufacturing sector should not be generalized to the rest of the economy.

IV.2. **Aggregate effects.** We now explore the aggregate impacts of the 2009 monetary stimulus on credit allocation to SOEs and non-SOEs. First, we compute the dynamic effects of monetary stimulus on each individual firm's bank loans as the difference between the actual loan data and the counterfactual loan data in the absence of monetary stimulation in 2009Q1-Q3. Second, we add up the individual effects over the firms that belong to a certain ownership type within a sector. This bottom-up approach to computing aggregate effects is detailed in Section II.2.

Figures 16 and 17 report the aggregate effects of the 2009Q1-Q3 monetary stimulus on bank loans to SOEs and non-SOEs for all four sectors.[29] For both manufacturing and real estate, the aggregate effects of monetary stimulus on loans to SOEs were much smaller than those on loans to non-SOEs. For infrastructure and others, however, the results are reversed. Adding up all these aggregate effects across the four sectors, we compute the stimulus effects on credit allocation between SOEs and non-SOEs at the aggregate level. The left panel of Figure 18 shows that the two lines representing the aggregate effects of non-SOEs and SOEs closely: 57% (43%) of the increase in bank loans due to the 2009 monetary stimulus was allocated to SOEs (non-SOEs). This magnitude is comparable to the SOE share in the overall net increase in bank loans during this period, as reported in Table 2. Comparing Figures 16,

[28]Another possible explanation for implicit government guarantees is that non-SOEs in these sectors may ultimately be connected to the government. No matter what the explanation is, our empirical finding that the average non-SOE in infrastructure and real estate received preferential access to bank credit obtains.

[29]Similar to the finding in Figure 11, most of the stimulus effect was caused by the change in the monetary policy rule.

17, and 18, one can see that bank loans advanced to SOEs in infrastructure explain 60% of the increase in all the loans allocated to SOEs, while non-SOEs in manufacturing explain 40.4% of the increase in all the loans to non-SOEs. In contrast to the conventional view that monetary stimulus disproportionately reallocated bank credit to SOEs, we find that non-SOEs are quantitatively as important as SOEs in understanding the aggregate effects of monetary stimulus on credit allocation.

This finding cannot be extrapolated directly from the average (micro) effects discussed in the preceding section. The average effect captures the average increase in newly originated loans to individual firms, while the aggregate effect is the sum of the increase in newly issued loans over all individual firms. For each ownership type, the aggregate effect is influenced by both the intensive margin (the average effect) and the extensive margin (the number of firms receiving bank loans at a given time). In manufacturing, the average effect and the aggregate effect have opposite implications: the average effect shows that SOEs had easier access to bank loans than non-SOEs (top right panel of Figure 15), but aggregated bank loans to non-SOEs dominated those to SOEs. The divergence is explained by the difference between the intensive margin and the extensive margin. As Table 3 shows, more than 70% of all manufacturing firms with positive newly issued loans were non-SOEs in our sample, indicating that the aggregate effect in manufacturing was dominated by the extensive margin, not by the average effect.

Among all firms with positive newly originated loans in infrastructure, SOEs dominated non-SOEs in number. This extensive margin leads to a larger aggregate effect on loans to SOEs than non-SOEs. For real estate and others, the average effect and the aggregate effect point to the same direction because firms that enjoyed preferential credit access were also a majority of firms that obtained positive bank credit. In real estate, those firms are non-SOEs; in others, those firms are SOEs.

Our empirical results also shed light on how important LGFVs were in credit allocation during the stimulus period.[30] Figure 19 displays the aggregate effects on newly originated loans to LGFVs for the four sectors, together with the aggregate effects on loans to SOEs. As one can see, LGFVs are a dominating force in infrastructure but not in all other sectors. These heterogeneous effects across sectors again highlight our point that an exclusive focus on manufacturing or any particular sector does not give an accurate picture of credit allocation in the overall economy.

To sum up, we find that non-SOEs are quantitatively as important as SOEs in understanding the aggregate effects of monetary stimulus on credit allocation. Moreover, we find that the average effects of monetary stimulus on bank loans allocated to individual firms may not be used to infer the aggregate effects. In the manufacturing sector, which is a focal study in the existing literature, the average effects point to a direction opposite to the aggregate effects. In general, whether the average effect and the aggregate effect point to the same direction depends on how strong the extensive margin is.

[30]By definition, all LGFVs are SOEs.

IV.3. **Macroeconomic implications.** Overall, the 2009 monetary stimulus caused a 6.6% increase in newly originated bank loans as a percent of GDP during the stimulus period, which explains 70.4% of the 9.4% increase in the ratio of total bank loans to GDP (comparing the right panel of Figure 18 to Figure 2). Most of newly issued bank loans during the stimulus period were advanced to finance time-to-build investment. Although the stimulus effects on these loans (as a percent of GDP) faded away after 2011 as shown in the right panel of Figure 18, the impacts on both investment-to-GDP and debt-to-GDP ratios persisted. Despite an already high investment rate at the end of 2008, the 2009 monetary stimulus raised the investment-to-GDP ratio by almost 5% at its peak (left panel of Figure 20) and the loans-to-GDP ratio by as high as 28% (right panel of Figure 20).

Our empirical finding that both SOEs and non-SOEs contributed to overall stimulus effects on total bank credit bear important macroeconomic implications. According to the CEIC data, the share of non-SOEs in total fixed asset investment is 53% in 2009-2010. Thus, both SOEs and non-SOEs are equally important for the sharp increase in the investment-to-GDP ratio. Our bottom-up empirical findings from the micro loan data suggest that credit allocation to SOEs, in particular LGFVs, may contribute to investment in infrastructure, while credit allocation to non-SOEs may lead to investment in the real estate and manufacturing sectors.

Perhaps a graver situation arising from the 2009 monetary stimulus is the accumulation of long-term debts. As the persistence of the stimulus effects on *outstanding* loans depends on the speed of loan retirements, which is slow for long-term loans, the 2009 monetary stimulus had its own unintended consequence—an intertemporal tradeoff of short-term growth via investment and long-term indebtedness. This problem has prompted the Chinese government to initiate a painful deleverage process on both types of firms in recent years.

V. Conclusion

This paper uses a bottom-up approach with both micro and macro data to establish empirical evidence on the effects of monetary stimulus on the macroeconomy and credit allocation across various key sectors and across different types of firms. To this end, we construct a proprietary micro dataset covering all newly issued bank loans by the 19 largest Chinese banks to individual firms that spans all sectors in the Chinese economy, including manufacturing, infrastructure and real estate. We carefully distinguish the average effects of monetary stimulus on individual firms of different ownership types from the aggregate effects of monetary stimulus on credit allocation between SOEs and non-SOEs.

Using the macro time series, we find that the 2009 monetary stimulus contributed to a temporary 3.1% increase of GDP growth, which accounts for 65% of the actual increase in GDP growth during this period. Higher GDP growth was achieved by a sharp increase in aggregate investment, not aggregate consumption, and by an increase mostly in long-term bank loans, rather than short-term loans. Using the micro data, we show heterogeneous patterns regarding the preferential credit access by individual firms under the monetary stimulus: while the average SOE in manufacturing sector enjoyed preferential bank credit, the opposite is true for real estate, and there is no obvious preferential credit in infrastructure. Moreover, we show that, due to a larger aggregate effect on bank loans to non-SOEs than to SOEs in manufacturing and real estate, at the aggregate level, credit allocation to non-SOEs were as important as that to SOEs. Our findings of credit allocation underlies an intertemporal tradeoff between short-run growth and long-term indebtedness in response to large monetary interventions.

Methodologically, we provide a two-stage empirical framework comprised of both a macro SVAR model and a dynamic panel model to estimate the average and aggregate effects of monetary stimulus from micro data. We impose minimal identifying restrictions on the macro model, and develop a computational strategy that separates estimation of the monetary policy equation from that of the rest of the system. This development makes it practical for one to quantify the dynamic impacts of monetary stimulus within the endogenous-switching framework. Our new econometric framework can be used to study the transmission mechanism of large or unconventional interventions by the monetary authorities in other countries.

TABLE 1. Share (%) of bank loans to SOEs in various key sectors from the micro loan data

Average	Manufacturing	Infrastructure	Real estate	Others	Aggregate
2008Q1-2008Q4	35.3	61.3	10.7	68.8	50.6
2009Q1-Q3	40.0	63.5	14.5	73.2	55.0
2009Q4-2010Q4	36.3	59.8	13.7	60.3	47.7
2007Q1-2013Q2	32.6	57.6	12.1	56.2	45.7

TABLE 2. The net increase during the monetary stimulus period (2009Q1-Q3) and the post-stimulus period (2009Q4-2010Q4) from the 2008Q1-Q4 average of bank loans to SOEs and non-SOEs in various key sectors from the micro loan data: 100 million RMB

Bank loans to	Manufacturing	Infrastructure	Real estate	Others	Aggregate
	2009Q1-Q3 (average)				
SOEs	658.1	2447.4	135.0	1268.3	4509.0
Non-SOEs	872.4	1308.5	733.4	441.7	3356.2
All firms	1530.5	3755.9	868.4	1710.0	7865.2
	2009Q4-2010Q4 (average)				
SOEs	402.9	1326.4	146.7	492.8	2368.9
Non-SOEs	667.0	978.9	814.3	391.2	2851.3
All firms	1069.9	2305.3	961.0	884.0	5220.2

TABLE 3. Share (%) of the number of SOEs in the total number of firms with positive bank loans in various key sectors

Average	Manufacturing	Infrastructure	Real estate	Others	Aggregate
2008Q1-2008Q4	27.7	56.8	10.2	69.2	43.0
2009Q1-Q3	29.4	57.7	11.6	69.8	43.5
2009Q4-2010Q4	25.6	52.4	10.1	63.4	37.6
2007Q1-2013Q2	25.0	51.5	10.8	62.9	38.8

Table 4. Variance decomposition attributed to a monetary policy shock (percent)

Quarter	4	8	12	16	20
	GDP (normal state)				
Benchmark model	13.7	19.5	20.2	18.9	17.1
Benchmark model excl Rs	12.7	18.3	20.1	20.0	18.7
Benchmark model excl FXR	14.7	20.5	21.4	20.3	18.5
Benchmark model excl Rs and FXR	12.8	18.2	20.1	20.1	19.2
	GDP (shortfall state)				
Benchmark model	36.4	44.3	45.0	43.4	40.9
	Benchmark model (normal state)				
CPI	0.4	2.1	4.2	6.0	7.2
Total bank loans	24.6	23.0	22.7	22.8	23.3
ST bank loans	5.8	4.2	3.3	3.0	3.2
Investment	13.4	16.1	15.8	15.0	14.2
Consumption	0.4	1.4	2.4	3.1	3.5

Note. The abbreviation "excl" stands for excluding, "Rs" for all interest rates, and "FXR" for foreign exchange reserves.

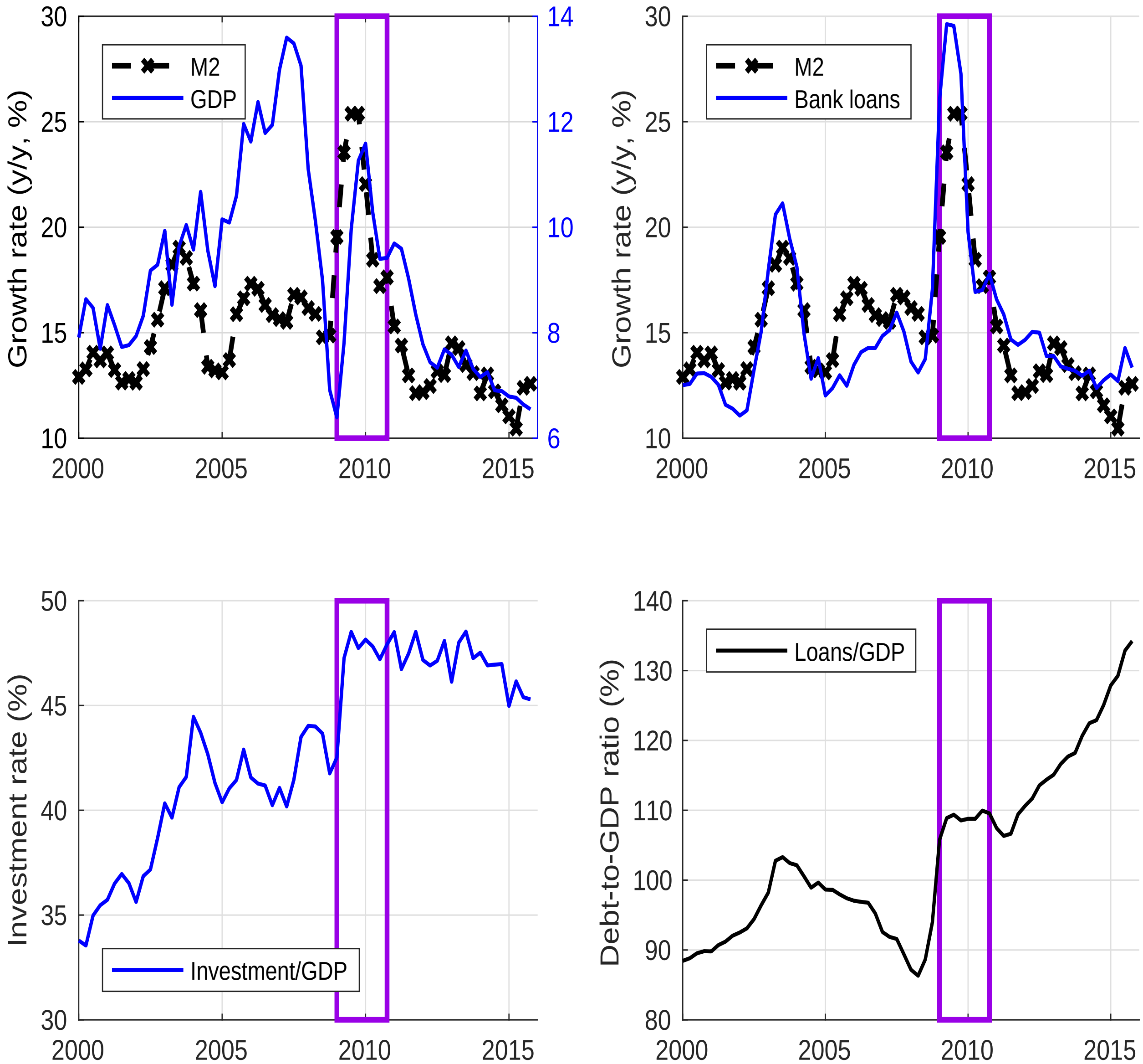

FIGURE 1. Macroeconomic time series. *Notes*: In the upper left panel of the figure, the scale for GDP growth is to the right and the scale for M2 growth is to the left. Unless specified explicitly, quarterly GDP discussed in the paper is not annualized as is typically done in the U.S. data. The rectangular box in each graph marks the period from 2009Q1 to 2010Q4. This is different from the stimulus period 2009Q1-Q3. At the end of 2008, China's State Council announced a plan to invest 4 trillion RMB over this period in an attempt to minimize the impact of the global financial crisis on its economy.

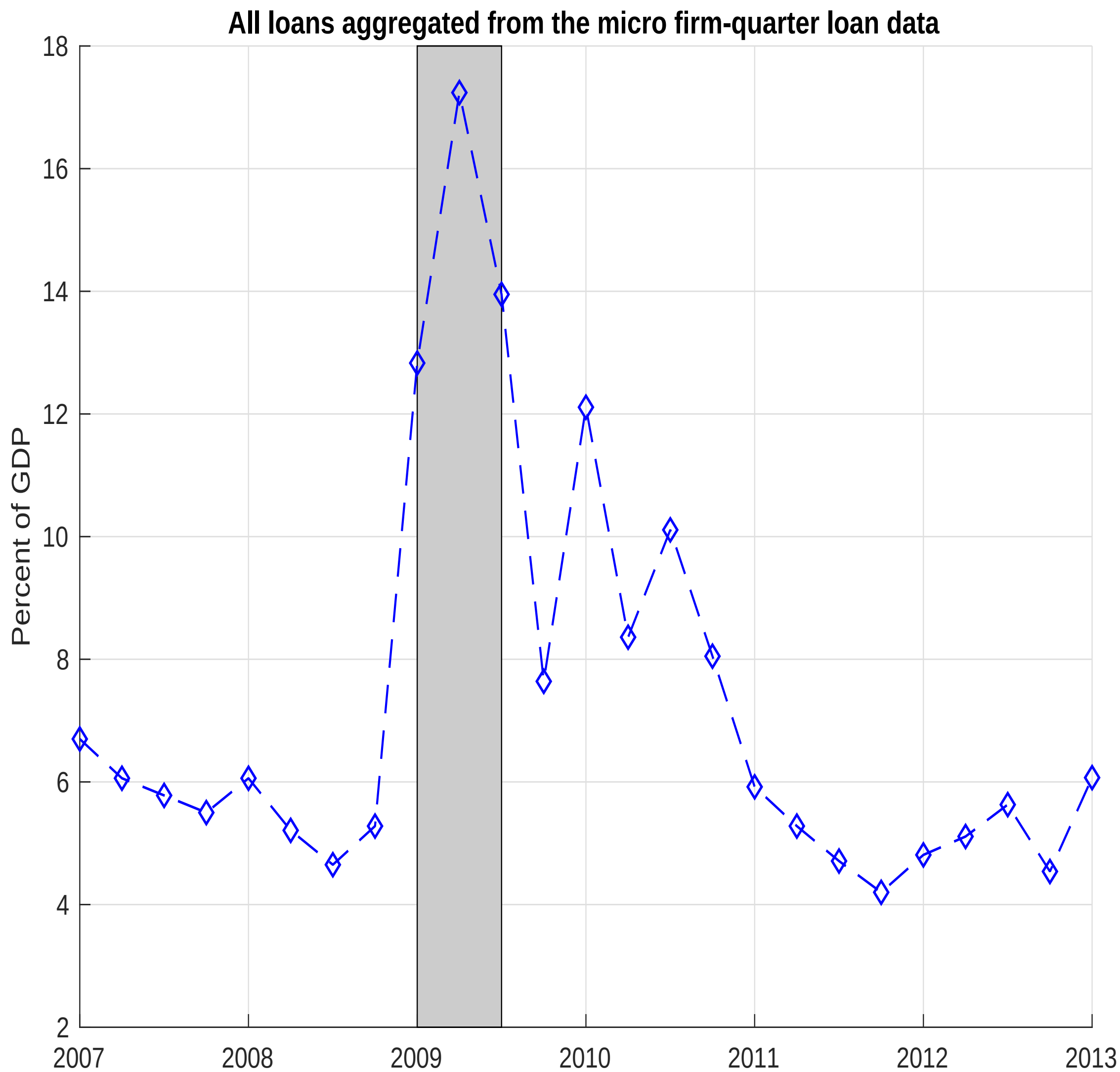

FIGURE 2. Quarterly series of aggregated bank loans as a percent of GDP prior to and after the stimulus period. *Notes*: The aggregated volume of bank loans sums all the firm-level loans from the micro data. The shaded bar marks the period of 2009Q1-Q3 during which the monetary policy rule was changed to be more stimulative.

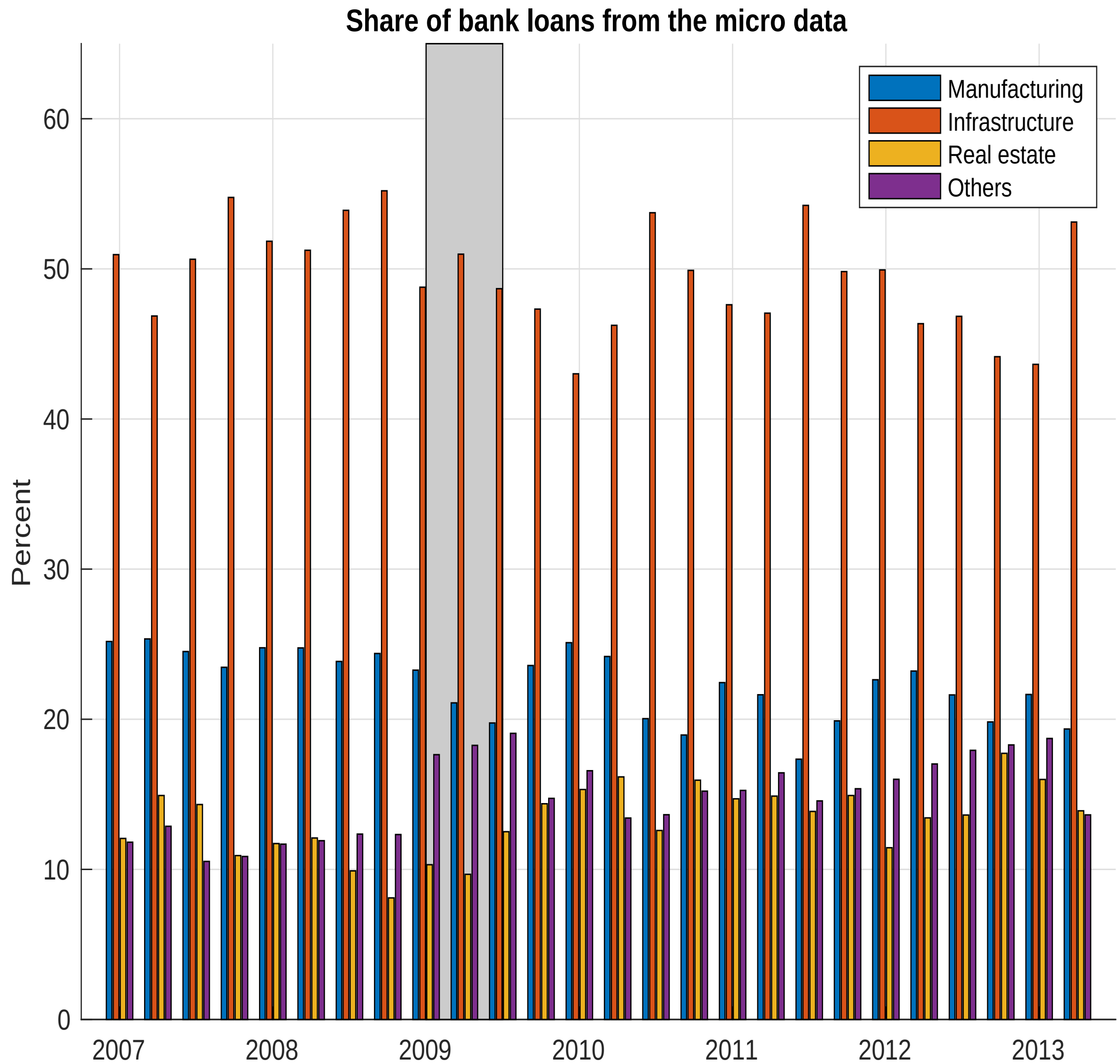

FIGURE 3. Share of bank loans allocated to the four key sectors in 2007-2013 from the micro loan data. *Notes*: The wide shaded bar marks the period of 2009Q1-Q3 during which the monetary policy rule was changed to be more stimulative.

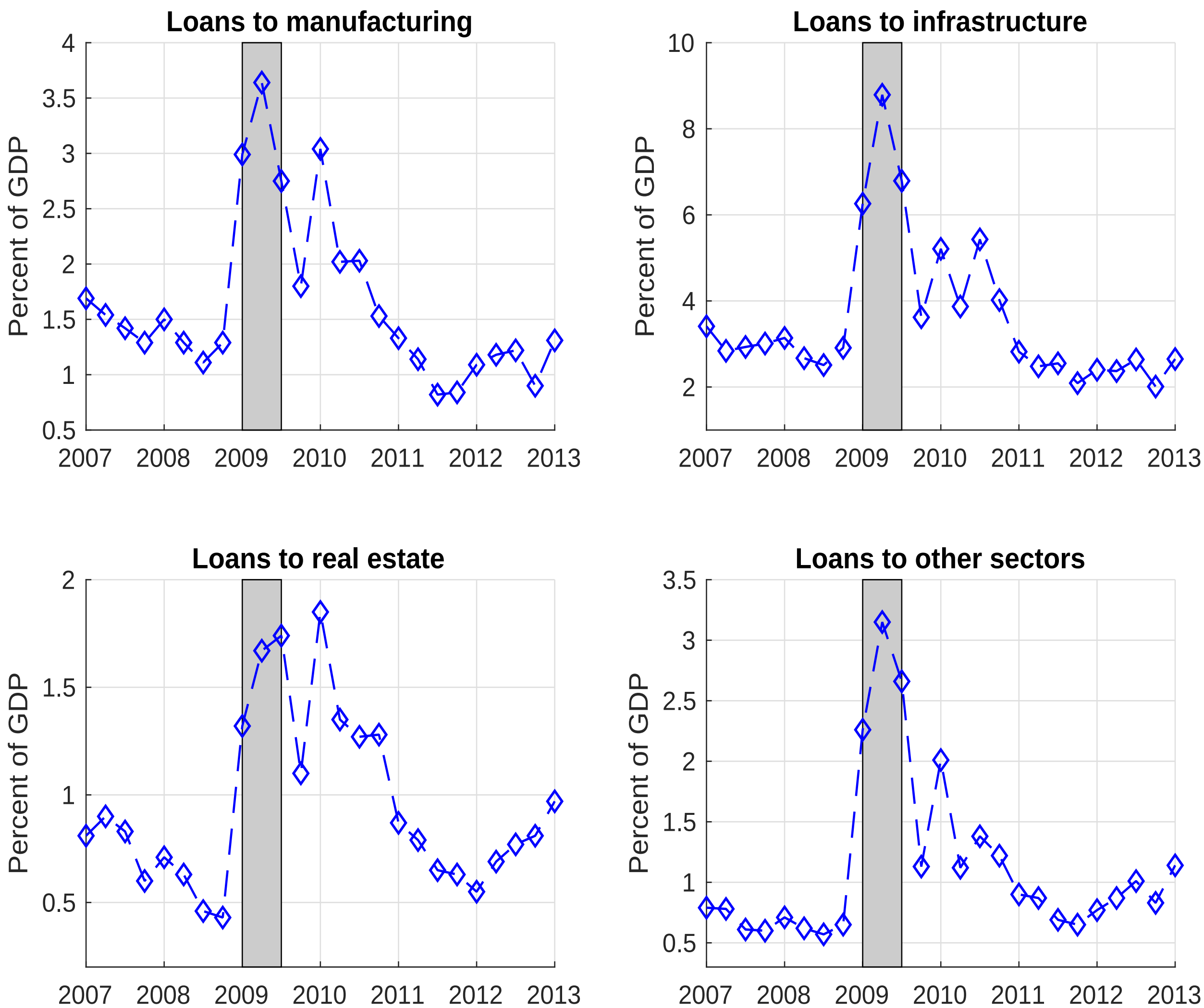

FIGURE 4. Quarterly series of bank loans, as percent of GDP, that were allocated to various key sectors prior to and after the stimulus period. *Notes*: These time series are aggregations of all firm-level loans from the micro data. The shaded bars mark the period of 2009Q1-Q3 during which the monetary policy rule was changed to be more stimulative.

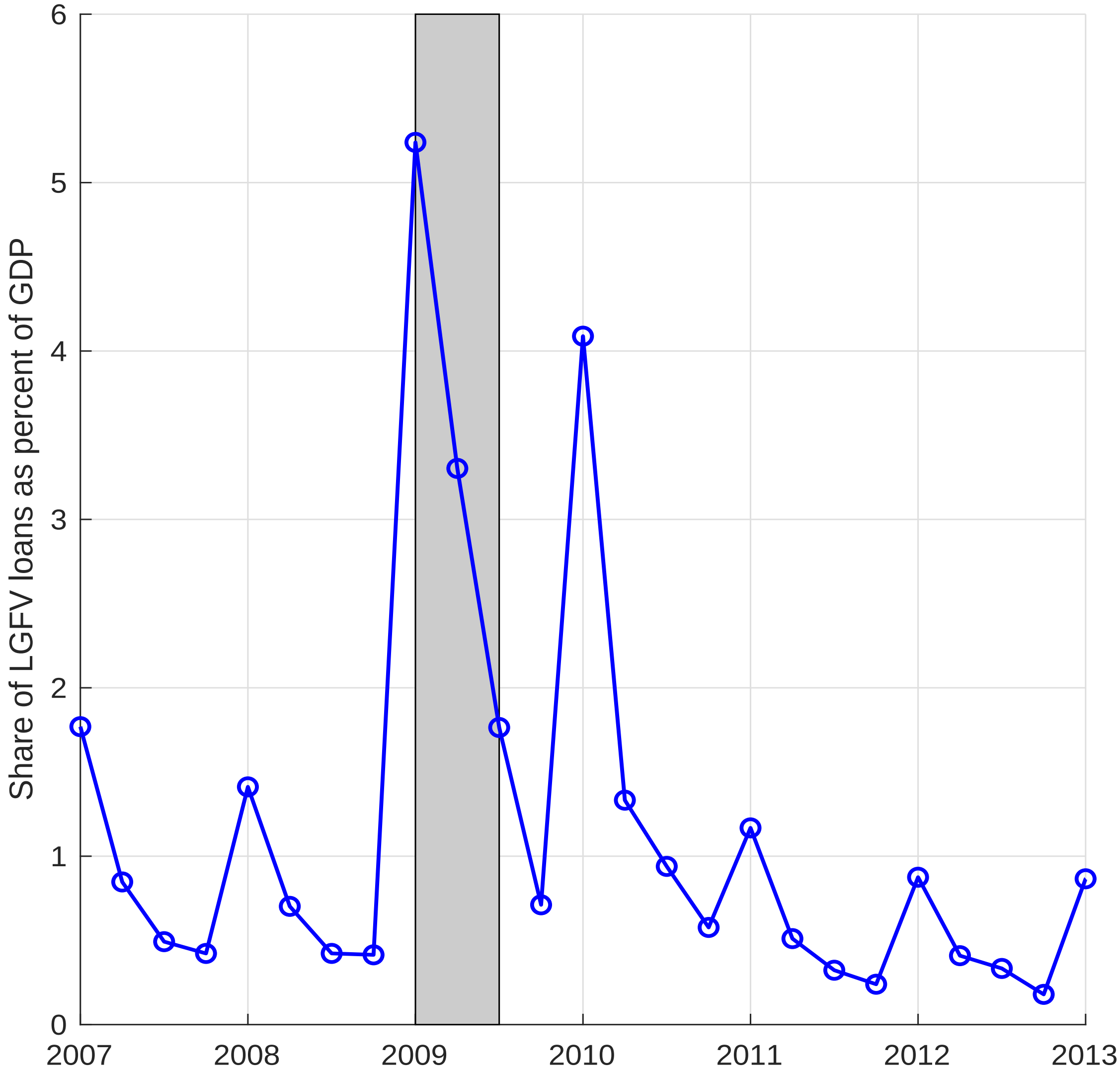

FIGURE 5. Share of bank loans to LGFVs as a percent of GDP in 2007-2013 from the micro loan data. *Notes*: The shaded bar marks the period of 2009Q1-Q3 during which the monetary policy rule was changed to be more stimulative.

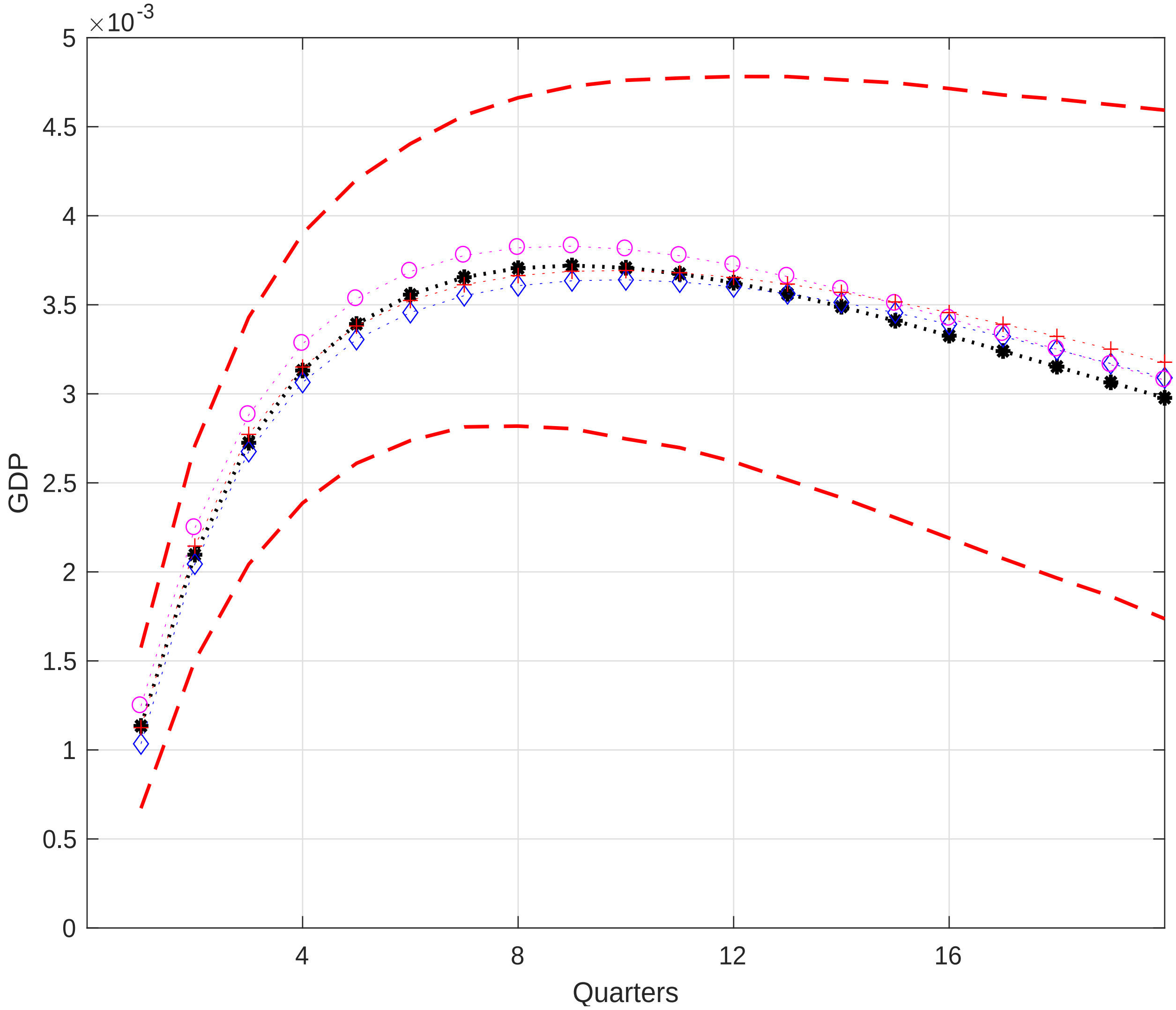

Figure 6. Dynamic responses of real GDP to a one-standard-deviation positive monetary policy shock in the normal state. *Notes*: The asterisk line represents the response estimated from the benchmark model and dashed lines represent the corresponding .68 probability bands. The diamond line represents the response estimated from the model excluding interest rates. The circle line represents the response estimated from the model excluding foreign exchange reserves. The plus line represents the response estimated from the model excluding both interest rates and foreign exchange reserves.

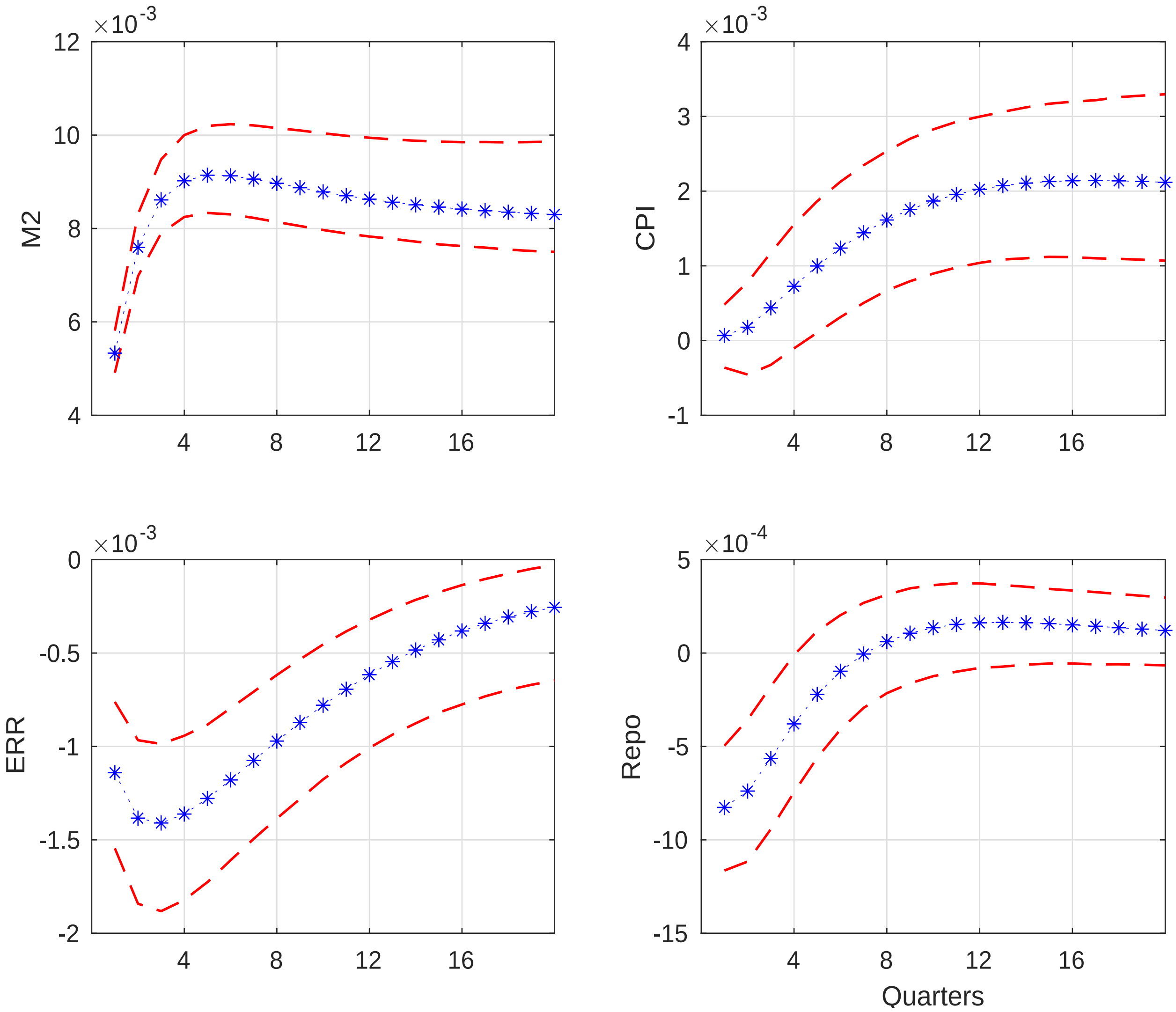

Figure 7. Dynamic responses of various key policy variables to a one-standard-deviation positive monetary policy shock in the normal state. *Notes*: Asterisk lines represent the estimated responses and dashed lines represent the corresponding .68 probability bands. "ERR" stands for the excess reserves ratio in the banking system, and "Repo" is the 7-day rate for national interbank bond repurchases.

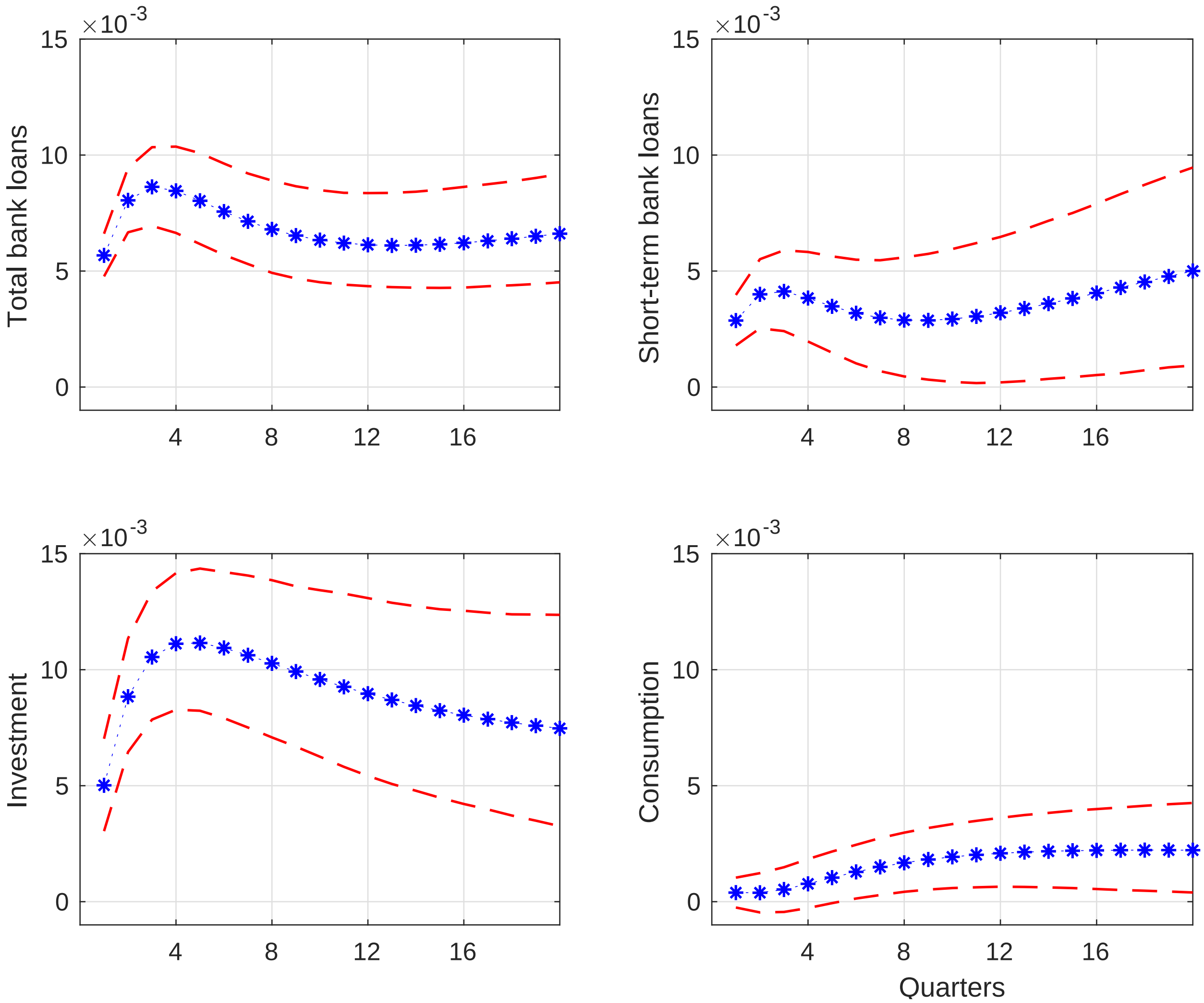

FIGURE 8. Dynamic responses to a one-standard-deviation positive monetary policy shock in the normal state: bank loans, investment, and consumption. *Notes*: Asterisk lines represent the estimated responses and dashed lines represent the corresponding .68 probability bands.

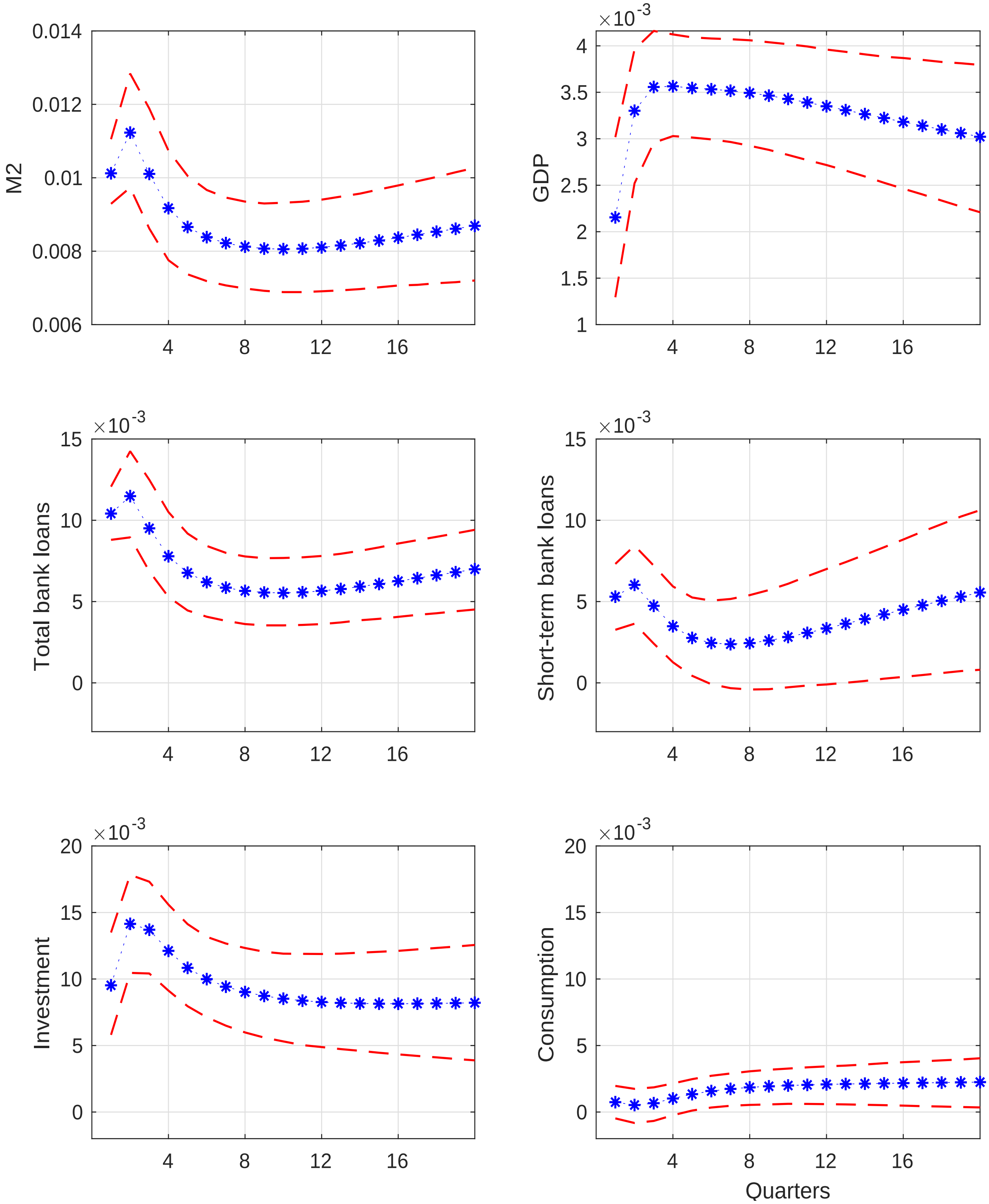

FIGURE 9. Dynamic responses to a one-standard-deviation positive monetary policy shock in the shortfall state. *Notes*: Asterisk lines represent the estimated responses and dashed lines represent the corresponding .68 probability bands.

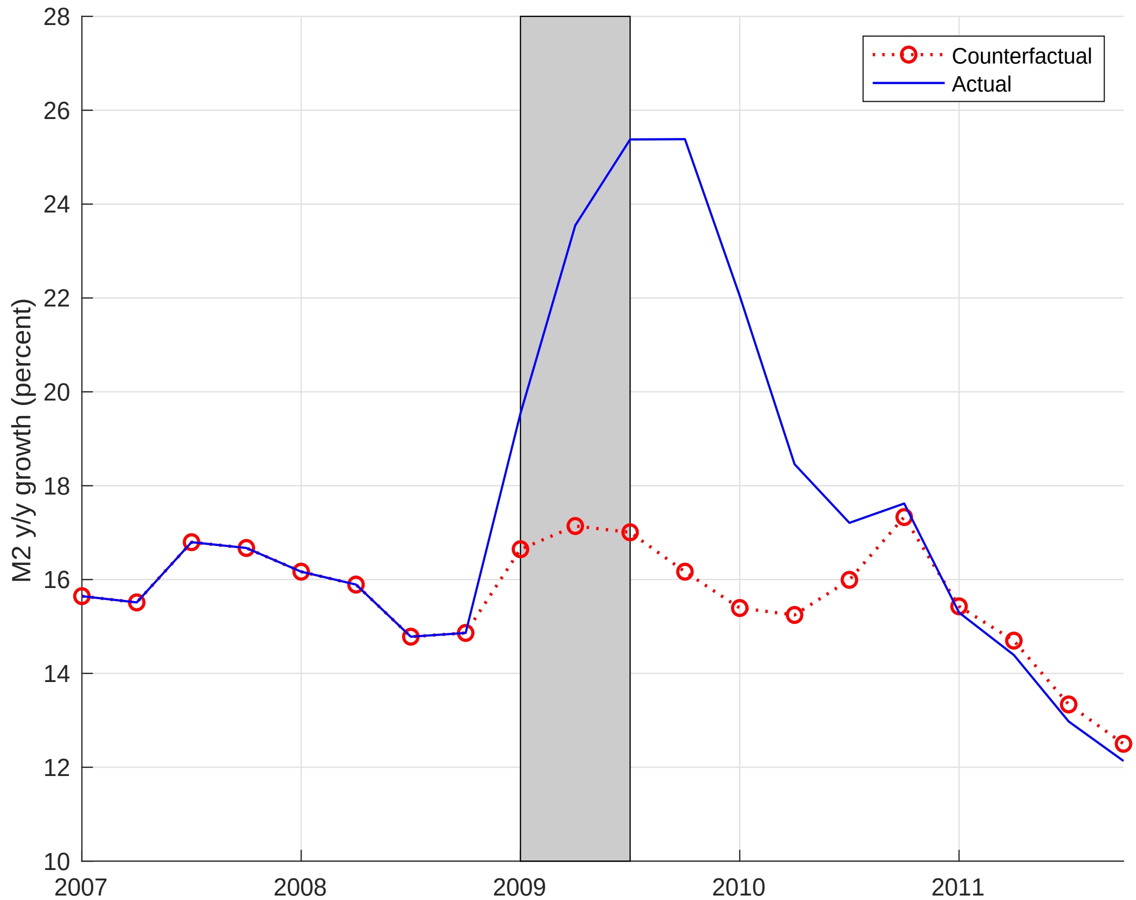

Figure 10. Actual and counterfactual historical paths of M2 year-over-year (y/y) growth rates. *Notes*: The shaded bar marks the period of 2009Q1-Q3 during which the monetary policy rule was changed to be more stimulative. The counterfactual path assumes that monetary policy had not changed during this stimulation period.

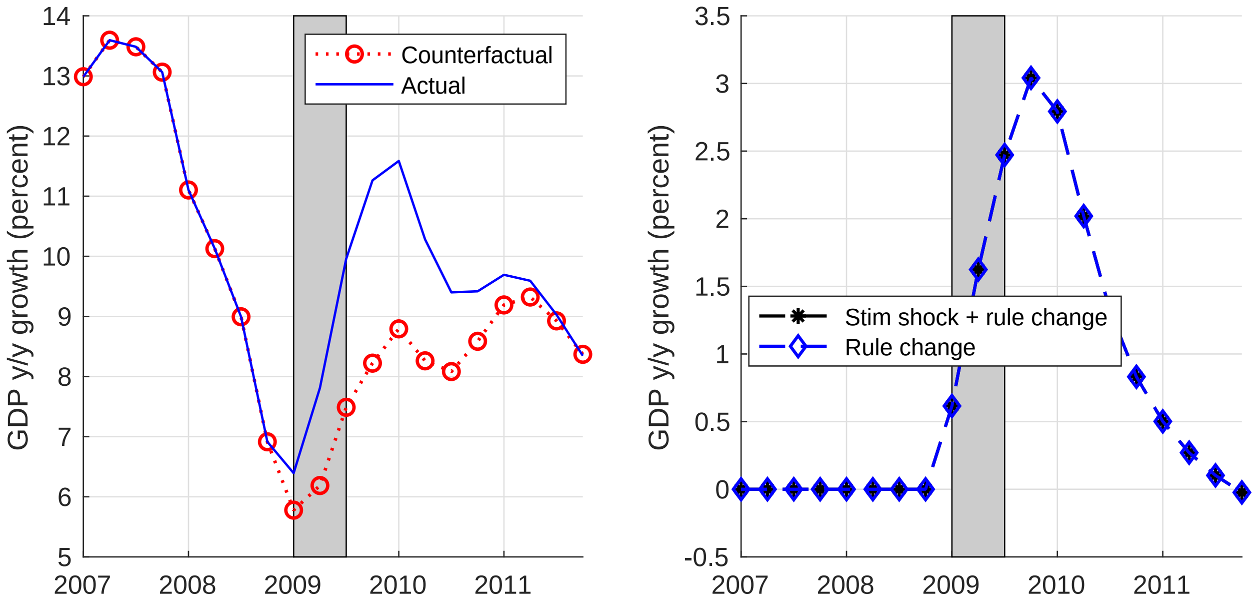

FIGURE 11. Actual and counterfactual historical paths of GDP year-over-year (y/y) growth rates. *Notes*: The shaded bar marks the period of 2009Q1-Q3 during which the monetary policy rule was changed to be more stimulative. The counterfactual path assumes that monetary policy had not changed during this stimulus period. The diamond line in the right panel indicates the contribution from the change in the monetary policy rule. The extra stimulus from monetary policy shocks added little more impact to the effect of the policy rule change.

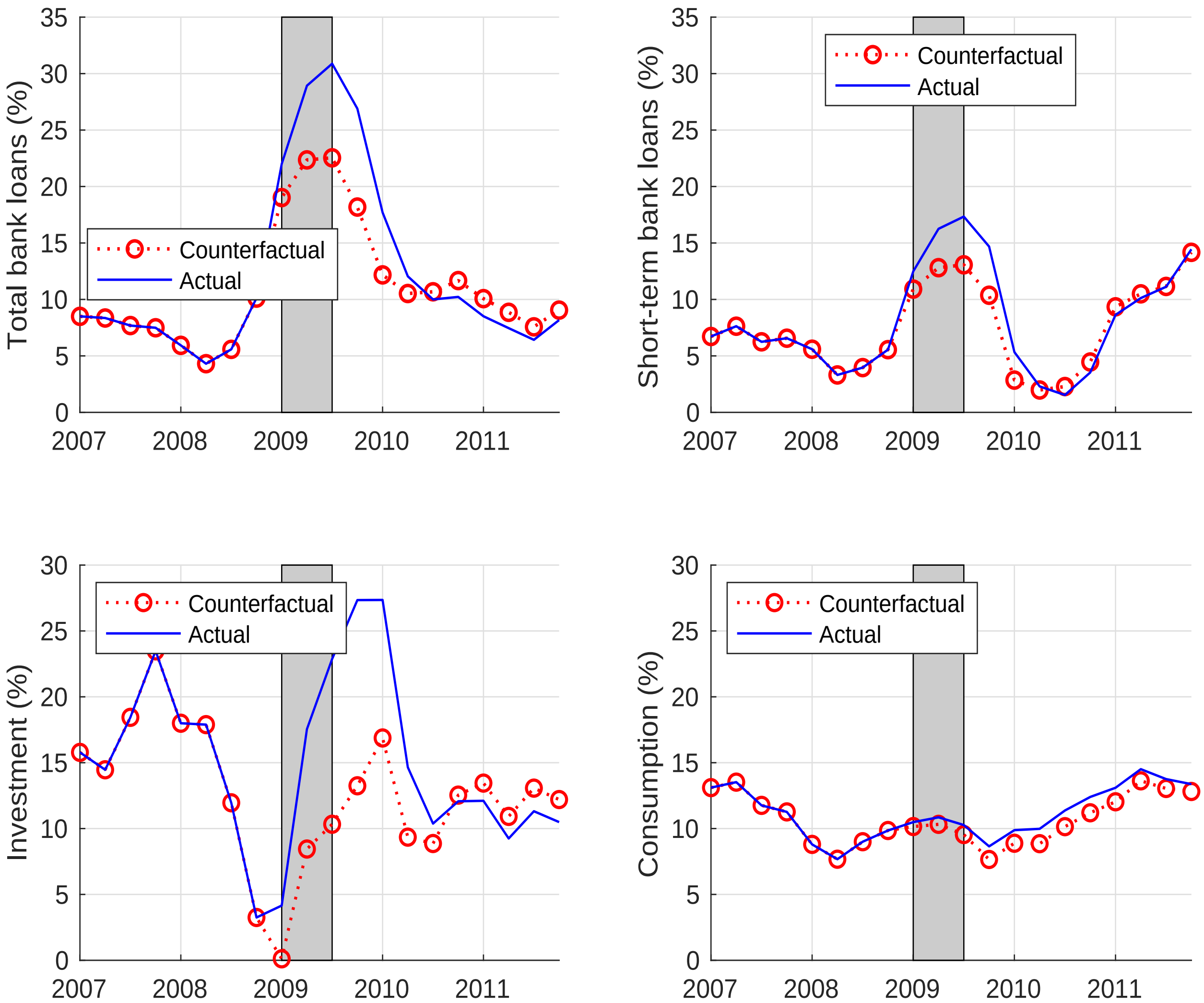

FIGURE 12. Actual and counterfactual historical paths of year-over-year growth rates of bank loans, investment, and consumption. *Notes*: The shaded bars mark the period of 2009Q1-Q3 during which the monetary policy rule was changed to be more stimulative. The counterfactual path assumes that monetary policy had not changed during the stimulus period.

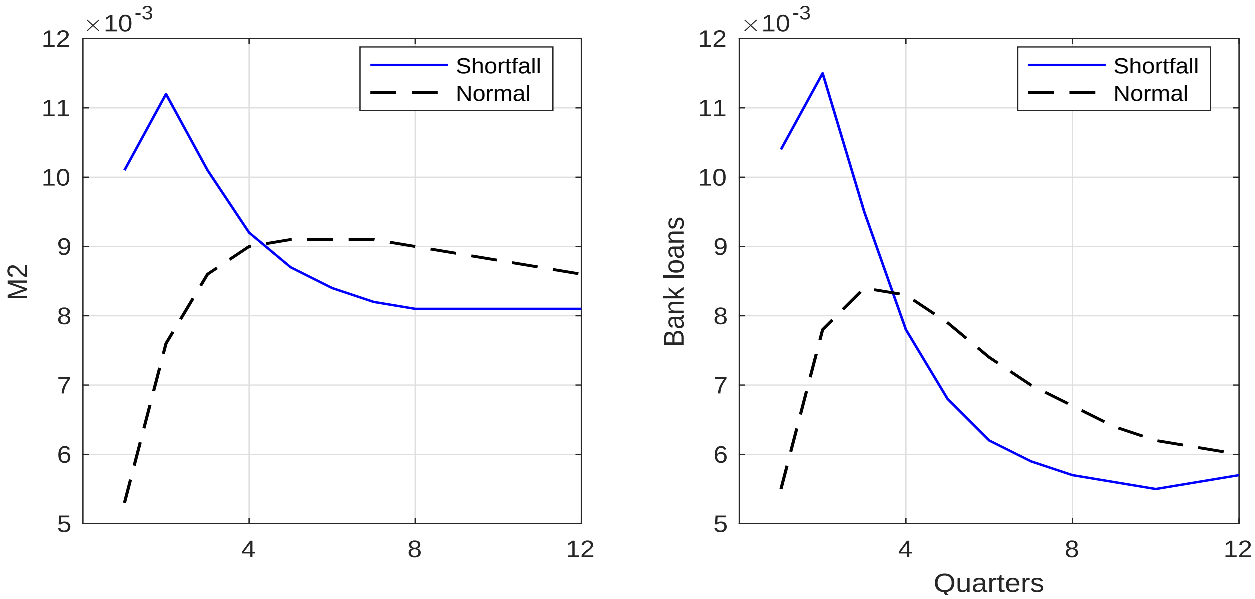

FIGURE 13. Impulse responses of M2 and bank loans to an expansionary monetary policy shock in the normal and shortfall states.

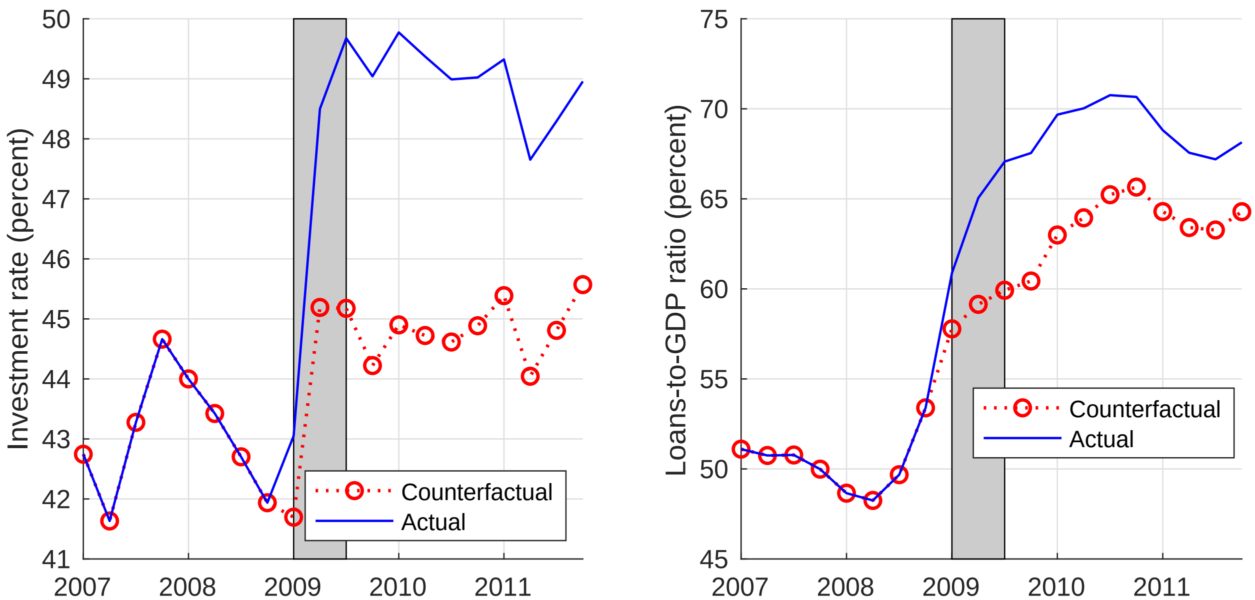

FIGURE 14. Actual and counterfactual historical paths of the investment-to-GDP ratio and the debt-to-GDP ratio (the ratio of medium and long term bank loans outstanding to annualized GDP). *Notes*: The shaded bars mark the period of 2009Q1-Q3 during which the monetary policy rule was changed to be more stimulative. The counterfactual path assumes that monetary policy had not changed during the stimulus period.

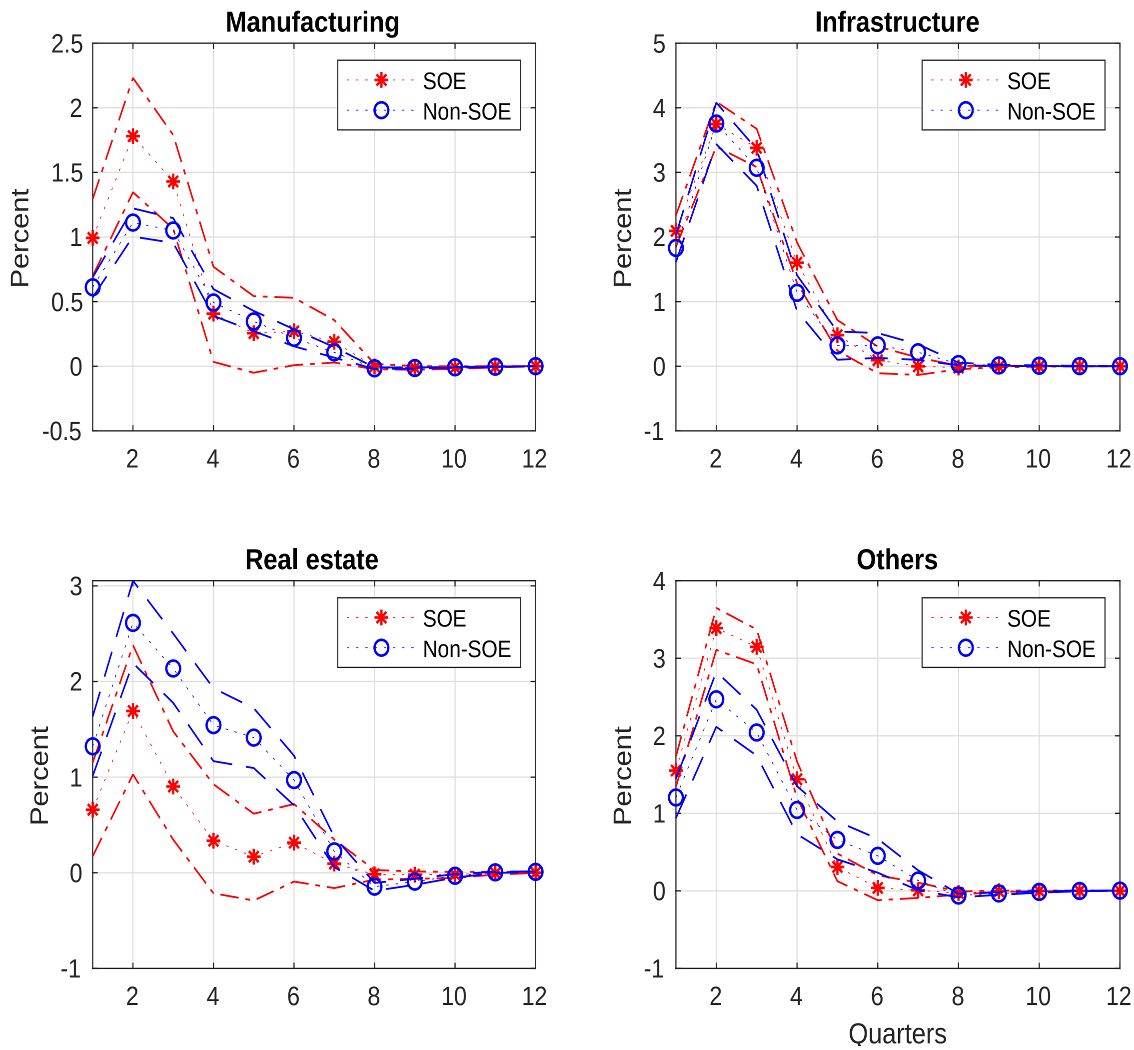

FIGURE 15. Firm-level dynamic effects on bank loans to the average SOE firm and the average non-SOE firm in response to monetary policy changes. *Notes*: The responses, estimated with the econometric method described in Section I.2 to the firm-quarter data, are expressed as percentage changes from the initial quarter (quarter 0). Dashed lines represent the corresponding .90 probability bands for non-SOEs and dash-dotted lines for SOEs.

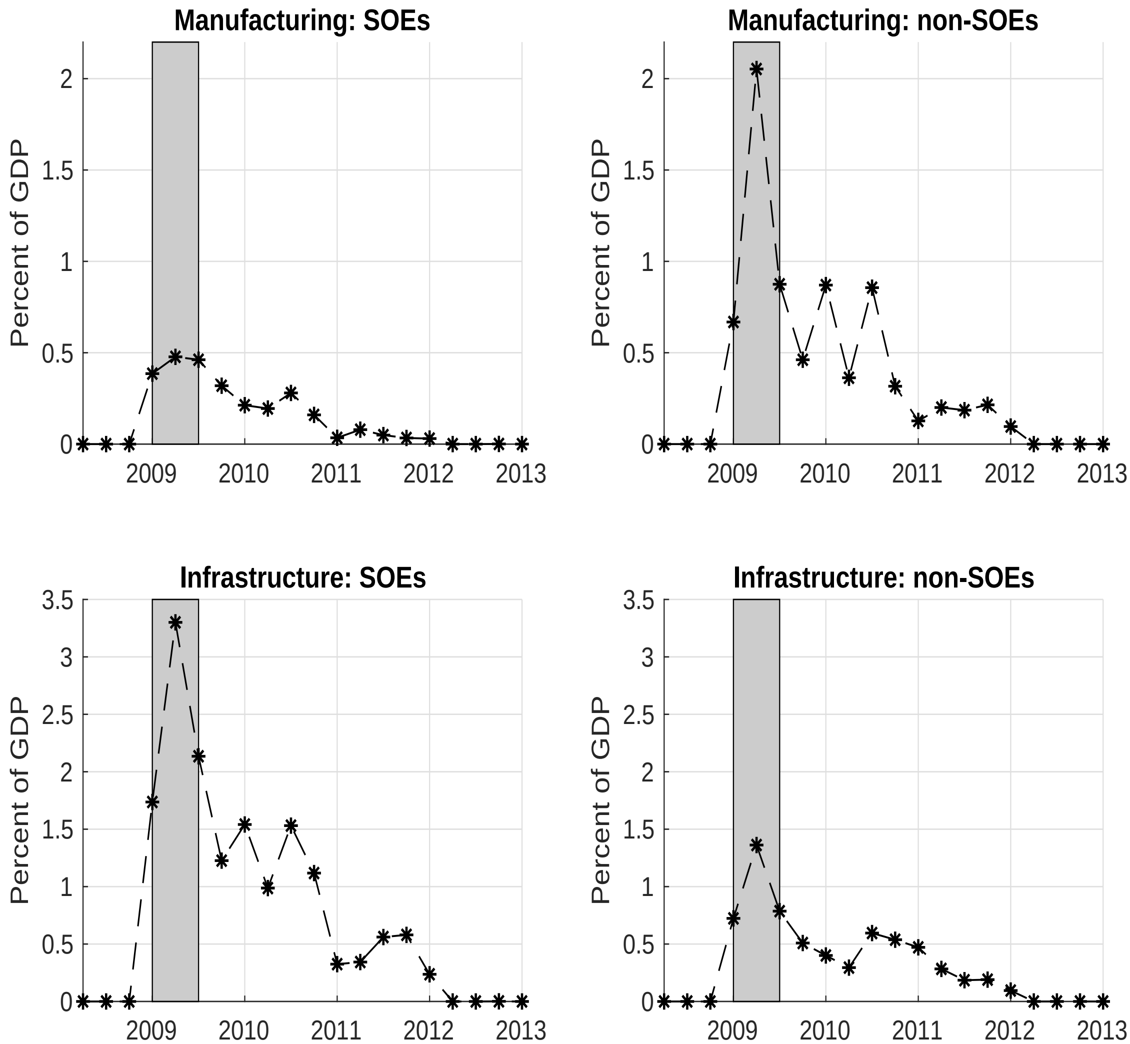

FIGURE 16. Stimulus effects on bank loans to SOEs and non-SOEs. *Notes*: The asterisk lines represent the effect of monetary policy changes during 2009Q1-Q3. The shaded bars mark the period of 2009Q1-Q3 during which the monetary policy rule was changed to be more stimulative.

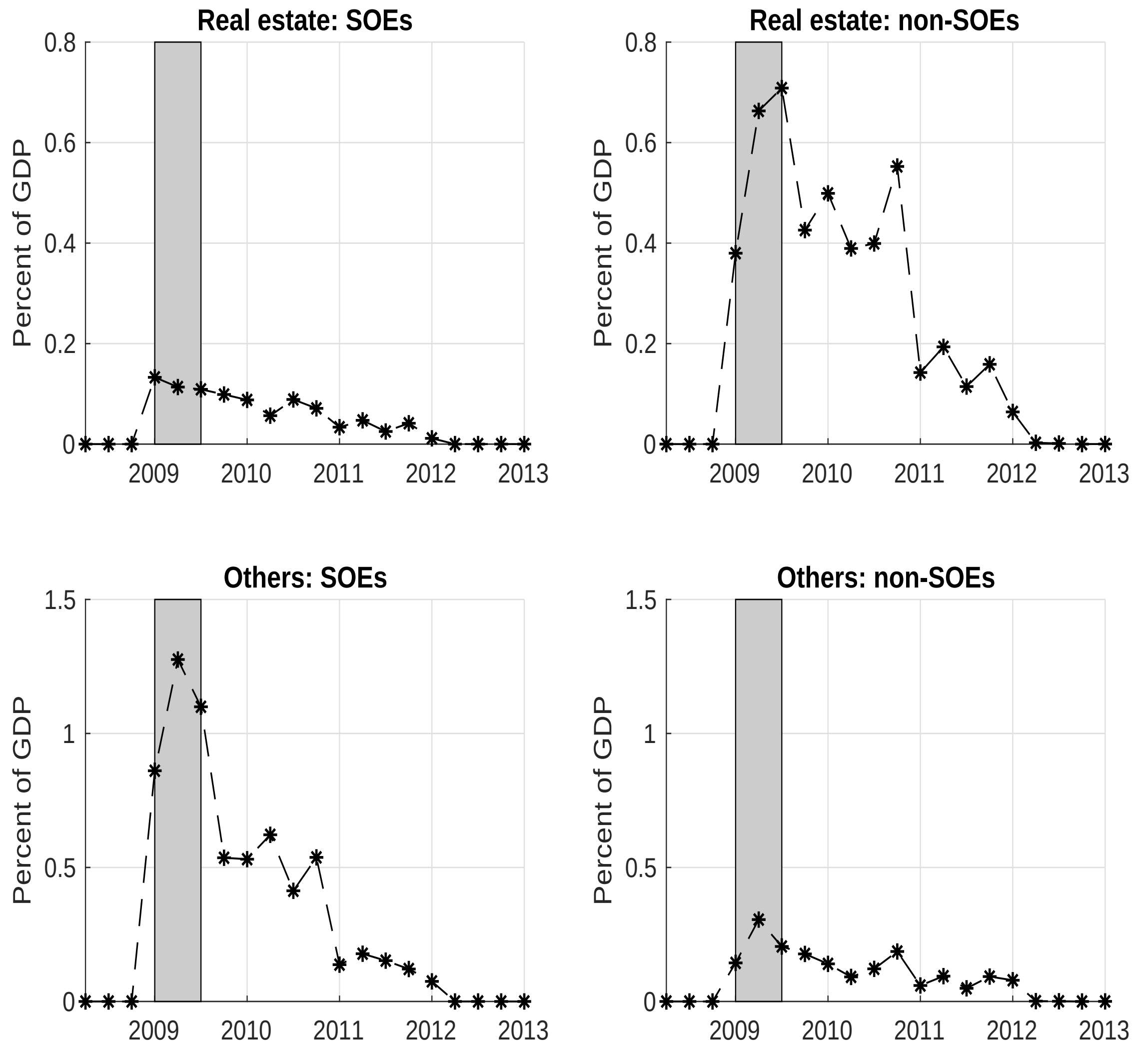

Figure 17. Stimulus effects on bank loans to SOEs and non-SOEs. *Notes*: The asterisk lines represent the effect of monetary policy changes during 2009Q1-Q3. The shaded bars mark the period of 2009Q1-Q3 during which the monetary policy rule was changed to be more stimulative.

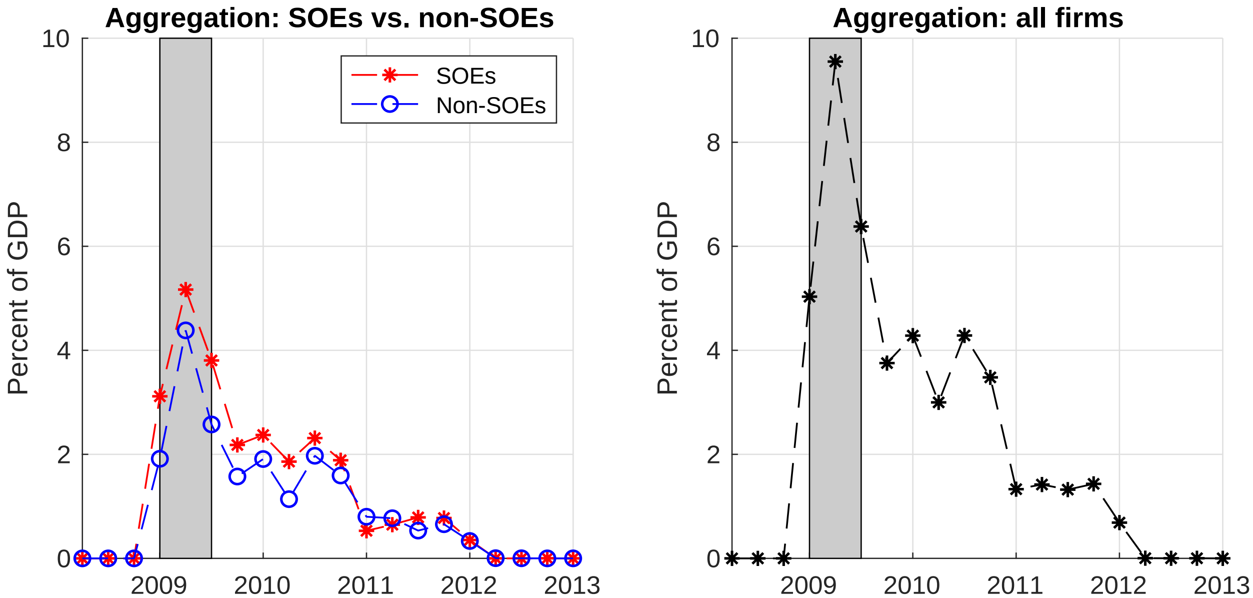

FIGURE 18. Aggregate stimulus effects on bank loans to SOEs and non-SOEs as well as on bank loans to all firms in the economy. *Notes*: The asterisk and circled lines represent the effect of monetary policy changes during 2009Q1-Q3. The shaded bars mark the period of 2009Q1-Q3 during which the monetary policy rule was changed to be more stimulative.

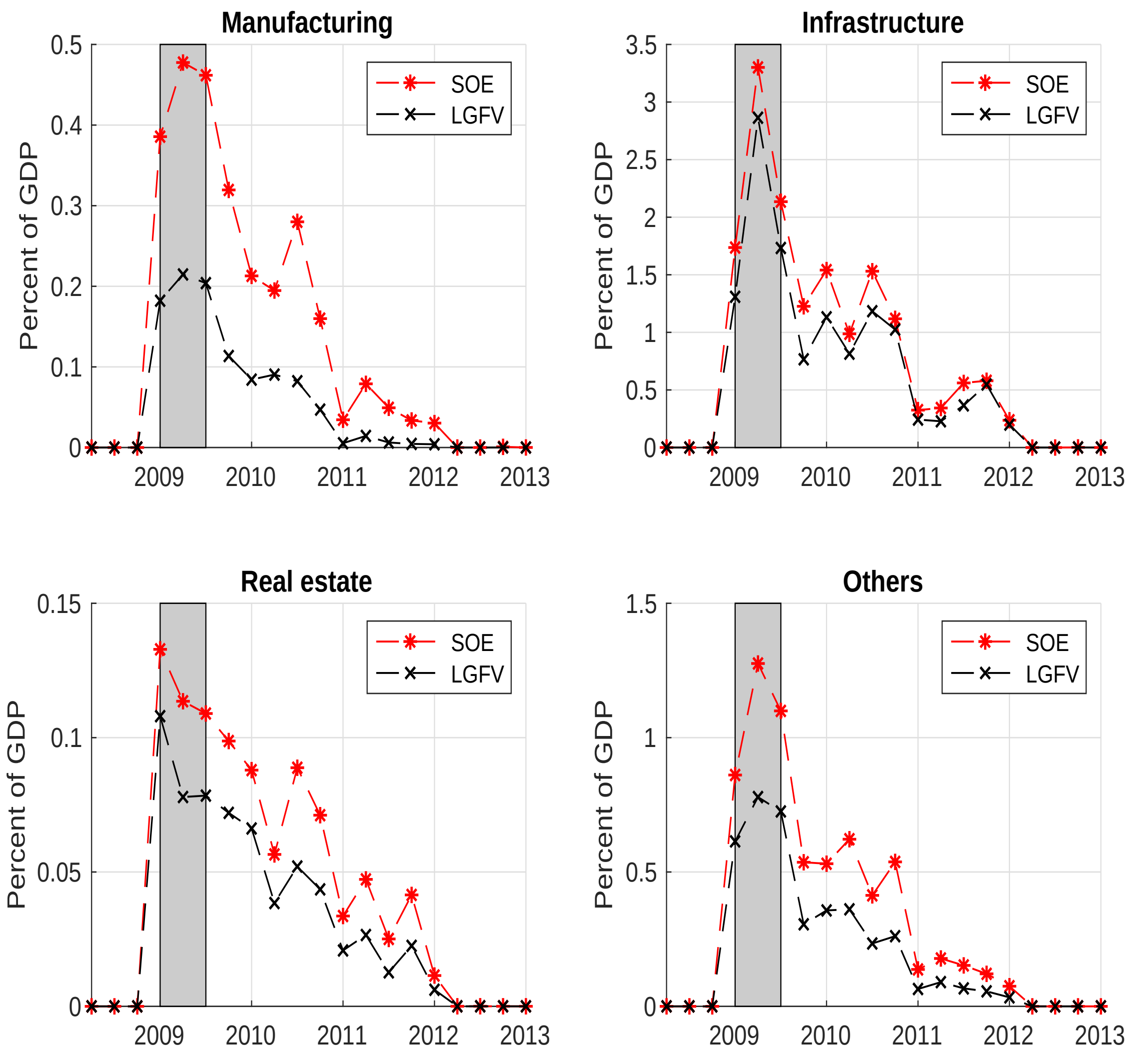

FIGURE 19. Stimulus effects on bank loans to LGFVs. The asterisk lines represent the aggregate effect of monetary policy changes on SOEs loan. The cross lines represent the contribution from LGFVs. The shaded bars mark the period of 2009Q1-Q3 during which the monetary policy rule was changed to be more stimulative.

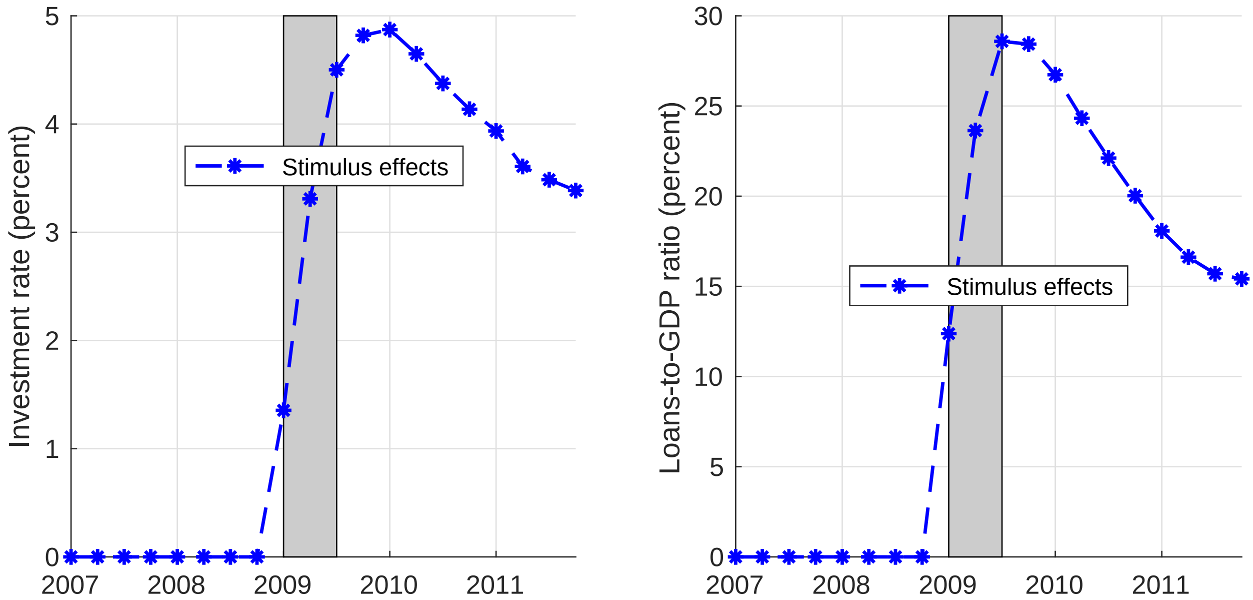

Figure 20. Stimulus effects on the investment-to-GDP ratio and the debt-to-GDP ratio (the ratio of medium and long term bank loans outstanding to quarterly GDP). *Notes*: In comparison to Figure 14, quarterly GDP is used for calculating the debt-to-GDP ratio. The shaded bars mark the period of 2009Q1-Q3 during which the monetary policy rule was changed to be more stimulative.

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Appendix A. Description of macro time series

The methodology of collecting and constructing the quarterly data series used in this paper is based on Higgins and Zha (2015) and Chang, Chen, Waggoner, and Zha (2016). The details of constructing all the series except M2, bank loans, and land prices are described in these two references. The main data sources are China's National Bureau of Statistics, the People's Bank of China, and CEIC. The proc X-12 procedure in the SAS software package is used for seasonal adjustment. To be compatible with the existing macro literature, all series bar interest and exchange rates are seasonally adjusted. All interpolated series are based on the method of Fernandez (1981), as described in Higgins and Zha (2015). One exception is net exports, which are interpolated with the method of Denton (1971). We provide, below, detailed descriptions of the macro variables used in the main text as well as in supplemental appendices.

- **M2**. M2 money supply, quarterly average of the monthly series (billions of RMB). For the last monthly observation, we use the level of M2 (CEIC ticker CKSAAC). The 12 monthly observations prior to the last observation are constructed recursively from the month-over-month gross growth rates of CKSAAC each multiplied by a constant adjustment factor. The adjustment factor is chosen so that the 12-month growth rate of the last observed value of our constructed series is equal to the last published 12-month growth rate (CEIC ticker CKSAACA). Once these last 13 observations are determined, we recursively construct the level series back to 1996M4 with the published year-over-year growth rate, back to 1994M12 with the year-over-year growth rate provided by the PBC, and back to 1990M3 with an interpolated year-over-year growth rate derived from the quarterly level of M2 (CEIC ticker CKAAC).
- **GDP**. Real GDP by value added (billions of 2008 RMB).
- **GDP growth target**. Real GDP growth target set by the central government of China.
- **CPI**. Consumer price index.
- **Investment price**. The price index of fixed asset investment.
- **ERR**. Excess reserves ratio computed as the ratio of excess reserves to total deposits in the banking system at the end of the quarter.
- **ARR**. Actual reserves ratio computed as the ratio of total reserves to total deposits in the banking system at the end of the quarter.
- **Lending rate**. One-year benchmark lending rate for commercial banks, set by the PBC, quarterly average.
- **Deposit rate**. One-year benchmark deposit rate at commercial banks for enterprises, set by the PBC, quarterly average.
- **Repo rate**. The 7-day market rate for national interbank bond repurchases, quarterly average.
- **Chibor rates**. The 1-day and 7-day China interbank offered rates, quarterly average.

- **Bank loans**. End-of-quarter financial institution loans outstanding (i.e., the third monthly observation of each quarter, RMB billion). We construct this series all the way back to 1978Q4 prior to seasonal adjustment. The last monthly observation is taken from the CEIC ticker CKSAC. The 12 monthly observations prior to the last observation are constructed recursively from the month-over-month gross growth rates of CKSAC each multiplied by a constant adjustment factor. The adjustment factor is chosen so that 12-month growth rate of the last observed value of our constructed series is equal to the last published 12-month growth rate (CEIC ticker CKSAD). Once these last 13 observations are determined, we recursively construct the level series back to 1997M4 with the published year-over-year growth rates. We then use data from WIND to backcast the series prior to 1997M4, assuming that the ratio of the series from WIND to our series prior to 1997M4 is the same as it is in 1997M4.
- **ST bank loans**. Short-term (ST) bank loans outstanding with the third monthly observation of each quarter (RMB billion). The constructed series goes back to 1994Q1. Multiplying the bank loans series by the ratio of CEIC ticker "CKAHLA–CN: Loan: Short Term" to CEIC ticker "CKSAC–CN: Loan", we construct the monthly level series. The series prior to 1999M1 is extrapolated with the WIND data on short-term bank loans using the same ratio extrapolation method as the construction of the bank loans series.
- **FXR**. Foreign exchange reserves (RMB billion).
- **Exchange rate**. The spot RMB/US$ exchange rate, quarterly average of the monthly series from the Federal Reserve Board.
- **Net exports**. Nominal net exports as a percentage of nominal GDP. Annual measure from national domestic product is interpolated by seasonally adjusted quarterly U.S. dollar series from General Administration of Customs converted to RMB.
- **Investment**. Gross capital formation based on the expenditure side of national domestic product interpolated by fixed-asset investment and deflated by the investment price index. The U.S. counterpart of this series is gross private domestic investment, except our Chinese series includes government and SOE investment.
- **Consumption**. Household consumption based on the expenditure side of national domestic products, interpolated quarterly by retail sales of consumer goods and deflated by the CPI. This series includes consumer durable goods.

Appendix B. Proof of Proposition 1

For system (4), we first show that the first equation (the monetary policy equation) is identified. According to Theorem 2 of Rubio-Ramírez, Waggoner, and Zha (2010), this equation is identified if the following statement is true: if $\widetilde{Q}\widetilde{A}_{0,t} = \widehat{A}_{0,t}$, where $\widetilde{Q}$ is an orthogonal matrix, and $\widehat{A}_{0,t}$ maintains the form of

$$\begin{bmatrix} \widehat{A}^{11}_{0,t} & \widehat{A}^{12}_{0,t} \\ \widehat{A}^{21}_{0,t} & \widehat{A}^{22}_{0,t} \end{bmatrix} = \begin{bmatrix} \widehat{A}^{11}_{0,t} & \underset{1\times n}{0} \\ \widehat{A}^{21}_{0,t} & \widehat{A}^{22}_{0,t} \end{bmatrix},$$

then $\widetilde{Q}$ must be of the form

$$\begin{bmatrix} \widetilde{Q}^{11} & \widetilde{Q}^{12} \\ \widetilde{Q}^{21} & \widetilde{Q}^{22} \end{bmatrix} = \begin{bmatrix} 1 & \underset{1\times n}{0} \\ \underset{n\times 1}{0} & \widetilde{Q}^{22} \end{bmatrix}. \tag{B.1}$$

To show that the above statement is true, note that $\widetilde{Q}\widetilde{A}_{0,t} = \widehat{A}_{0,t}$ is equivalent to

$$\begin{bmatrix} \widetilde{Q}^{11}\widetilde{A}^{11}_{0,t} + \widetilde{Q}^{12}\widetilde{A}^{21}_{0,t} & \widetilde{Q}^{12}\widetilde{A}^{22}_{0,t} \\ \widetilde{Q}^{21}\widetilde{A}^{11}_{0,t} + \widetilde{Q}^{22}\widetilde{A}^{21}_{0,t} & \widetilde{Q}^{22}\widetilde{A}^{22}_{0,t} \end{bmatrix} = \begin{bmatrix} \widehat{A}^{11}_{0,t} & \underset{1\times n}{0} \\ \widehat{A}^{21}_{0,t} & \widehat{A}^{22}_{0,t} \end{bmatrix}.$$

Since $\widetilde{A}^{22}_{0,t}$ is invertible for the system and $\widetilde{Q}^{12}\widetilde{A}^{22}_{0,t} = 0$, we have $\widetilde{Q}^{12} = 0$. Because $\widetilde{Q}$ is an orthogonal matrix, it must be that $\widetilde{Q}^{21} = 0$ and $\widetilde{Q}^{11} = 1$. This proves (B.1).

We now show that impulse responses of y_t to $\varepsilon_{m,t}$ are invariant to the rotation matrix Q or the ordering of elements in y_t. Note that the rotation matrix Q in subsystem (2) is the same as $\widetilde{Q}^{22}$. Because the first equation of system (3) is identified and the rotation matrix $\widetilde{Q}$ for the whole system satisfies (B.1), the rotation matrix Q would affect the impulse responses of y_t to ξ_t but not those to $\varepsilon_{m,t}$.

The ordering of elements in y_t relates to a permutation, not a rotation. Since the first equation of system (3) is identified, the invariance of impulse responses of y_t to $\varepsilon_{m,t}$ to any ordering follows directly from Theorem 4 of Zha (1999).

Appendix C. Proof of Proposition 3

To show the first equation in system (4) can be estimated independently of the rest of the system, it is sufficient to show that the likelihood function (or the posterior probability density function when a proper prior is introduced) for the first equation can be maximized without affecting the likelihood or the posterior probability density for the rest of the system.

Denote

$$\underset{(1+n)\times 1}{z_t} = \begin{bmatrix} M_t \\ y_t \end{bmatrix},$$

the i^{th} row of $\widetilde{A}_{\ell,t}$ by $\tilde{a}^i_{\ell,t}$, and the i^{th} element of $\tilde{c}_t$ by $\tilde{c}^i_t$, where $i = 1, \ldots, 1+n$ and $\ell = 0, \ldots, 4$. The likelihood (LH) function for system (4) is

$$\begin{aligned}
\text{LH} \propto \left|\det(\widetilde{A}_{0,t})\right|^T \exp\left\{-\frac{1}{2}\sum_{t=1}^{T}\sum_{i=1}^{1+n}\left[\tilde{a}^i_{0,t}z_t - \tilde{c}^i_t - \sum_{\ell=1}^{4}\tilde{a}^i_{\ell,t}z_{t-\ell}\right]^2\right\} \\
= \sigma_{m,t}^{-T}\exp\left\{-\frac{1}{2}\sum_{t=1}^{T}\left[\tilde{a}^1_{\ell,t}z_t - \tilde{c}^1_t - \sum_{\ell=1}^{4}\tilde{a}^1_{\ell,t}z_{t-\ell}\right]^2\right\} \times \\
\left|\det(\widetilde{A}^{22}_{0,t})\right|^T \exp\left\{-\frac{1}{2}\sum_{i=2}^{1+n}\sum_{t=1}^{T}\left[\tilde{a}^i_{0,t}z_t - \tilde{c}^i_t - \sum_{\ell=1}^{4}\tilde{a}^i_{\ell,t}z_{t-\ell}\right]^2\right\}.
\end{aligned} \tag{C.1}$$

The first part of the right hand side of (C.1) is the likelihood for the first equation and the second part is the likelihood for the rest of the system. Clearly, the maximum likelihood estimation (MLE) of the first equation can be performed independently of the MLE of the second equation. Moreover, it follows from system (4) that the coefficients $\widetilde{A}^{22}_{0,t}$, $\tilde{a}^i_{\ell,t}$, and $\tilde{c}^i_t$ are constant across time for $i = 2, \ldots, 1+n$. Thus, the second term of the right hand side of (C.1) is time invariant and is equivalent to the estimation of the linear VAR system.

Sims and Zha (1998)'s Bayesian prior is designed for the structural form (4), not for the conventional form (3). This important feature ensures that when the prior is applied to the second part of system (4), the posterior probability density function has exactly the same form as the second part of the right hand side of (C.1). Thus, the posterior estimation of the rest of the system can be performed independently of estimation of the first equation. Conditional on the estimated value of $\widetilde{A}^{22}_{0,t} \equiv A_0$, moreover, each equation in the second block of system (C.1) can be estimated independently of other equations.

Appendix D. A role of the external sector

One aspect of monetary policy under discussion focuses on how monetary policy reacts to movements in the exchange rate market. This and many other details are abstracted from the simple policy equation. A natural question is whether the endogenous part of monetary policy encompasses possible reactions to exchange rate movements. If the answer were negative, then our exogenous monetary policy shocks would contain endogenous movements related to the external sector. To test this hypothesis, we regress the estimated monetary policy shock series on the four lags of the foreign exchange rate as well as net exports (as percent of GDP). For completeness, we also regress the estimated endogenous components of monetary policy on the same variables. Table D.1 reports the regression results. These results indicate that the foreign exchange rate and net exports have no explanatory power for exogenous monetary policy shocks, while movements in the external sector are effectively captured by endogenous monetary policy. The identified monetary policy shocks, therefore, are not contaminated by an endogenous response to fluctuations in the RMB exchange rate.

TABLE D.1. Endogenous and exogenous components of monetary policy

	p-value			Adjusted R^2		
	Shock	Systematic	Output only	Shock	Systematic	Output only
Exchange rate	0.361	0.000***	0.032**			
Net exports	0.968	0.000***	0.000***			
Fit				0.015	0.450	0.456

Note. The testing hypothesis is that all coefficients of the exchange rate are zero or that all coefficients of net exports are zero. The dependent variable is either estimated monetary policy shock or estimated systematic component of monetary policy. The two-star superscript indicates a 5% significance level and the three-star superscript indicates a 1% significance level.

Foreign exchange reserves are a combination of the exchange rate and trade surplus; thus, they have been an important factor for capital control. PBC's sterilization operations by selling central bank bills or raising the reserve requirement ratio to freeze the excess liquidity in the banking system would affect foreign exchange reserves significantly (Chang, Liu, and Spiegel, 2015). But how important are foreign exchange reserves for the transmission of monetary policy to *domestic output*? We study this issue by removing foreign exchange reserves from the list of variables in the benchmark model. Figure 6 displays the estimated response of GDP (the circle line) for this case. One can see that the result is very close to the response from the benchmark model, confirming that the effects of monetary policy in China work mainly through bank loans to domestic investment, not through the external sector.

In the spirit of the simple Taylor rule (Taylor, 1993), the endogenous component of China's monetary policy is "sufficiently encompassing" to the extent that fluctuations in GDP growth and CPI inflation capture other factors such as net exports and foreign exchange reserves (Taylor, 2000). The Chinese central government's overriding goal is to target *real GDP growth* and promote this growth *beyond the target.* The main task of monetary policy is to help achieve this goal, all else becoming a means to this end.

APPENDIX E. A ROLE OF INTEREST RATES

Much of the recent policy discussion centers on reforms of moving gradually away from control of M2 growth as the primary policy instrument toward control of short-term nominal interest rates as in the U.S. and other developed economies. Yet there are few academic studies on how effective the interest rate channel would be for the Chinese economy.

Our empirical analysis provides strong evidence that interest rates have been *ineffective* in transmitting monetary policy into China's real economy. When we remove the three interest rates from the list of variables in the benchmark model, the estimated response of GDP to a monetary policy shock is almost identical to its benchmark counterpart (Figure 6). This finding is consistent with the existing empirical result that variations in market interest rates cannot explain macroeconomic fluctuations (Sheng and Wu, 2008) and supports the argument that the transmission of monetary policy works through credit volumes rather than through interest rates.[31]

Our finding is in contrast to Bernanke and Blinder (1992), who use the federal funds rate to identify the effect of a monetary policy shock. As Bernanke and Blinder (1992) show, interbank interest rates in the U.S. economy are transmitted into the real economy through broad financial markets. In China's state-dominated financial system, quantity-based monetary policy has been more effective in directly influencing the supply of bank loans, *regardless of what happens to interest rates* in interbank markets.[32] Our evidence indicates that bank lending volumes constitute the key transmission mechanism for the effect of monetary policy on the real economy.

There are several institutional reasons for the normal interest-rate channel to fail in the monetary transmission mechanism. First, since bond markets in China are not fully developed, long-term interest rates for investment are largely insulated from changes in short-term interest rates. Second, lending and deposit rates in the banking system have not been fully liberalized to reflect the risk to bank loans.[33] Third, firms in strategic industries, protected by the government from bankruptcy, are insensitive to changes in interest rates.[34] As a result, there are no efficient financial markets to price out the external finance premium for firms.

[31]The external sector is also unimportant to monetary transmission. When we remove foreign exchange reserves from the list of variables in the benchmark model, the impulse responses (circle and plus lines in Figure 6) are essentially identical to its benchmark counterpart.

[32]To control bank credit volumes effectively, the PBC uses additional policy instruments, such as "window guidance" and regulatory rules, to force commercial banks to increase or decrease lending volumes or activities and to direct loans to certain industries, regardless of the prevailing interest rates. Moreover, the PBC controls credit volumes by planning the aggregate credit supply for the coming year and then by negotiating with individual commercial banks for credit allocations.

[33]For a long time, China has adopted a dual-track interest rate system (Yi, 2009). As early as 1996, China removed control of interbank lending rates (i.e., Chibor and Repo rates), but deposit and lending rates have since then been under strict control of the government. Liberalization of the overall financial market has been slow in China. See Liu, Wang, and Xu (2017) for theoretical implications of interest rate liberalization on the Chinese economy.

[34]Li, Liu, and Wang (2016) argue that strategic industries in China have been enjoying monopoly power given by the government, rather than facing market competition.

In the following appendices, all labels for equations, figures, tables, definitions, and propositions begin with S, standing for *supplement* to the main text.

Appendix S1. An alternative measure of SOEs in manufacturing

According to Hsieh and Song (2015), the use of a registration type as a measure of the firm's ownership may cause potential bias in identifying SOEs. This might potentially overturn the result that there were more new loans issued to non-SOEs than SOEs in manufacturing at the aggregate level. In this section, we use the shareholder's information to identify SOEs, a measure proposed by (Hsieh and Song, 2015), and verify the robustness of our results regarding the effects of monetary stimulus on credit allocation between SOEs and non-SOEs.

Since there is no shareholder information for sectors other than the manufacturing/industrial sector, we can only examine manufacturing firms whose detailed information of registered capital is retrieved from the Chinese Industry Census (CIC). We follow Hsieh and Song (2015) to define a firm as an SOE if the state-owned registered capital is equal to or larger than 50% or the controlling shareholder is the state for publicly traded firms. With this alternative measure of SOEs, we repeat our estimation.

We follow a two-stage empirical framework to first estimate the average firm-level dynamic effects on bank loans to SOEs versus non-SOEs and then add up these micro effects at the firm level to the manufacturing sector. We find that an average manufacturing SOE enjoyed favored access to bank credit (as shown in Figure S1) while the aggregate impacts on credit allocation to manufacturing non-SOEs were quantitatively more important than manufacturing SOEs (as shown in Figure S2).

Under this alternative measure of SOEs, the share of bank loans to SOEs was on average 44% during 2009Q1-Q3 and 41% during 2009Q4-2010Q4. Since there are fewer firms in our sample that contain shareholders' information, the total number of firms for estimation would be less than that in the estimation sample for our baseline model. And more than 70% of all manufacturing firms with positive newly issued loans are non-SOEs in the sample with the alternative measure of SOEs, indicating that the aggregate effect in manufacturing was dominated by the extensive margin, not by the average effect.

Appendix S2. Robustness check with Non-seasonally adjusted data

In our baseline estimation, we seasonally adjust both newly originally loans and assets for each firm. In this section, we check the robustness of our findings with non-seasonally adjusted micro data. Figure S3 reports the dynamic responses of bank loans allocated to the average SOE and the average non-SOE across key sectors. Comparing Figure S3 with Figure 15, we see that the dynamic responses between the two cases are very similar. In particular, our finding of the cross-sector heterogeneity in credit allocation to SOEs versus non-SOEs is robust: in the manufacturing sector the average SOE enjoyed preferential credit access, while the opposite is true for real estate. In infrastructure, there is no obvious

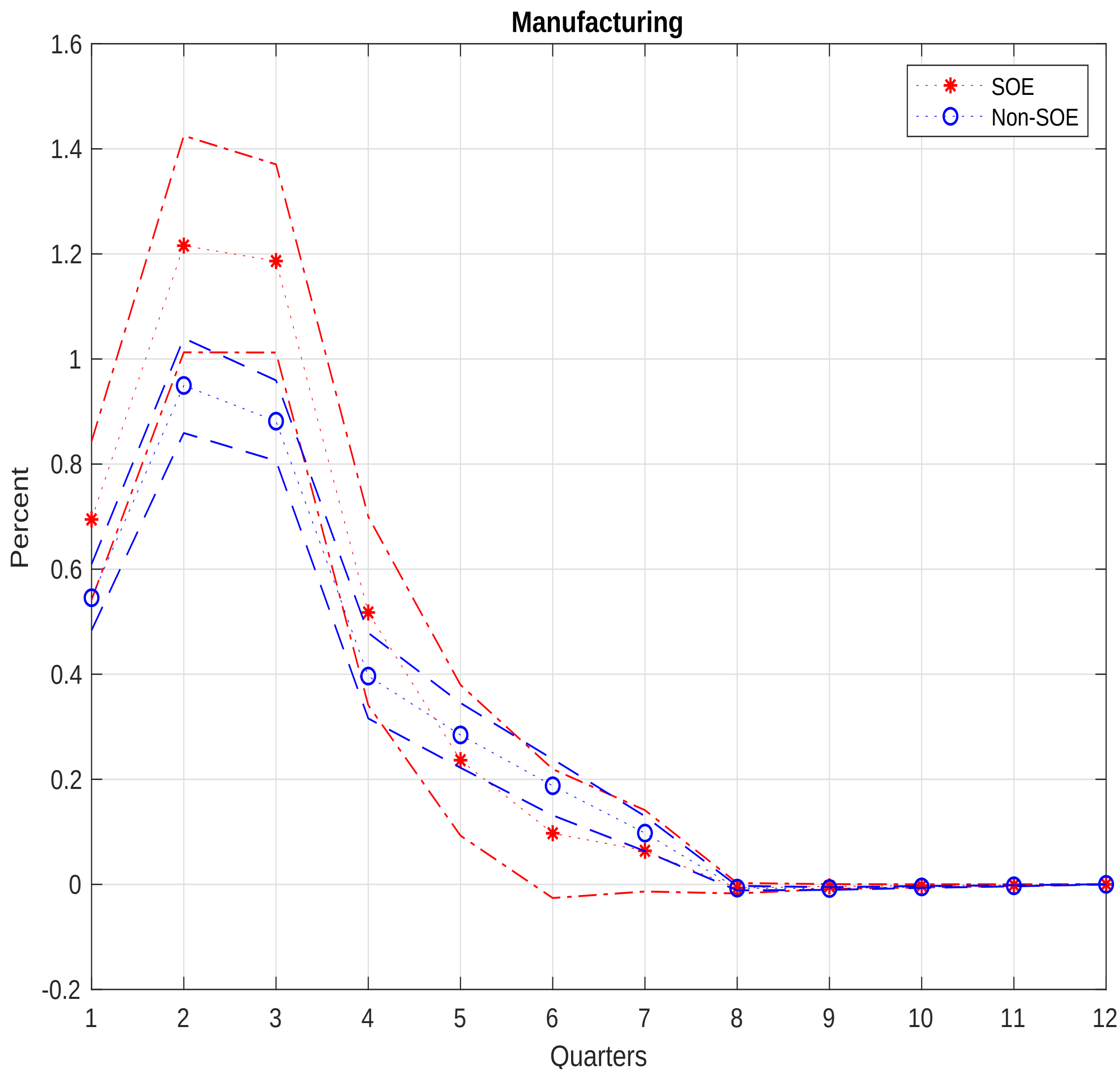

Figure S1. Firm-level dynamic effects on bank loans to the average SOE firm and the average non-SOE firm in response to monetary policy changes in the manufacturing sector with an alternative measures of SOEs. *Notes*: The responses, estimated with the econometric method described in Section I.2 to the firm-quarter data, are expressed as percentage changes from the initial quarter (quarter 0). Dashed lines represent the corresponding .90 probability bands for non-SOEs and dash-dotted lines for SOEs.

favoritism for credit allocation. Thus, our previous results are robust to the micro data without seasonal adjustments.

Appendix S3. Robustness check with firm-specific control variables

In our baseline dynamic panel model, two independent variables are firms-specific: the firm's fixed effects and lagged newly originated loans. These two variables are potentially correlated with other firm-specific variables that affect bank loans to individual firms. We

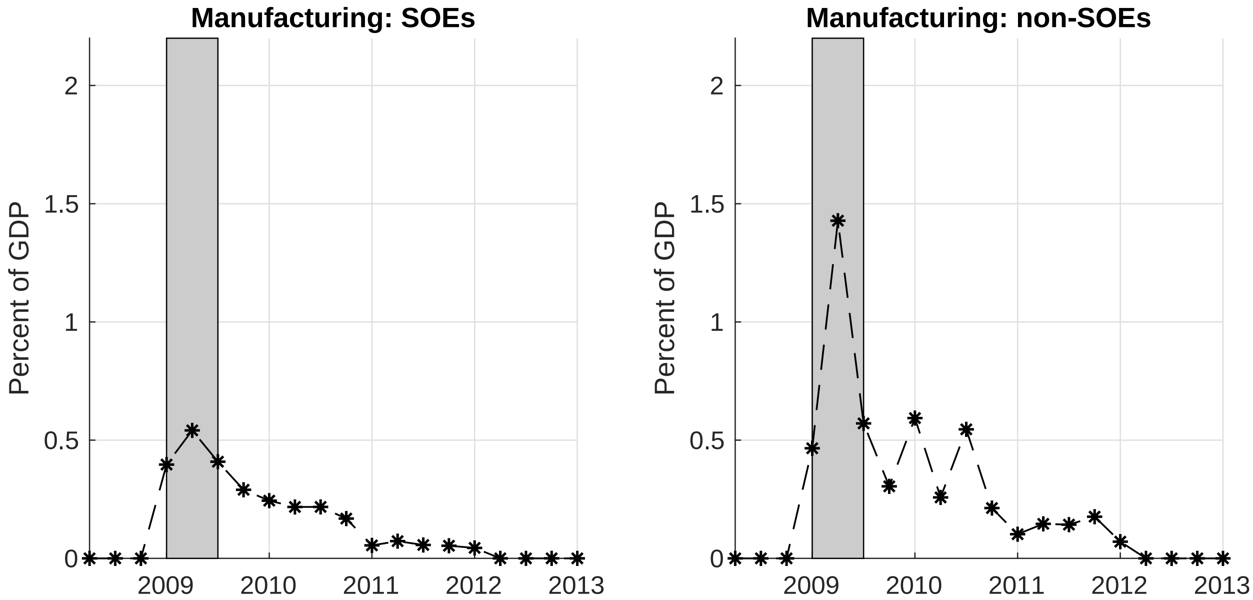

Figure S2. Stimulus effects on bank loans to SOEs and non-SOEs in the manufacturing sector at the aggregate level with an alternative measures of SOEs. *Notes*: The asterisk lines represent the effect of monetary policy changes during 2009Q1-Q3. The shaded bars mark the period of 2009Q1-Q3 during which the monetary policy rule was changed to be more stimulative.

now examine how robust our estimated average effects of monetary stimulus are when we add other firm-specific control variables that are available in our sample.

We include leverage (total liabilities divided by total assets), the loan guarantee ratio (the ratio of outstanding loans guaranteed by third-parties), NPL (the ratio of the non-performing loans to total outstanding loans), the state bank dummy (a dummy variable indicating whether the bank is one of the five state banks in China: Industrial & Commercial Bank of China, Bank of China, China Construction Bank, Agricultural Bank of China, and Bank of Communications), and the number of banks with outstanding loans (NumBanks) to control for firm-specific characteristics. All these firm-specific variables are related to loan accessibility.

Figure S4 reports the dynamic effects on bank loans to the average SOE firm and the average non-SOE firm in response to monetary policy changes with these firm-specific control variables. Again, the average effects of monetary stimulus on credit allocation to an individual SOE versus an individual non-SOE are heterogeneous across sectors. More important, the magnitudes of the dynamics effects are close to their baseline counterparts. Thus, our estimation results are robust to whether or not firm-specific control variables are included. The key reason for the robustness of our results is as follows. Since firm-specific controls are unlikely to be correlated with the 2009 monetary stimulus, the estimated coefficients of monetary policy changes are unlikely to change with or without firm-specific control variables in our dynamic panel regressions.

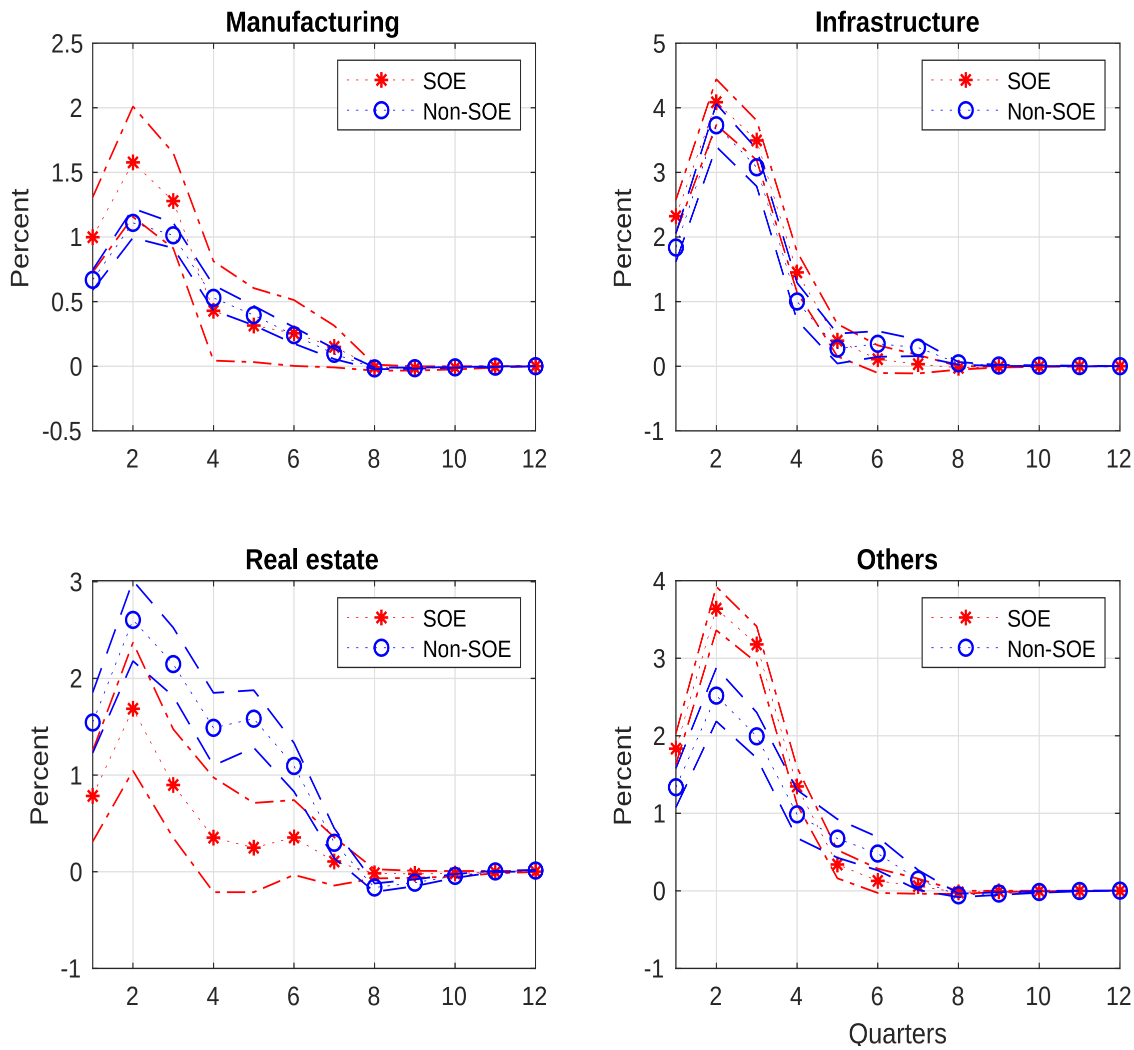

FIGURE S3. Firm-level dynamic effects on bank loans to the average SOE firm and the average non-SOE firm in response to monetary policy changes with non-seasonally adjusted micro data. *Notes*: The responses, estimated with the econometric method described in Section I.2 to the firm-quarter data, are expressed as percentage changes from the initial quarter (quarter 0). Dashed lines represent the corresponding .90 probability bands for non-SOEs and dash-dotted lines for SOEs.

EMORY UNIVERSITY AND FEDERAL RESERVE BANK OF ATLANTA; CENTRAL UNIVERSITY OF FINANCE AND ECONOMICS; FEDERAL RESERVE BANK OF ATLANTA; FEDERAL RESERVE BANK OF ATLANTA; FEDERAL RESERVE BANK OF ATLANTA, EMORY UNIVERSITY, AND NBER

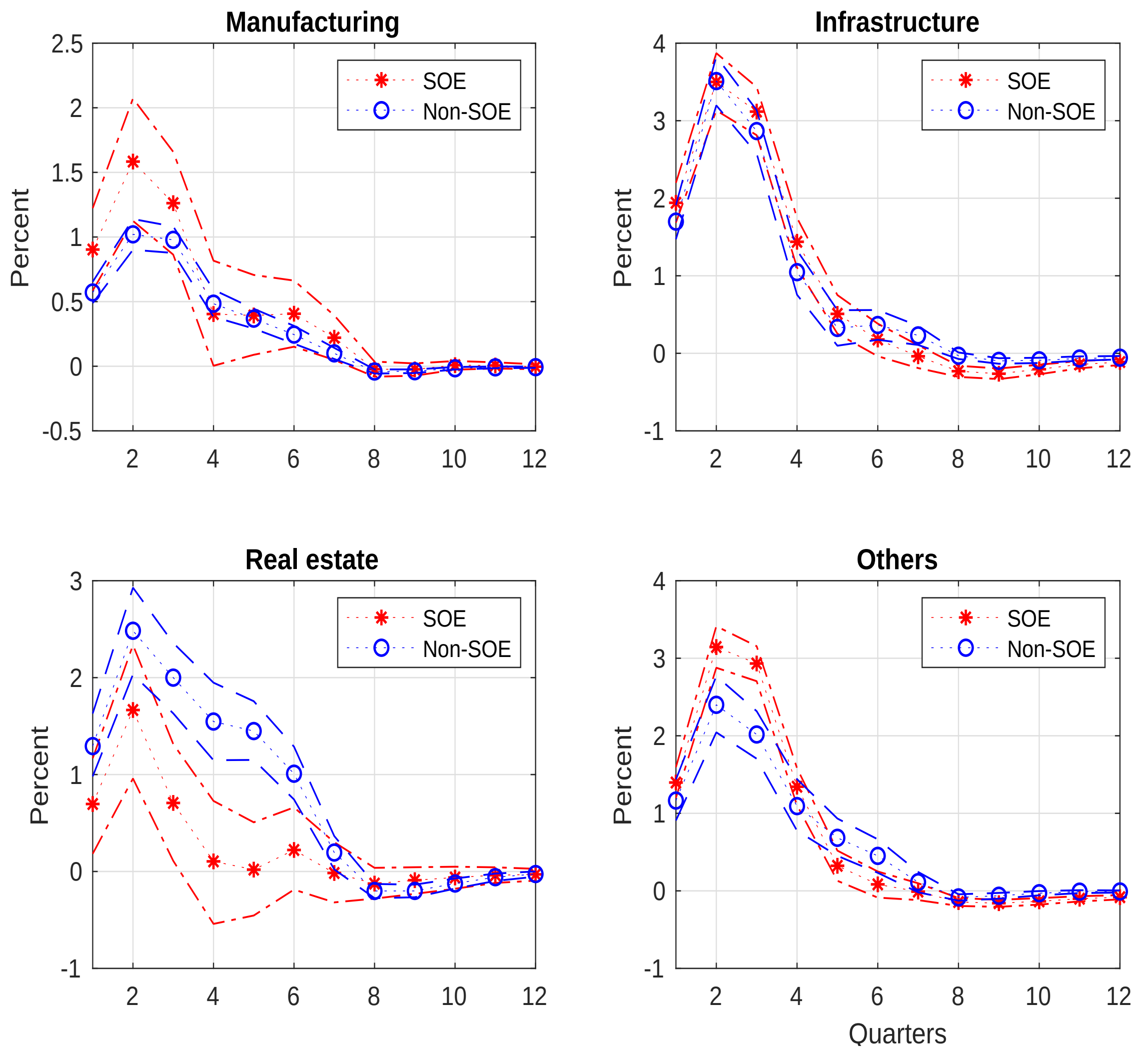

Figure S4. Firm-level dynamic effects on bank loans to the average SOE firm and the average non-SOE firm in response to monetary policy changes with firm-specific control variables. *Notes*: The responses, estimated with the econometric method described in Section I.2 to the firm-quarter data, are expressed as percentage changes from the initial quarter (quarter 0). Dashed lines represent the corresponding .90 probability bands for non-SOEs and dash-dotted lines for SOEs.