Do Reformers' Words Matter? A Narrative Approach to China's Macroeconomic Management

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Abstract. Conventional monetary and fiscal policy transmission studies are inadequate to capture the full picture of China's macroeconomic management approach. This study adopts a narrative approach to analyse the Politburo's economic policy meetings and quantifies the economic impact of unconventional demand-side or supply-side policies. The findings suggest that demand-side policies are most effective in stimulating output, while supply-side policies are crucial in promoting innovation. The study underscores the importance of fiscal and supply-side policies to sustain future growth.

JEL: E3, E5, E6 **Keywords:** policy shocks, narrative approach, SVAR

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Contents

1. Introduction

Understanding the effects of economic management policies is crucial both for academic purposes and for real-world policy-making. The conventional literature has extensively studied the effects of monetary and fiscal policy shocks, but generally falls short on other policies that do not fall into these two categories.

This paper argues that conventional studies are inadequate for understanding macroeconomic management in countries like China, where the approach to economic management is drastically different from developed economies. The latter typically employ market-based methods, using a predictable and rule-based set of tools in day-to-day economic management. Policies are meant to provide incentives to market participants, leaving outcomes being predominantly determined by market forces. China, on the other hand, typically adopts a top-down approach to achieve specific macroeconomic management objectives. In general, top leaders meet to discuss the current economic situation and form a policy stance. Then various tools, including fiscal and monetary tools as well as direct demand or supply management, are deployed in a coordinated manner to achieve certain macroeconomic management goals.

Taking the management of the real estate market as an example, policymakers have long been aware of the possibility of a speculative bubble in the real estate market. As a result, regulations to rein in the overheated market have been introduced on an ongoing basis for nearly two decades. Regulators use a variety of tools, including raising interest rates, tightening eligibility requirements for buyers, and instructing local governments to allocate more residential land. The last two measures are neither fiscal nor monetary, but direct interventions to curb demand and increase supply. Given the importance of the real estate market, which constitutes the dominant share of household wealth, these interventions would have further implications for the entire macroeconomy. A narrow focus on conventional fiscal and monetary policies would miss out on a significant part of the policy toolbox.

Therefore, studying China's macroeconomic management requires a more versatile approach to capture different types of policy interventions and evaluate their effectiveness. However, this approach poses a particular challenge for quantitative economic research, as it is almost impossible to measure all types of policies given their wide variety. Moreover, for a particular type of policy, there is not always a clear instrument, such as short-term interest rates, to track policy changes.

This paper adopts a narrative approach to evaluate China's macro management policies. I manually review the reports of the main top-level economic decision-making conferences — including the Politburo meetings, the Central Financial and Economic Affairs Commission (CFEAC) meetings, the Central Economic Work Conferences (CEWC) — and codify marginal policy changes based on the changing statement of the meeting reports.

China's economic policymaking has evolved over time, with a shifting balance of power between the Party and the State Council. Nevertheless, following the Politburo meetings is a convenient way to track economic policy updates, as all analysts in the Chinese capital market do. The Politburo is the country's highest decision-making body, to which the State Council reports. And it provides a continuous update on fiscal, monetary and other policies most relevant to the economy at the time.

The coded policy changes are grouped into four categories: monetary policies, fiscal policies, demand-side policies, and supply-side policies. Then a Bayesian FAVAR framework is employed to investigate the economic impact of different types of policies. A FAVAR framework is particularly suitable for the purpose, partly because it mitigates concerns about data quality issues — in a sense, all variables are noisy measures of the underlying driving forces; and also because it allows us to incorporate a large set of economic variables that almost spans the information set of the policymakers — so that the residuals of the VAR can be treated as structural shocks for impulse response analysis. To ensure that the results are not biased by human reading of the policy documents, a dictionary-based method is also implemented as a robustness check.

Given the extensive literature analysing monetary and fiscal policy shocks, this paper focuses mainly on demand-side and supply-side policies that are not monetary or fiscal in nature. Managing demand and supply may involve coordinating monetary or fiscal policies, but this is not always the case. For instance, demand-side policies may consist of infrastructure investment decisions or restrictions on real estate purchases; supply-side policies may involve shutting down overcapacity factories or cutting red tape for businesses.

Several key findings emerge from the study. First, demand-side policies are found to have the strongest effect in stimulating output growth. Supply-side policies have only a limited effect. Second, there is a decline in the effectiveness of monetary policy, while fiscal policy and supply-side policies are becoming more important over time. Third, an investigation of the transmission mechanism shows that demand-side policies are, as expected, effective in increasing investment and consumption. Supply-side policies have only a limited effect on investment and no effect on consumption. However, the "supply-side structural reform" does reduce the debt ratio of industrial enterprises and improve their profitability. There is also some evidence that supply-side policies are helpful in promoting innovation, as measured by the number of patent applications. These results are robust to alternative policy measures, more control variables, or using instrumental variables.

This paper contributes to the large literature on the impact of policy shocks on the macroeconomy. Ramey (2016) provides a comprehensive review of this literature. The use of narrative approach to identify shocks also has a long history. Notable works include, Hamilton (1985) applying a narrative approach to study oil shocks, Romer and Romer (1989) using FOMC minutes to identify monetary policy shocks, Ramey and Shapiro (1998) using defence news to identify government spending shocks, and Romer and Romer (2010) using legislative documents to identify tax shocks. Text-based methods have become increasingly popular because they provide useful information that is not available from other sources. An excellent summary of recent developments in this field is provided by Gentzkow et al. (2019). For example, Baker et al. (2016) use text analysis of news outlets to quantify economic policy uncertainty (EPU), while Groseclose and Milyo (2005) use text method to study political bias in the media.

This study also contributes to the growing literature on China's macroeconomic management. Related studies that have used text-based methods include, for example, Shu and Ng (2010) and Sun (2013), who use narrative approach to identify China's monetary policy shocks by analysing the central bank's monetary policy reports; Das and Song (2022), who study China's monetary and fiscal policy coordination using the State Council's meeting notes; and Huang and Luk (2020), who use a dictionary method to study economic policy uncertainty through analysis of Chinese newspapers. However, to the best of my knowledge, no study has yet used top-level economic meeting reports for policy analysis, especially for policies beyond conventional monetary and fiscal ones. Therefore, this study makes unique contribution to understand China's macroeconomic management approach and its effectiveness.

The remainder of the paper is structured as follows: Section 2 provides a brief review of the institutional background of China's economic policy making and introduces the methods of data collection. Section 3 presents the econometric framework. Section 4 reports the baseline results. Section 5 provides additional robustness checks. Section 5 extends the main result with mechanism inspection. Section 7 concludes.

2. Institutional Background and Data Construction

2.1. China's Macroeconomic Management Approach

China's macroeconomic management has similarities with developed economies, but it also has unique features. The Chinese authorities use both conventional monetary and fiscal instruments along with unconventional ones. Two distinctive features stand out: Firstly, policies are usually implemented in a coordinated manner to achieve specific objectives, and the authorities use a variety of policy instruments. Neither monetary nor fiscal policy can be fully captured by a single instrument, such as interest rates or fiscal expenditure. Secondly, authorities also often use unconventional policies, such as administrative orders, to directly manage demand or supply.

Rather than having independent institutions executing designated functions, China's macroeconomic management is carried out in a top-down, dictatorial manner. Top party and government leaders meet to assess the current economic situation and formulate a policy stance. Specific policies are then implemented by central government ministries and local governments to achieve the policy goals. Illustrations of monetary and fiscal policy implementations serve to shed light on this process.

The People's Bank of China (PBC) is responsible for conducting monetary policy. However, it is not an independent central bank. The PBC works under the guidance of the State Council, which in turn reports to the Politburo. Therefore, monetary policy is not an independent decision of the central bank, but one of the policy instruments to achieve a unified goal. Monetary policy itself is implemented through a variety of instruments, such as reserve requirement ratios, interest rate regulations and credit restrictions. The overall monetary policy stance is expressed in the relevant policy documents, but cannot be captured by a single instrument, such as short-term interest rates, which is usually the single policy target in most developed economies.

Fiscal policy is implemented through the coordination of different government departments and state-owned enterprises. The government budget position is therefore not an adequate measure of fiscal policy. Fiscal stimulus packages could be implemented by state-owned enterprises or local government financing vehicles (LGFVs), which are not recorded in the government budget. Other government ministries, such as the National Development and Reform Commission (NDRC), which has the power to approve investment projects, may also be involved. This again highlights the need for a holistic approach to capture the policy stance.

Authorities can go beyond conventional monetary or fiscal policy and intervene directly to manage supply and demand. For example, regulators have long been involved in regulating the property market to avoid a speculative bubble. They set different interest rates depending on how many existing properties a buyer occupies. Eligibility to buy a property varies from city to city to reduce excess demand in overheated markets. In some cases, local governments are instructed to increase the supply of residential land to balance rising demand.

A recent example of China's use of unconventional macroeconomic management is the "supply-side structural reform" (SSSR). As the lingering effect of the ultra-expansionary policies adopted in response to the Global Financial Crisis, the economy was plagued by overcapacity, sagging industrial profits and heavy debt problems. In 2016, the authorities launched the SSSR to address these problems. Policies include shutting down low-quality production capacity, subsidising laid-off workers, deleveraging state-owned enterprises, and improving corporate profitability (Naughton, 2016; Boulter, 2018). The ultimate goal is to shift the structure of production towards higher-quality and innovation-driven industries. The effectiveness of these policies will be assessed in later sections. These regulatory measures may or may not involve fiscal or monetary instruments, but they play an important role in curbing demand and restructuring supply, which could have profound macroeconomic consequences.

As a developing economy undergoing continuous reforms, macroeconomic management is often accompanied by various reform measures. This is especially true during difficult economic times when more reforms are needed. Some examples include reforms to the financial system and state-owned enterprises, cutting red tape and streamlining administrative processes, easing restrictions on rural migration, further opening up to foreign investment, and so on. These reforms can improve market performance, reduce the cost of doing business and increase potential supply and demand. In mature economies, reforms are rare and do not contribute much to day-to-day economic management. In China, however, these reforms are constantly being undertaken and are as important to economic outcomes as other instruments in the policy toolbox.

In short, monitoring particular variables, such as interest rates or the government budget, is not enough to capture the full scope of macro management policies and reforms. This is due to the wide range of policy intervention possibilities used by the authorities to manage the economy. A more flexible and versatile approach, such as narrative and text-based method, may be a better option to understand the whole picture of policy interventions and how they interact with the economy.

2.2. The Evolution of Economic Policy Making

The purpose of this paper is to track crucial top-level economic policy meetings in an attempt to identify policy changes that are relevant to economic management. Therefore, it is essential to understand how economic policymaking works in order to identify the key decision-making meetings and documents.

China's economic policy-making has evolved over time. However, the process is still not fully transparent. This section is an outline of the basic structures of the decision-making bodies for the purpose of data collection. The Party-State structure implies two parallel sets of institutions. The Politburo is the highest decision-making body of the Party, and the State Council is the head of the government bureaucracy. The conventional view is that the State Council is responsible for the formulation of economic policies and day-to-day management decisions, which are then ratified by the Politburo (Bottelier, 2018, Chapter 2). However, recent reforms have shifted decision-making power from the State Council to the Party. The State Council has become more of an executive body (He, 2020).

In addition to the power swing between the Party and the State Council, there are also tensions between the central and local governments. The country is famous for its system of “economic decentralisation under political centralisation”, which is believed to be the institutional foundation for its remarkable economic growth (Xu, 2011). In recent years, however, there has been a tendency to centralise policy-making, with an emphasis on “top-level design” rather than a bottom-up, trial-and-error approach (He, 2020). This is why market analysts are monitoring the top-level messages very closely — the slightest deviation from the norm can possibly move the market in a substantial way.

Although China’s economy has been largely reformed to operate according to market principles, it still retains some features of central planning. For example, the Party still adheres to the Soviet-style Five-Year planning for setting economic development strategies. In addition, the Party and the State Council convene an annual Central Economic Work Conference (CEWC), the top-level meeting on economic and financial matters that sets the policy direction and key agenda for the coming year.

Monthly meetings of the Politburo provide more frequent policy updates. After each meeting, a concise report of the top leaders’ decisions and plans is released to the public. Meetings in April, July, October (occasionally) and December are devoted to discussing economic issues, including updates on the assessment of economic conditions and policy changes. The State Council holds regular weekly meetings that focus on more specific issues. In recent years, as decision-making power has shifted from the State Council to the Party, the Central Financial and Economic Affairs Commission (CFEAC), formerly known as the Central Leading Group for Finance and Economic Affairs (CLGFEA), has also played an important role in policymaking. However, the CFEAC meets less frequently, usually once or twice a year.

2.3. Codifying Key Economic Policy Changes

I codify economic policy changes that sourced mainly from the Politburo meetings and the annual CEWCs. There are several reasons for this choice. First, these are the top-level meetings that market analysts follow most closely. Second, the meeting reports are published regularly and generally follow a consistent format that provides updates on the most relevant policy issues. For example, the meeting report usually begins with an assessment of current economic conditions, the main challenges facing the country at the moment, the monetary and fiscal policy stance, followed by updates on other key economic policies such as real estate regulations, poverty alleviation programmes, and so on. CFEAC meetings have also been crucial in the last decade. I also include them when they provide additional information. The Politburo Standing Committee (PSC) might hold emergency meetings in between Politburo meetings in urgent situations such as the pandemic. These meetings are also incorporated if they provide updates on economic policies.

Most of the Politburo meetings and CEWCs contain similar wording to previous reports, as policy remains largely consistent with only marginal changes over time. When a report contains a different wording or a new statement, it signals a policy change. As an illustration, the following example compares the statement of the macro policy stance of two consecutive Politburo meetings (translated by the author):

> *Excerpt from Politburo meeting on 30 April 2015* ... maintain consistent and stable macroeconomic policies, while making greater efforts in targeted regulation and timely pro-cyclical fine-tuning. [The meeting] also attached high priority to coping with economic downward pressure, accelerating the pace of reform and opening-up, while maintaining an overall balance between stabilising growth, promoting reform, undertaking structural transformation, improving living standards and safeguarding against risks. [The meeting

stressed the importance of] motivating all market participants and making solid efforts in policy execution to promote sustainable and sound economic development and overall social stability.

Excerpt from Politburo meeting on 30 July 2015 ... maintain consistent and stable macroeconomic policies; on the basis of range-based macro management, make greater efforts in targeted regulation and timely pro-cyclical fine-tuning. [The meeting] also attached high priority to coping with economic downward pressure, preventing and mitigating systematic risks, accelerating the pace of reform and opening-up, while maintaining an overall balance between stabilising growth, promoting reform, undertaking structural transformation, improving living standards and safeguarding against risks. [The meeting stressed the importance of] motivating all market participants and making solid efforts in policy execution to keep the economy running within a reasonable range and promote sustainable and sound economic development and overall social stability.

The amended statement (in red color) signals that the policy stance has shifted to be more cautious about "systematic risks" and more proactive to "keep the economy running within a reasonable range". These marginal policy changes are extracted and sorted into six categories: fiscal policy, monetary policy, demand-side policy, supply-side policy, agricultural policy, and institutional reforms. I manually assign a number between -5 and 5 to quantify the direction and magnitude of the policy based on the tone of the statement. Expansionary policies are coded as positive numbers, while contractionary policies are coded as negative. In the above example, combined with the broader context of the report, the policy changes are scored 1 each for fiscal, monetary, demand-side and supply-side policies. As all four types of policies are moving slightly expansionary.

Agricultural policies and institutional reforms are not included in this study. Agricultural policies are of a different nature. Given the meagre share of agriculture in total

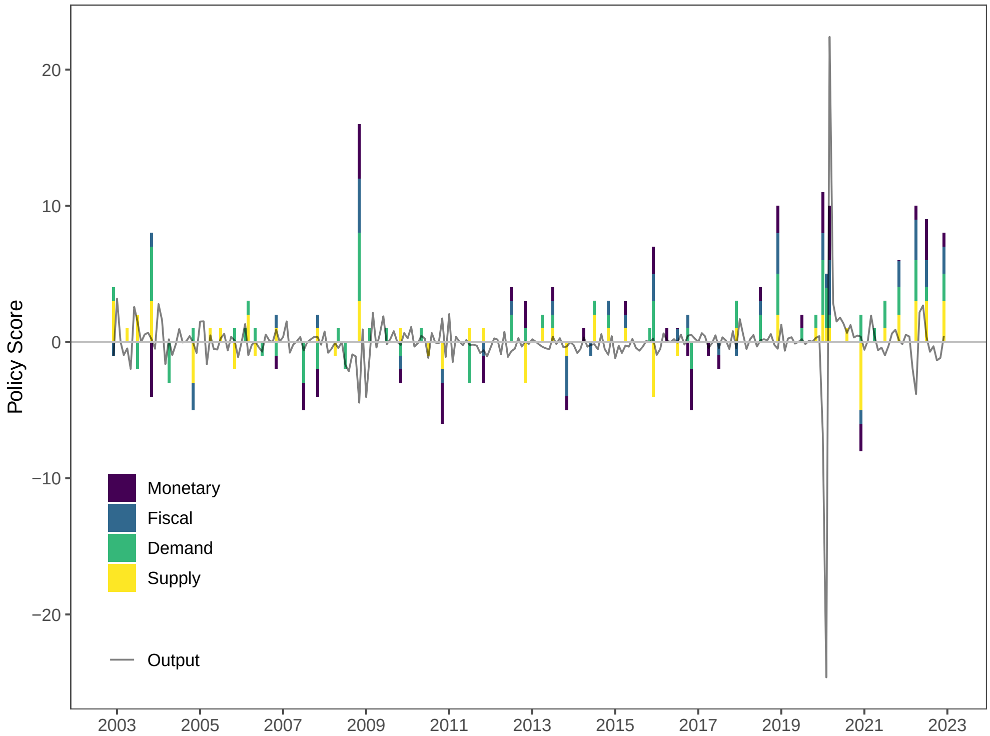
GDP, changes to agricultural policies can barely make any difference in terms of aggregate output. Institutional reforms, although important in the long run, would not have a direct impact on short-term economic outcomes. Since the purpose of this study is macro management, the focus are given to those policies that could influence demand and supply and move the economy at business cycle frequencies.

I opt for manual coding of the policy scores because automated text analysis algorithms such as LDA do not give satisfactory results. Manual coding is inevitably prone to subjective interpretation of the context. Fortunately, most policies can be unambiguously identified as expansionary or contractionary, as illustrated below. Additionally, I offer further robustness checks utilizing an objective dictionary-based method, which will be described in the next section.

Monetary or fiscal policy statements are very easy to identify narratively, as they are explicitly stated in the reports. Expansionary demand-side policies include phrases such as "expanding domestic demand", "increasing infrastructure investment", "stabilising economic growth", and so on. While phrases such as "curbing inflation", "reducing redundant investment", "deleveraging" are regarded as negative demand policies. Positive supply-side policies may include "promoting high-quality growth", "cutting red tape", "reducing the cost of doing business", "enhancing intellectual property right protection", "opening up to foreign investment", "increasing housing supply" and so on. On the other hand, policies such as "stopping energy-intensive and highly polluting projects" and "reducing overcapacity" are negative supply-side policies because they have the effect of shrinking supply.

Two points need to be emphasised regarding the coding of policy changes. I deliberately focus on *marginal* changes, that is how a policy deviate from its last statement. For demand and supply side policies, the intention is to isolate these policies from fiscal and monetary policies. Inevitably, demand or supply management necessitates the corporation with fiscal or monetary policies. The identification issue will be addressed in

Figure 1: Manually Coded Policy Scores



Notes: Manually coded policy scores from Politburo meetings and Central Economic Work Conferences. Positive numbers indicate expansionary policies; negative numbers indicate contractionary policies. The overlaid line is the output indicator (the first principal component of industrial production, consumption, investment, etc).

Section 3. Figure 1 visualises the coded policy scores. The dotted line is the measure of economic activity (the first principal component of industrial production, consumption, investment, and so on). There is a clear countercyclical policy-making pattern.

The data cover the period from 2002 to 2022, which includes the 16th-19th Politburo, with each Politburo presiding for a five-year term. The data are compiled at a monthly frequency. While the Politburo meets quarterly to discuss economic issues, the specific dates of these meetings are not fixed. In addition, the PSC and the CFEAC meet at irregular intervals. Representing these meetings as monthly observations allows for more flexibility. As a convention, meetings held after the midpoint of a month are coded as observations for that month, otherwise coded as observations for the previous month.

2.4. An Alternative Dictionary-Based Approach

To mitigate concerns that manually coded values are prone to subjective bias, I also use a dictionary-based approach to quantifying policies as a robustness check. This approach uses the frequency of keywords associated with particular policies.[1] It is the same method that is commonly used to codify Economic Policy Uncertainty (EPU) (Baker et al., 2016).

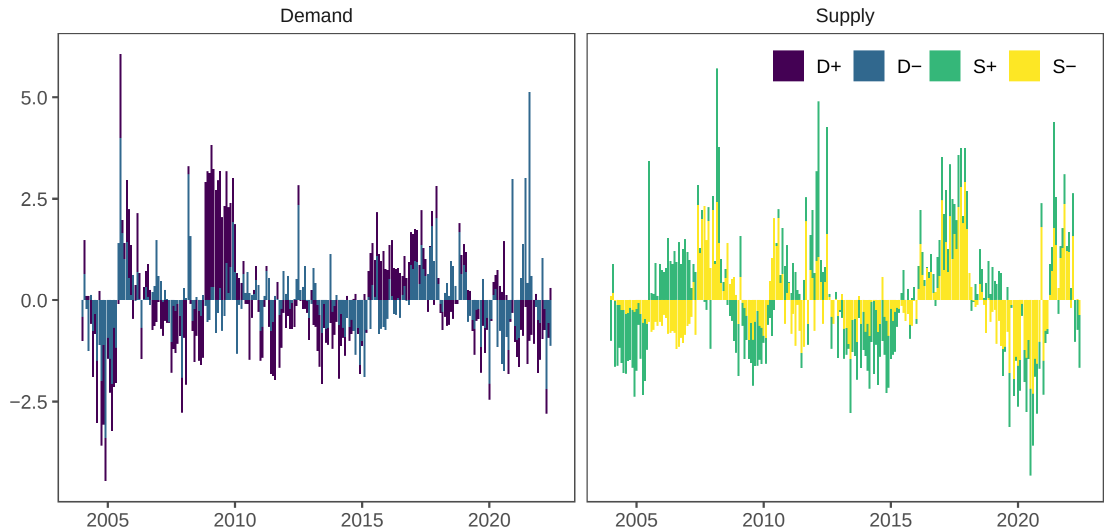
Using the dictionary-based method has two additional advantages. First, the baseline policy coding focuses only on very high-level meetings, which inevitably misses many lower-level meetings that may also be important in the conduct of macroeconomic management. The dictionary-based method searches through all policy documents from all levels of government and thus provide a more comprehensive encoding of policy changes insofar as the coverage of the keywords.

Another concern with the baseline approach is that it may not be entirely appropriate to condense a large number of policies into a single positive or negative value. Policies could be both expansionary and contractionary at the same time. For example, the government could encourage consumption (a positive demand policy) while at the same time discouraging investment (a negative demand policy). The baseline method collapses policies into one number based on an assessment of the overall tonality of the statement, but it might make more sense to consider positive and negative demand (supply) policies separately in some scenarios. The dictionary-based method allows this separation.

I count the frequency of keywords such as "stimulating investment/consumption" and "stabilising growth/employment" to index expansionary demand policies. Contractionary demand policies are represented by keywords such as "reducing redundant investment", "curbing inflation" or "regulating the real estate market". Supportive supply-side policies are represented by keywords such as "free trade", "opening up",

[1] The database of all policy documents is available from the third-party provider RINGDATA (https://www.ringdata.com).

Figure 2: Dictionary-based Policy Scores



Notes: Dictionary-based policy scores (frequency of sets of keywords) for demand- and supply-side policies. $D+$ and $D-$ represent expansionary and contractionary demand-side policies; $S+$ and $S-$ represent expansionary and contractionary supply-side policies. Seasonally adjusted and Box-Cox transformed.

"structural transformation" and "enhancing intellectual property right protection". On the other hand, "reducing overcapacity", "carbon neutrality" and "supply-side reforms" are considered contractionary.

These keywords are carefully chosen. An oversimplified set of keywords may miss important policies, while an overly comprehensive set of keywords would include almost all policy documents and would not be helpful. My strategy is to focus on simple phrases that are catchy slogans at the time. Overly vague phrases such as "common prosperity" are excluded since it is not possible to pinpoint the exact direction of the policy. The full list of keywords can be found in Appendix A.

Figure 2 visualises the indexed keyword frequencies for both positive and negative demand and supply policies. The series are seasonally adjusted and Box-Cox transformed. It should be noted, however, that the keyword frequencies are only a loose approximation of policy changes. They are therefore used as a robustness check.

2.5. Remarks on Other Economic Time Series

The full list of variables can be found in Appendix B. All time series are seasonally adjusted and differenced to stationarity. China did not publish seasonally adjusted time series before 2011. Data before 2011 are seasonally adjusted by the author and concatenated with the official data afterwards. Due to the Lunar New Year holiday effect (which arbitrarily falls between January and February), values for January and February require special treatment. The National Bureau of Statistics (NBS) usually reports the first two months as a combined value, especially for production-related variables. For such series, the combined value is divided equally and assigned to each month. Then the X-13ARIMA-SEATS algorithm is applied for seasonal adjustment. For the series with the first two months reported separately, the X-13 algorithm is applied with a holiday regressor that adjusts for a period around the lunar new year date. The optimal parametrisation of the holiday effect differs from series to series. I generally follow the parametrisation of Roberts and White (2015). Log transformations are applied to all variables except ratios, rates and survey indices.

3. The Econometric Framework

I employ a vector autoregression (VAR) framework to investigate the impact of policy shocks to the macroeconomy. The model can be written as

$$A_0 y_t = \Sigma_{l=1}^{p} A_l y_{t-l} + C z_t + \epsilon_t,$$

where $1 \leq t \leq T$. y_t is an $n \times 1$ vector of endogenous variables, and z_t is an $m \times 1$ vector of exogenous variables. $\{A_0, A_1, \ldots, A_p, C\}$ are parameter matrices with A_0 invertible. p denotes the number of lags. T is the total number of observations. ϵ_t is the vector of structural shocks and is assumed to be Gaussian with zero mean and covariance matrix I_n.

The reduced-form representation of the system is

$$y_t = \sum_{l=1}^{p} B_l y_{t-l} + D z_t + u_t,$$

where $B_l = A_0^{-1} A_l$, $D = A_0^{-1} C$, $u_t = A_0^{-1} \epsilon_t$. Let $\Sigma = \mathbb{E}[u_t u_t'] = (A_0' A_0)^{-1}$. Therefore, $u_t \sim \mathcal{N}(0, \Sigma)$. Let $x_t = [y_{t-1}, \ldots, y_{t-p}, z_t]'$, $B' = [B_1, \ldots, B_p, D]$. The system can be compactly written as $y_t' = x_t' B + u_t'$. Or, in the form of data matrices, $Y = XB + u$, in which Y and X are $T \times n$ and $T \times k$ matrices respectively, containing the stack of observations from 1 to T, and B is the $k \times n$ matrix of parameters, where $k = np + m$. The matrices B and Σ are reduced-form parameters, while $\{A_0, \ldots, A_p, C\}$ are structural parameters.

Variables and identification For the purpose of this study, I include seven variables in y_t as the baseline specification: price and output measures, the stock market index, and the four policy scores. Price and output are the main indicators of business cycles. However, there is no single monthly indicator for output, such as GDP, which is only available quarterly. Instead, the first principal component of several output-related monthly variables, such as industrial production, steel production and rail freight, is used as an alternative indicator. There is no single measure for price either. In a similar approach, the first principal component of several price indices is used, including the consumer price index, the producer price index and the property price index. The stock market index is included as a proxy for market expectations, in case policymakers make decisions based on expectations of future developments. The stock market index is the average of the two main stock market indices — the Shanghai Stock Exchange Composite Index and the Shenzhen Stock Exchange Component Index. All variables are differenced to stationary. The baseline model does not include the COVID-19 period and the exogenous variables include only one constant. When working with data from the pandemic period, time dummies and lockdown indices are included as exogenous variables. Thirteen lags are included in the model to allow for rich dynamics of policy responses.

Impulse response analysis requires the identification of policy shocks that are orthogonal to economic conditions. A recursive structure is used to achieve this — the policy variables are ordered after all the economic variables, taking into account that policymakers make decisions using the economic data as their information set. The ordering ensures that fiscal and monetary policy shocks are orthogonal to business cycle shocks, and demand and supply policy shocks are orthogonal to both business cycle shocks and fiscal and monetary policy shocks. This arrangement aims to identify demand and supply policy shocks beyond the conventional fiscal and monetary policy shocks. The identification assumption is that the variables included span the information set of policymakers, so that the residuals of the VAR can be interpreted as policy shocks. Note that although only three variables are explicitly included in the model, they are the principal components of a much larger set of variables. Thus, the model already captures a considerable amount of information. Section 5.2 will further address the problem of omitted variables.

Prior specification I use the Normal-Inverse-Wishart prior over the parameters (B, Σ). The choice of this conjugate prior allows analytical solutions, thus simplifying the computational complexity. It is also a standard choice in Bayesian VAR literature. Let $b = \mathrm{vec}(B)$. The conjugate prior is specified as

$$b \sim \mathcal{N}(b_0, \Sigma \otimes \Omega), \ \Sigma \sim \mathcal{IW}(S_0, \alpha_0).$$

The prior for the coefficients b follows a "Minnesota-like" structure, assuming that each variable follows its own AR(1) process, and that the variance shrinks for longer lags. That is, b_0 is specified such that $\mathbb{E}[(B_l)_{ij}|\Sigma] = \rho$ if $i = j$ and $l = 1$, and 0 otherwise. The AR(1) coefficient is set to $\rho = 0.8$ in the baseline as all variables are stationary but show some degree of persistence. Ω is a $k \times k$ matrix that expresses the uncertainty for each entry of the coefficient matrices in each equation. Ω is set in such a way that $\text{Var}[(B_l)_{ij}|\Sigma] = \lambda^2(l^\theta \sigma_j^2)^{-1}$ and all other entries in Ω are zeros. Hyper-parameter λ controls the overall tightness, l is the number of lags whose variance shrinks by an exponential rate θ, and σ_j^2 is the unknown residual variance for the j-th variable. λ is the key parameter. The larger the λ, the looser the prior, the more the data speaks. But it could also mean a less precise estimate if the data do not provide strong evidence. Conversely, as $\lambda \to 0$, the prior becomes tighter and reduces the weight of the data. The baseline scenario sets $\lambda = 1$. This is not a particularly strong prior, so more weight will be put on the data. It also sets $\theta = 1$, so that more distant lags do not shrink to zero quickly. Appendix C tests the robustness of different prior values.

For the prior on Σ, as a convention, the degree of freedom is set to $\alpha_0 = n + 2$, and S_0 is a diagonal matrix whose entries are estimated from the residual variance of the AR(1) process of each variable. One of the shortcomings of the Normal-Inverse-Wishart prior is that it imposes a Kronecker structure on the covariance matrix of b, that is it creates a dependence between the variance of the VAR coefficients and the variance of the residuals. Different prior settings that relax this constraint are tested in Appendix C. The robustness test suggests, however, the Kronecker structure does not particularly bias the inference.

4. Main Results

This section presents the main findings by estimating the VAR model described the last section.[2] The baseline impulse-response functions for key variables are reported in this section, followed by robustness checks in Section 5. A deeper inspection of the transmission mechanism is pursued in Section 6.

[2]The Bayesian VAR is estimated using BEAR toolbox (v5.1) developed by Dieppe et al. (2016).

4.1. Response of Output and Price to Policy Shocks

The baseline model covers the entire sample from 2002 to 2019. The model is estimated with 13 lags to account for the fact that there is a lag between a policy decision and its implementation, and a further lag before any economic effects take hold. Unless otherwise specified, the COVID-19 period 2020-2022 is excluded, as the lockdowns and unprecedented stimulus plans completely distort the normal relationships between economic variables. The pandemic period is dealt with in a separate section.

Figure 3 shows the response of output and price to four types of policy shocks. The median of the posterior draws is shown as the path of the impulse response functions (IRFs), along with the 68% and 90% credible sets as shaded areas, for a two-year horizon. The top two panels show the impact of fiscal and monetary shocks. Consistent with the theory and most findings in the literature, both of them have positive impacts. Based on the loading matrix of the principal component analysis, one unit change in output corresponds to about 0.6 per cent monthly growth in GDP (7 per cent annual growth). Therefore, one standard deviation (SD) shock to fiscal or monetary policy can increase annual GDP growth by up to 1.5 per cent. Of the four types of policy shocks, the demand shock has the greatest impact. One SD demand shock can add 2.4 per cent to equivalent GDP growth over one and a half years. This is particularly impressive given that the demand policy shock is deliberately identified as the one that does not transmit through monetary or fiscal channels. However, this is consistent with the institutional fact, as a large part of demand-side policy in China, such as infrastructure investment, is actually carried out by state-owned enterprises (SOEs) (El-Shagi and Zhang, 2022). The supply side, although constantly used by policymakers to improve business conditions and promote industrial upgrading, has little impact on output, at least in the two-year horizon. There is only a small spike in output shortly after the shock, and it makes no significant difference throughout the horizon.

To gain a complete understanding of the business cycle dynamics, Figure 3 also shows the response of the price index to policy shocks. A unit change in the first principal component corresponds to a monthly growth rate of the CPI of around 0.11 per cent (1.3 per cent annually). As expected, fiscal policy, monetary policy and demand policy all have a positive impact on prices, with fiscal policy having the largest effect. On the contrary, supply policy has a negative effect on price, which is consistent with the behaviour of price when supply increases while demand remains constant. This confirms the credibility of the identification of supply-side shocks.

In short, the narrative approach to policy measures shows economic effects consistent with those found in the conventional literature when it comes to monetary and fiscal policy. Demand-side policy shocks have the largest impact on aggregate output. They are the most effective tool for countercyclical macroeconomic management. Supply-side policies have only a limited effect on output. This does not, however, diminish the importance of supply-side policies, which will be discussed in more detail in later sections.

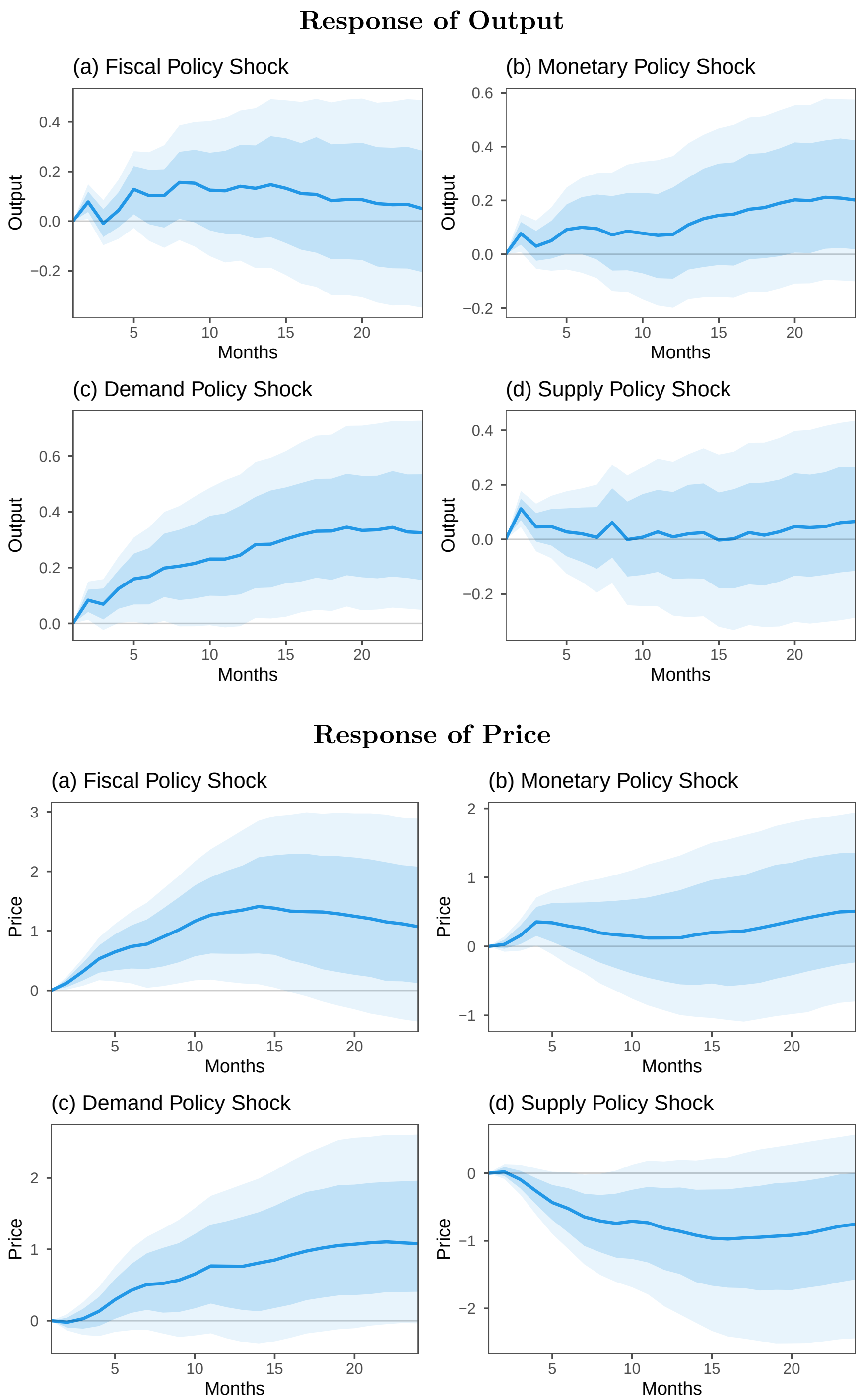
4.2. Forecast Error Variance Decomposition

This section reports the forecast error variance decomposition (FEVD) to quantify the contribution of each type of policy shock in explaining output and price variances (Figure 4). To make a comparison with shocks identified by other methods, I replace the narrative measure in the baseline model with the monetary policy shocks constructed by Das and Song (2022), where monetary policy shocks are identified as high-frequency changes in interest rate swap (IRS) rates around a monetary policy announcement.[3] The high-frequency identification approach is widely used in the monetary policy literature and is highly credible. To accommodate data availability, the sample period starts in 2006.

The FEVD shows that, for output, the contribution of demand and supply policy is as

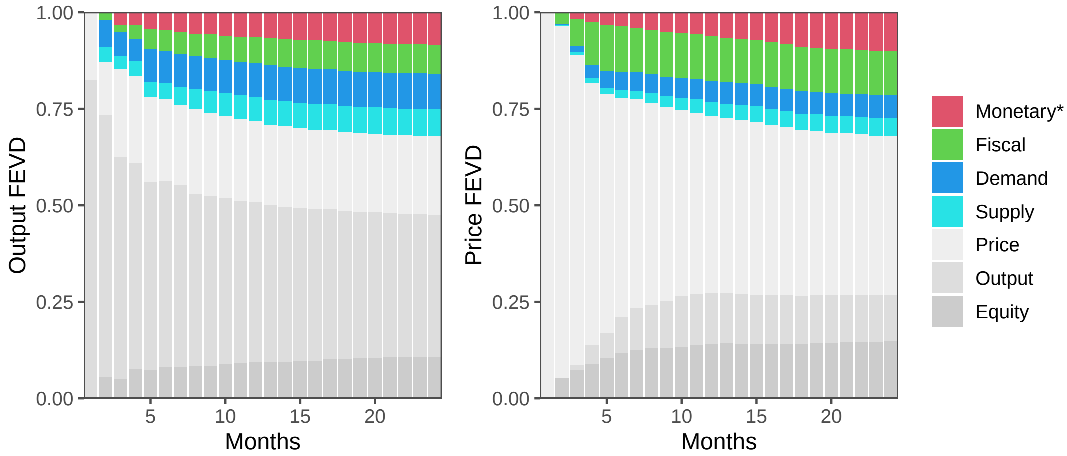
[3] The monetary policy shocks identified by Das and Song (2022) are originally at daily frequency, I aggregate them to monthly data by summing all daily shocks that occurred in a month.

Figure 3: Cumulative Impulse Responses to Policy Shocks



Notes: Cumulative impulse response of output and price to policy shocks. Output and price are the first principal components of groups of variables. Policy encoding is described in Section 2.3. Estimated with monthly data from 2003 to 2019. Shaded areas represent the 68% and 90% credible sets respectively.

Figure 4: Forecast Error Variance Decomposition



Notes: Forecast error variance decomposition (FEVD) with the baseline model. The monetary policy shock is identified by Das and Song (2022) with high-frequency method. Other policy shocks are identified using narrative methods. Estimated with monthly data from 2006 to 2019.

large as that of monetary policy and fiscal policy. For prices, fiscal policy explains most of the variance in forecast errors, followed by monetary policy. Demand and supply policies still play a significant role. The result is consistent with the argument in Section 2 that China's macroeconomic management tools are much more versatile than conventional fiscal and monetary policies. Other policy channels are equally important in explaining economic outcomes.

4.3. Sub-Period Comparison

It is widely believed that China's economy underwent a significant policy and structural transformation in the years following the Global Financial Crisis (GFC), particularly around 2013. The economy shifted from a high growth paradigm to a lower growth paradigm. This transition has been thoroughly studied by Garnaut et al. (2013). In terms of changes in macroeconomic management styles, the new paradigm involved less massive stimulus and more focus on rebalancing the economy toward domestic consumption and promoting new sources of growth, such as innovative industries.

To explore whether the policy effect differs across periods, this section splits the sample into two periods: **Period I** (2003-2012) and **Period II** (2013-2019), corresponding to the Politburo chaired by Hu Jintao and Xi Jinping, respectively. Figure 5 shows the response to policy shocks in the two sub-periods, with blue lines for Period I and red lines for Period II. For compactness of the main text, only results on output are reported hereafter.

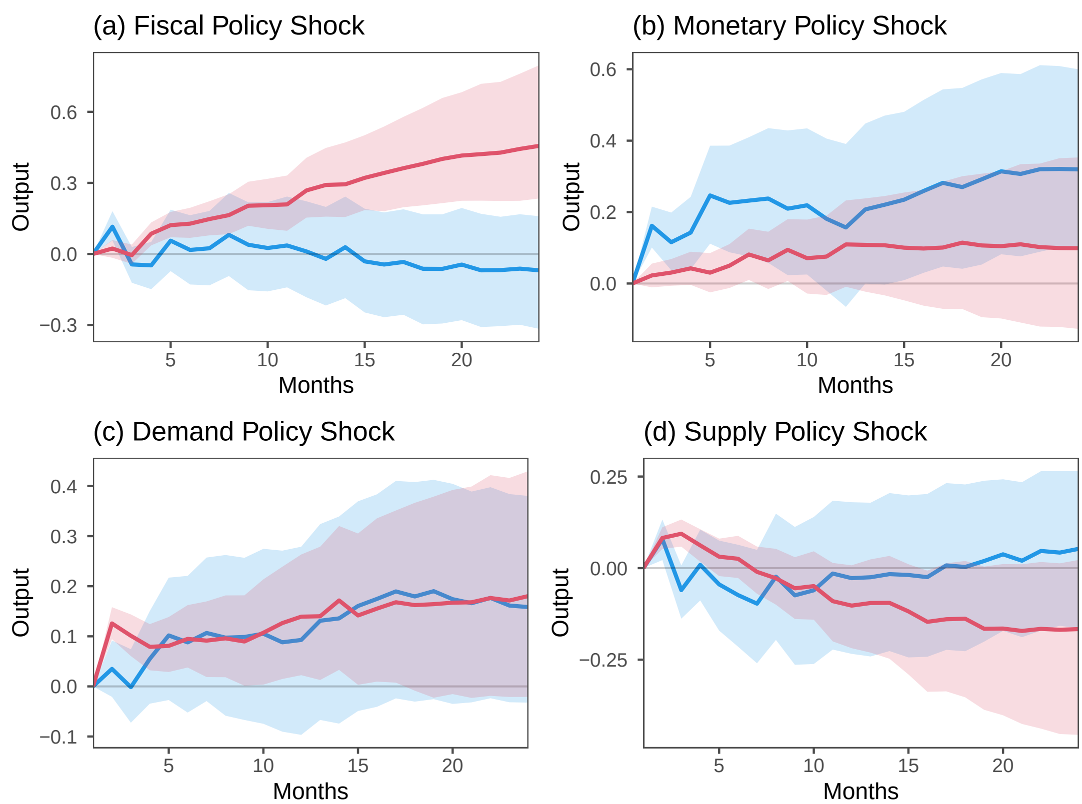
With regard to monetary and fiscal policy, there is a clear pattern: the effectiveness of monetary policy deteriorates, while the effectiveness of fiscal policy increases. In particular, monetary policy has a strong and lasting stimulating effect in the first period, but only a marginal effect in the second period. The effect of fiscal policy is exactly the opposite. Demand-side policies are equally effective in both periods. Supply-side policies, while having no visible effect in the first period, have a positive effect in the second period in the short run, but diminish gradually in the long run.

4.4. The Impact of COVID-19

The COVID-19 pandemic outbreak has a huge and unexpected impact on the economy due to widespread lockdowns and unprecedented government stimulus. This section tests the robustness of the results to the pandemic period by re-estimating the model including 2020-2022. To account for the exogenous outbreak of the pandemic, I include three exogenous variables in the VAR model: a dummy for January-February 2020, a dummy for March-April 2020, and the stringency index from the Oxford COVID-19 Government Response Tracker (OxCGRT).[4] Unlike most countries in the world, the COVID-19 outbreak in China was largely concentrated in one city and was quickly contained by strict lockdowns. It caused a sudden collapse in economic activity in the first two months of 2020, followed by a rapid recovery after the spread of the virus was contained. Two dummies are used to take into account anomalous movements

[4]The OxCGRT dataset is available on https://github.com/OxCGRT/covid-policy-tracker.

Figure 5: Cumulative Response of Output for the Two Periods



Notes: The figures compare the cumulative response of output to policy shocks for two periods. Period I (2003-2012) is shown in blue, while Period II (2013-2019) is shown in red. Shaded areas represent the 68% credible bands.

in economic variables in these months. The OxCGRT stringency index measures the strictness of the government's measures to contain the spread of the virus. It is included in the model, since the stricter the containment measures, the greater the difficulties for the economy.

Figure 6 shows the IRFs with and without the pandemic data. The responses are broadly consistent, with the exception of the response to the monetary policy shock. The stimulative monetary policy does not expand but contracts the economy when the pandemic data are included. Demand policy has an even stronger effect. This may be due to the inadequacy of monetary policy and the extraordinary demand stimulus package to counter the negative impact of the pandemic.

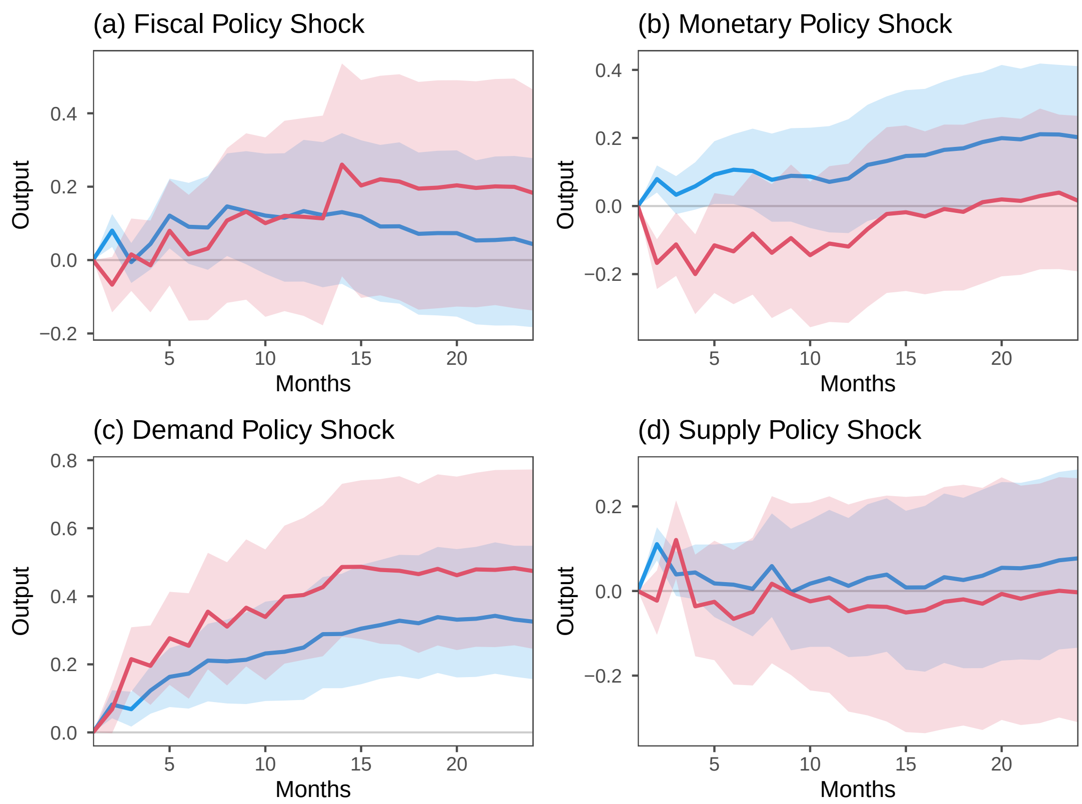
To summarise the findings so far, the results suggest that demand-side policies have the strongest stimulating effect on the economy, while supply-side policies are less effective. The FEVD shows that unconventional demand and supply policies are as important as conventional fiscal and monetary policies in macroeconomic management. Given the structural change in the economy over time, monetary policy becomes less effective, while fiscal and supply-side policies become more important. The inclusion of the pandemic period does not materially alter the result, but it implies dampen efficacy of the monetary policy.

5. Robustness Checks

5.1. Dictionary-Based Measure

This section tests the robustness of the results by replacing the baseline encoding of policy scores with a dictionary-based measure as described in Section 2.4, that is, counting the frequency of certain keywords appearing in policy documents as a measure of the strength of particular policies. It is hardly possible to identify monetary or fiscal policies by keywords alone, as they are not usually expressed in iconic keywords or phrases.

Figure 6: Cumulative Response of Output with COVID-19 Data



Notes: The figures compare the cumulative response of output to policy shocks with and without COVID-19 data. Pre-COVID IRFs (2003-2019) are shown in blue; IRFs with COVID period (2003-2022) are in red. Shaded areas represent the 68% credible bands.

However, it is possible to approximate the strength of demand-side and supply-side policies by counting the frequency of keywords associated with the main policy project at the time. The keyword frequency is used to quantify four types of policies — positive (negative) demand (supply) policies. The VAR model is re-estimated with the baseline policy measures replaced by the new measures. Fiscal and monetary policy are not included in the new model. However, given that the focus of this paper is on demand and supply policies, it still provides a useful robustness check to the baseline results.

Figure 7 shows the output and price responses to demand and supply policy shocks. Both output and prices increase with an expansionary demand policy. A contractionary demand policy, on the other hand, has a subdued effect, but it does not immediately dampen output or prices. Surprisingly, positive supply policies do not stimulate output but suppress it; negative supply policies, on the other hand, are initially neutral and later become contractionary. The neutral response to supply shocks in the baseline is thus the composite effect of both positive and negative policies. The response of output to supply policies seems counter-intuitive. This may be due to the measurement error of the keyword-based index, which is at best an approximation. Section 6 attempts to explain the supply-side policy mechanism in more detail. However, the price response is more in line with expectations. Supply policies that encourage more supply put a downward pressure on prices, while supply-reduction policies provide an upward support for prices.

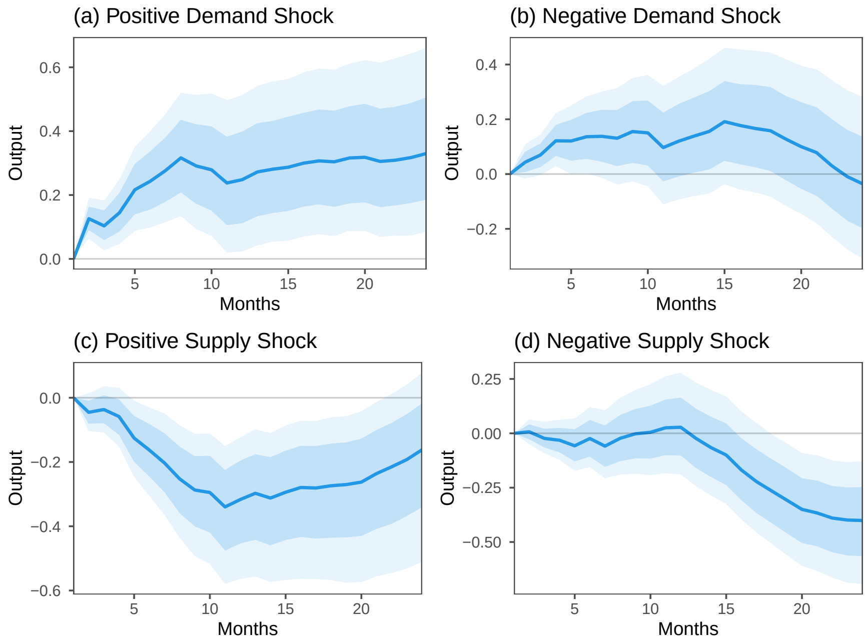
Overall, the alternative measure does not provide evidence at odds with the baseline, even though it is constructed using a completely different method. This adds to the credibility of the baseline results.

5.2. Factor-Augmented VAR

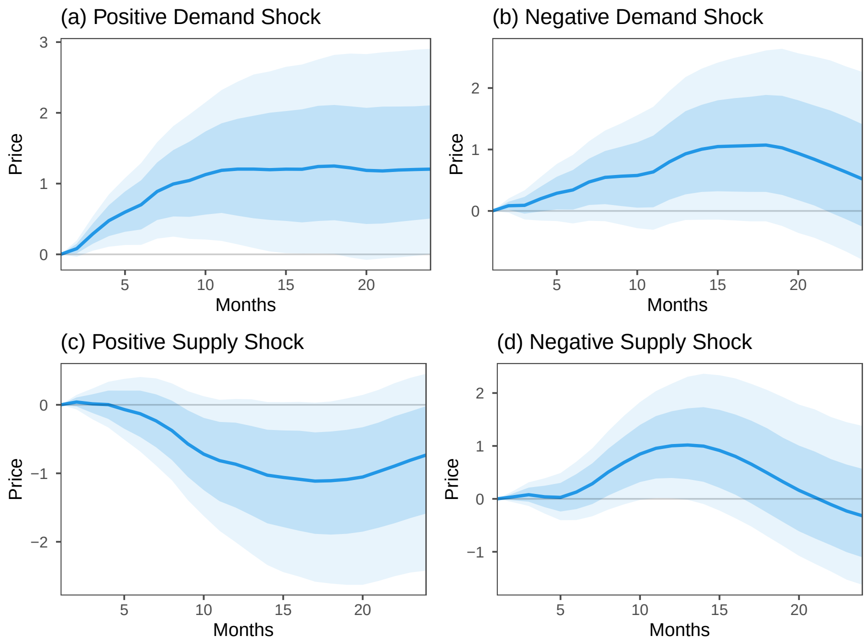
Another concern is possible omitted variable bias. The identification assumption is that all economic variables that could influence policymakers' decisions have been included, so that the residuals of the VAR can be interpreted as policy shocks orthogonal to

Figure 7: Cumulative Impulse Responses to Policy Shocks, Alternative

Response of Output



Response of Price



Notes: Cumulative impulse response of output and price to policy shocks. Output and price are the first principal components of groups of variables. Policies are measured by the frequencies of the corresponding keywords in all policy documents Section 2.4. Estimated with monthly data from 2004 to 2019. Shaded areas represent the 68% and 90% credible sets respectively.

economic conditions. Failure to include critical variables used by policymakers would lead to biased results. To mitigate the concern, this section uses a Factor-Augmented VAR (FAVAR) to incorporate more information into the model. As shown by Bernanke et al. (2005), FAVAR is an effective method to reduce biases due to missing information.

In particular, the factor model assumes a large number of economic variables, x_t, are driven by a few underlying factors, f_t, plus idiosyncratic noise, ξ_t.

$$x_t = \Lambda f_t + \xi_t,$$

x_t is an $n \times 1$ vector, f_t is a $k \times 1$ vector, where $n >> k$. Λ is the factor loading matrix. A factor-augmented VAR model can be represented as

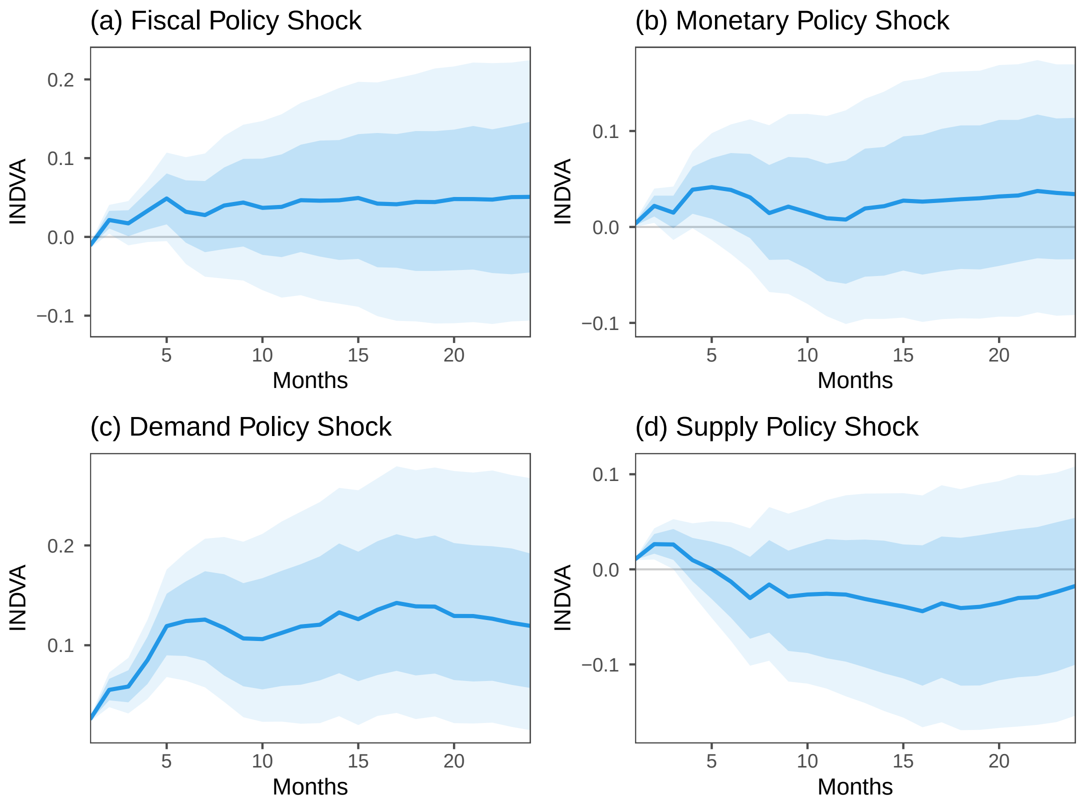
$$A_0 \begin{bmatrix} f_t \\ y_t \end{bmatrix} = \Sigma_{l=1}^{p} A_l \begin{bmatrix} f_{t-1} \\ y_{t-1} \end{bmatrix} + \epsilon_t,$$

where y_t is an $r \times 1$ vector of observable variables. The FAVAR model includes no constant, as the variables are demeaned before entering the model. Here y_t contains only the policy variables. All other variables are considered unobservable and are represented by factors. The full list of variables included in x_t can be found in Appendix B.

I estimate the model using a two-step procedure, first extracting f_t as principal components and then estimating the VAR model as usual. The scree plot shows that the first three principal components account for most of the variance in the data. Nevertheless, I include five principal components. For structural identification, the policy variables are ordered last. Since policy meetings are always held at the end of the month, it is not possible for even forward-looking economic variables to respond to policy changes in that month.

The factor loading matrix allows us to recover the impulse response of each variable from the factors. Figure 8 shows the response of Industrial Value-Added (INDVA), the closest alternative measure to GDP at monthly frequency, to policy shocks. The patterns

Figure 8: Cumulative Response of Output to Policy Shocks, FAVAR



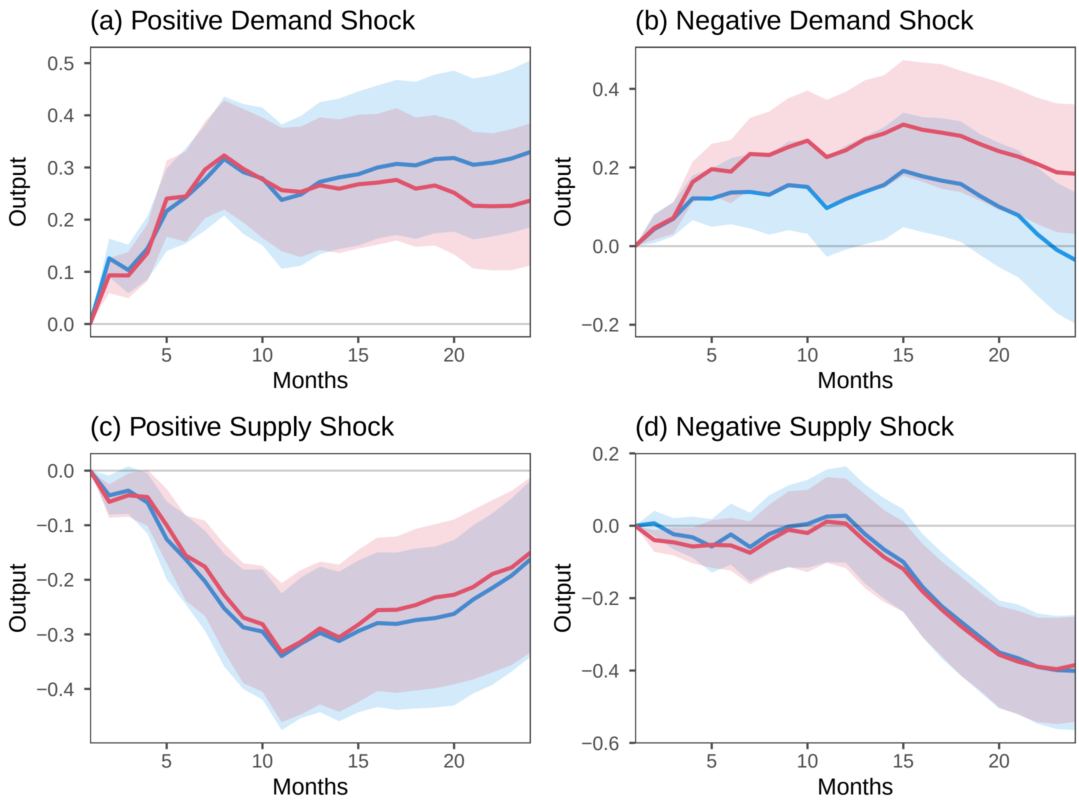
Notes: Cumulative response of Industrial Value-Added (INDVA) to policy shocks estimated from the FAVAR model. Estimated using the full list of monthly time series from 2003 to 2019 (Appendix B). Shaded areas represent the 68% and 90% credible sets respectively.

are highly consistent with the baseline results. This confirms that the baseline results are not particularly biased by omitted variables. An extended list of IRFs estimated from the FAVAR model can be found in Appendix D.

5.3. Instrument Variable Estimation

I use an "internal instrument" method to further verify the identification of the policy shocks. The instrument is constructed using the frequency of keywords such as "political system reform" or "education system reform" in policy documents. The intensity of these reforms could be correlated with supply and demand policy variables, as policies

Figure 9: Cumulative Response of Output to Policy Shocks, IV



Notes: Cumulative response of output to policy shocks estimated with an internal instrument. Policy measures use the dictionary-based method. Estimated with monthly data from 2004 to 2019. The IRFs without IV are shown in blue; IRFs using IV are shown in red.

are made in coordination, but would have hardly any short-run to medium-run effect on economic outcomes, thus qualifying as an instrument. As demonstrated by Plagborg-Møller and Wolf (2021), the internal instrument approach is equivalent to ordering the instrument first in the SVAR with Cholesky structure. I use this method and re-estimate the model of Section 5.1 with the instrument. The results, as shown in Figure 9, are largely consistent with the previous estimation, which reaffirms the credibility of the results.

6. Inspecting the Mechanism

The FAVAR allows the recovery of impulse response functions of any underlying variable. I utilise it to further investigate the transmission mechanism of policy shocks. The transmission of monetary and fiscal policy is well understood in the literature. Therefore, this section is devoted to the analysis of demand-side and supply-side policies. Unless otherwise stated, the results presented in this section are derived from the FAVAR estimated in Section 5.2. I highlight only a few key variables in this section. More impulse response functions can be found in Appendix D.

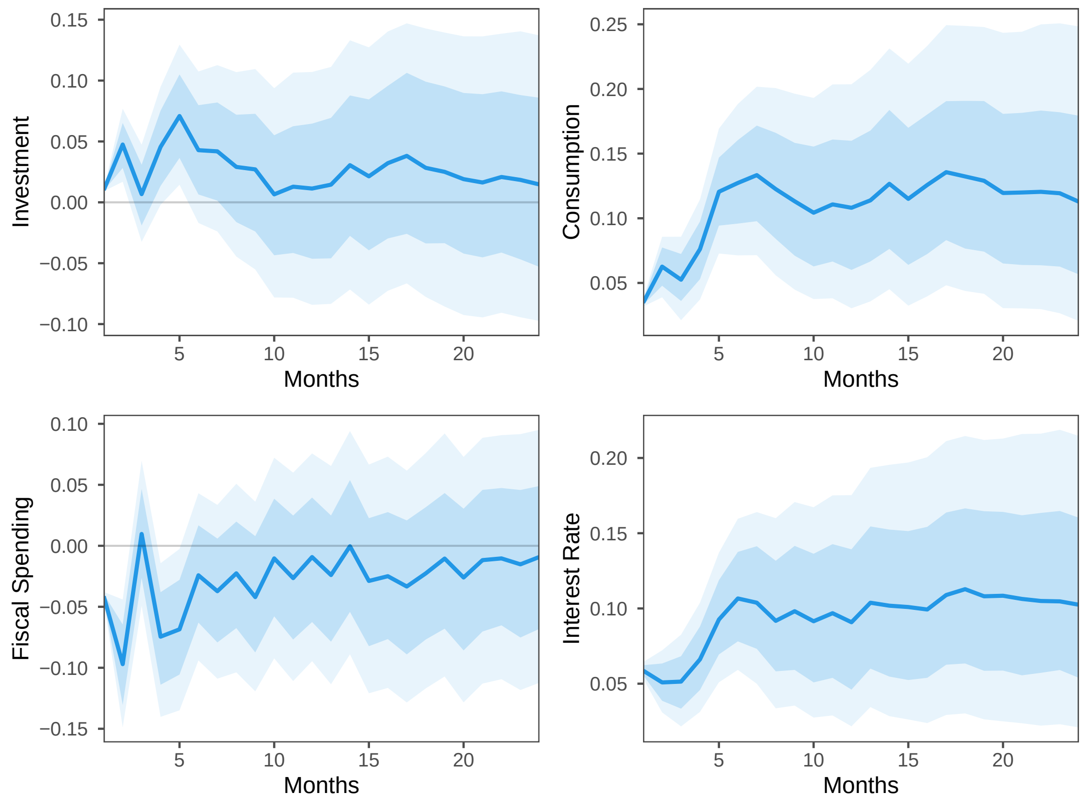
6.1. Transmission of Demand-Side Policy

The transmission of demand-side policies is straightforward. These policies stimulate investment and consumption, which in turn drives output. Figure 10 shows the response of a few selected variables to a demand policy shock. Both investment and consumption respond positively. Investment experiences short-term surge, while the increase in consumption is more persistent. The bottom two graphs highlight the fact that demand-side policies do not necessarily involve fiscal and monetary stimulus. Fiscal spending responds negatively to the demand policy shock, nor do we see a lower interest rate following the shock. As discussed in Section 2, demand stimulus can take various forms, such as SOE-led infrastructure investment or programmes to subsidise the purchase of electrical appliances by rural residents. As the baseline results suggest, these policies are highly effective in bolstering output and play a crucial role in countercyclical macro management outside the conventional monetary and fiscal spheres.

6.2. Transmission of Supply-Side Policy

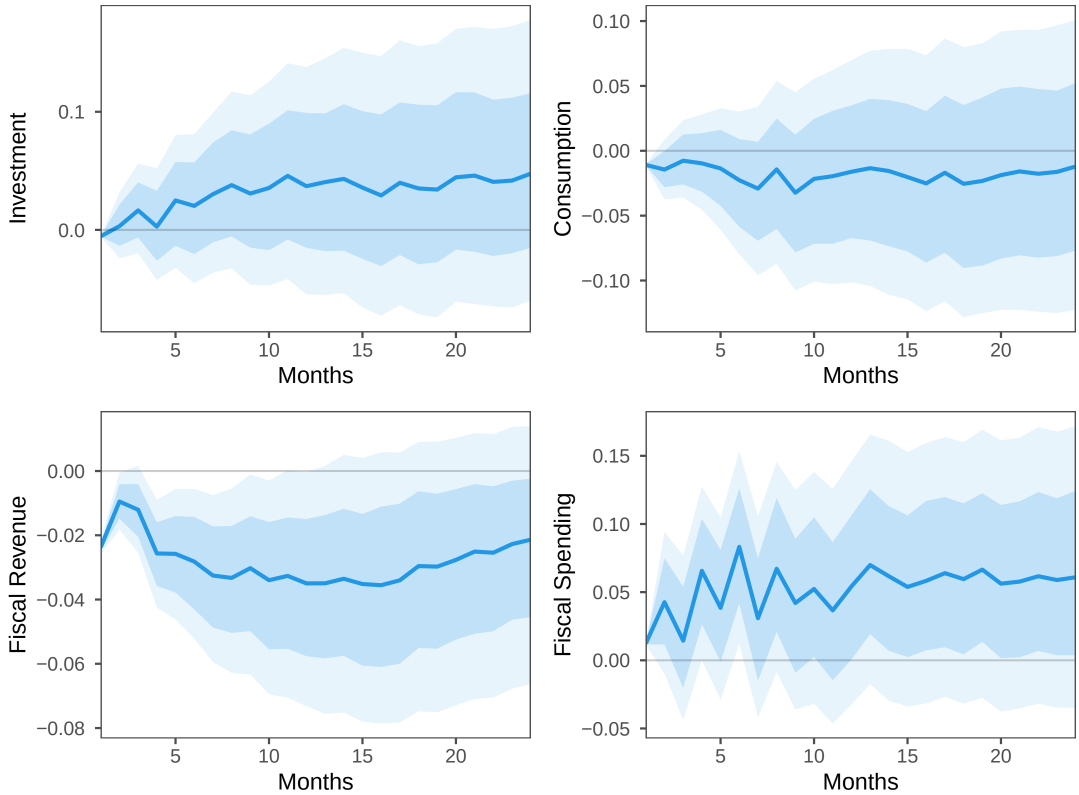
Supply-side policies are designed to increase aggregate supply rather than aggregate demand, which may include cost-reducing policies such as deregulation, free trade, as well as supply-side restructuring policies such as pollution regulation, overcapacity reduction,

Figure 10: Cumulative Impulses Responses to Demand Policy Shock, FAVAR



Notes: Cumulative responses of selected variables to demand policy shocks. Demand policy shocks are defined in Section 2.3. IRFs are generated from the FAVAR model described in Section 5.2. Variable definitions are in Appendix B.

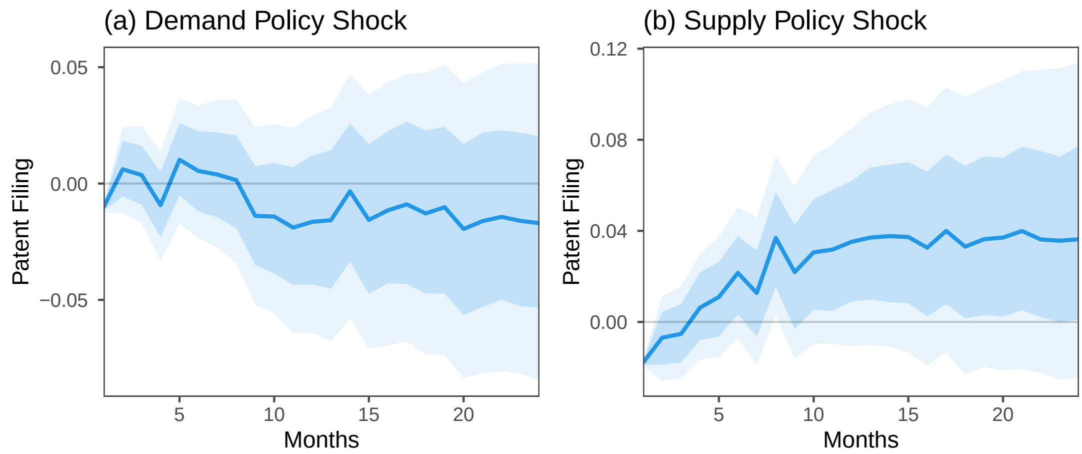
Figure 11: Cumulative Impulses Responses to Supply Policy Shock, FAVAR



Notes: Cumulative responses of selected variables to supply policy shocks. Supply policy shocks are defined in Section 2.3. IRFs are generated from the FAVAR model described in Section 5.2. Variable definitions are in Appendix B.

and so on. The supply-side policies promise to promote economic growth by encouraging business activities and consequently increasing the production of goods and services and employment. However, the baseline results show a neutral response of output to supply policy shocks. To unravel this puzzle, Figure 11 examines the responses of some key variables to supply policy shocks. It shows that the supply-side policy is often accompanied by fiscal support — fiscal expenditure is expanded, while revenue is contracted. The effect on investment is positive, but not significant, and the effect on consumption is negligible. The overall impact on output is close to neutral, as the stimulus is not strong enough to overcome the weak state of the economy.

Figure 12: Cumulative Response of Patent Application to Policy Shock



Notes: Cumulative responses of patent applications to demand and supply policy shocks. Patent data are from Google Patents Public Datasets on BigQuery. IRFs are generated from the FAVAR model described in Section 5.2.

However, supply-side policies are not designed to counter downward pressure in the short term, but to improve the business environment and promote innovative industries in the medium to long term. As the government outlined in the 2016 Supply-Side Structural Reform (SSSR), the aim is to "reduce ineffective and lower-end supply, while increasing effective and medium- and high-end supply" (Boulter, 2018). This also includes subsidising strategic innovative industries such as artificial intelligence, 5G network and new energy vehicles. To evaluate the impact of supply-side policies on innovation, I use the number of patents as a proxy for innovation and include it in the FAVAR model. [5] It shows that supply-side policies do increase the number of patent applications, while demand-side policies have no such effect (Figure 12). Therefore, although supply-side policies are relatively ineffective in stimulating output in the short run, they do serve the purpose of promoting innovation and potentially inducing economic restructuring and upgrading in the long run.

[5] Patent data are from Google Patents Public Datasets on BigQuery. See `https://cloud.google.com/blog/topics/public-datasets/google-patents-public-datasets-connecting-public-paid-and-private-patent-data`.

6.3. An Anatomy of the Supply-Side Structural Reform

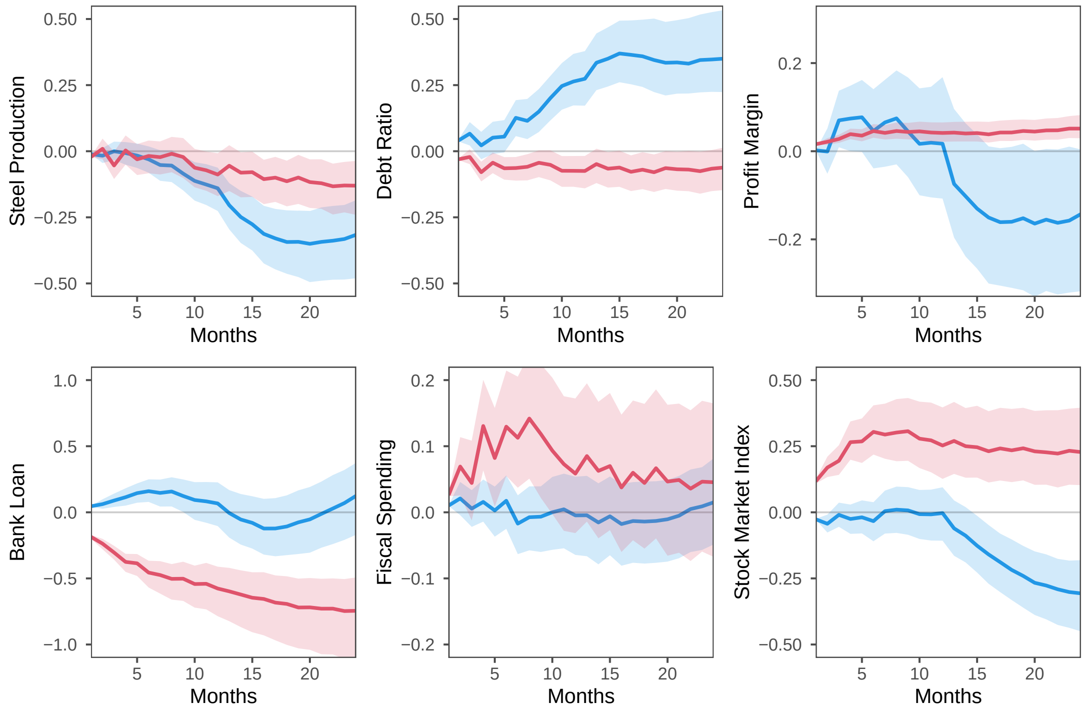
The supply-side structural reform (SSSR) has been the most prominent economic policy agenda in the last decade of China's reform history. It is therefore helpful to provide an anatomy of the reform to gain a better understanding of how supply-side policies work. The decision to implement the SSSR is partly to address the structural imbalance caused by the extraordinary stimulus package implemented in response to the GFC, but it is also a response by policymakers to the realisation that expansionary demand policies can no longer sustain growth and they are therefore resorting to a new approach.

There are five key objectives of the SSSR: cutting industrial overcapacity, reducing the housing stock, deleveraging the corporate sector, reducing business costs, and addressing "vulnerabilities" in the economy. The aim of the policy is not to shrink the economy, but to reduce the reliance on low-end industries, promote innovation and ultimately transform the supply structure to a more technology-intensive and higher value-added one (Boulter, 2018).

To assess the effectiveness of the SSSR, I estimate the FAVAR model with the policy variables replaced by the dictionary-based measures used in Section 5.1.[6] Figure 13 contrasts the response of several variables over the two periods to a negative supply shock. There is a clear diverging pattern between the two periods. In period II, a negative shock is transmitted to lower steel production, lower debt ratios, higher profit margins, declining bank lending and higher fiscal spending. The market reaction is also different: the stock market reacts negatively to a supply contraction in Period I, but reacts markedly positively in Period II. Therefore, at least in the short run, the SSSR succeeded in reducing overcapacity and improving profitability in certain sectors and also improved the market exception, although the long-term promise of promoting an innovative growth structure remains to be seen.

[6] To account for the loss of observations in the sub-samples, the model is estimated with three factors.

Figure 13: The Impact of Supply-Side Structural Reform, FAVAR



Notes: The figures compare the cumulative responses of selected variables to negative supply shocks. Period I (2004-2012) is shown in blue, Period II (2013-2019) in red. Negative supply shocks are defined in Section 2.4. IRFs are generated from the FAVAR model described in Section 5.2.

7. Conclusion

This paper underlines the inadequacy of conventional studies of fiscal and monetary policy in understanding China's macroeconomic management. I use a narrative approach to show how the decisions made by top policymakers on "unconventional" demand-side and supply-side policies are also crucial in driving economic outcomes. The results suggest that the most effective way to boost economic output in the short run is through demand-side policies, such as infrastructure investment and consumption promoting policies. Supply-side policies, such as deregulation of businesses and structural reforms, by contrast, have neutral effect in terms of output. However, supply-side policies are crucial for promoting innovation, which is not sufficiently addressed by demand-side policies. There is also a tendency over time for monetary stimulus to become less effective, while the importance of fiscal and supply-side policies are increasing. These findings are robust to alternative policy measures, more control variables, and instrumental variable estimation.

The study of unconventional macroeconomic management policies is still in its early stages, and there is a lot of ground to be covered by future work. One possible direction for future research could be to identify more precise measures of the structural shocks associated with these policies. Narrative measures are inevitably subject to ambiguity and vagueness and have a relatively low frequency. More precise measures would allow more robust identification and more accurate impact analysis. It would also be interesting to explore how these policies are affected by or spill over to other economies abroad. These questions are left for future research.

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Appendix A Keyword Table

This section presents the list of keywords that were employed as the robustness check, utilizing a dictionary-based measure as described in Section 2.4. This measure involves counting the frequency of specific keywords appearing in policy documents, which serves as an indicator of the strength of particular policies. By counting the frequency of keywords associated with the primary policy project at the time, it can approximate the strength of both demand-side and supply-side policies.

Economic policies are sorted into four categories: positive demand policies, negative demand policies, positive supply policies, and negative supply policies. Each associated with the primary policy concern through time. Institutional reforms are used as an instrument as described in Section 5.3.

The keywords are originally searched in Chinese. The list is translated by the author. It is essential to note that the translation of keywords from policy documents may not always be exact. As such, readers are advised to exercise caution when interpreting the translated text.

Table A.1: Economic Policy Keywords

Category	Keywords
Positive demand-side policies	expanding domestic demand; encouraging consumption; increasing investment; increasing effective demand; stabilising growth; stabilising employment
Negative demand-side policies	blind investment; over investment; duplicated construction; economic overheating; inflation control; regulating real estate market
Positive supply-side policies	structural transformation; strategic emerging industries; further opening up; free trade; cutting red tape; improving government services; tax reduction; intellectual property right protection; resuming work and production; flexible employment

Negative supply-side policies	energy conservation; emission reduction; eliminate pell-mell production capacity; excess capacity; supply-side structural reform; antitrust; carbon neutral
Institutional reform	political system reform; education system reform; healthcare system reform; cultural system reform

Appendix B Variable List

All variables used in the FAVAR model are listed below. Unless otherwise stated, the source is the National Bureau of Statistics (NBS) of China. Data are downloaded from CEIC. Seasonal adjustment is performed by the author using the X-13 procedure. Another source of data is the seasonally adjusted macro series from Higgins and Zha (2015), available from the Federal Reserve Bank of Atlanta. [7] Time index ranges from 2002:12 to 2022:12.

Table B.1: Variable Description

Variable	Unit	Trans	Remarks
Consumer Price Index	Index	$\Delta \log$	Constructed by accumulating the monthly percentage changes. Seasonally adjusted (2000:01=100).
Core Consumer Price Index	Index	$\Delta \log$	—
Producer Price Index	Index	$\Delta \log$	—
Corporate Goods Price Index	Index	$\Delta \log$	A price index based on goods transacted between corporates. Collected by the People's Bank of China. Seasonally adjusted (2000:01=100).
Yiwu Small Commodity Price Index	Index	$\Delta \log$	A price index on "small commodities", such as toys, shoes, accessories, etc. Data starts from 2006:09. Observations prior to that date is extrapolated with Core CPI. Seasonally adjusted (2000:01=100).

[7] See https://www.atlantafed.org/cqer/research/china-macroeconomy.aspx.

Housing Price Index	Index	$\Delta \log$	Based on "the 70 Cities Index" by NBS. The series was published quarterly before 2005, and monthly afterwards. The data before 2005 are extrapolated to monthly using the Denton's method. It should be noted the methodology of constructing the series changed twice, in 2005 and 2011. Only the price index for Tier 1 and Tier 2 cities are included. Seasonally adjusted (2000:01=100).
GDP Deflator	Index	$\Delta \log$	From Higgins and Zha (2008:04=100).
Industrial Value Added	Billion RMB	$\Delta \log$	Data before 2007 are available from NBS. Data between 2007 and 2011 are extrapolated using Gross Industrial Output. Data after 2011 are deducted from the official seasonally adjusted MoM growth rates.
Fixed Asset Investment	Billion RMB	$\Delta \log$	Data before 2011 are from Higgins and Zha. Data after 2011 are deduced from the official seasonally adjusted MoM growth rates.
Retail Sales of Consumption Goods	Billion RMB	$\Delta \log$	—
Import	Billion RMB	$\Delta \log$	From Higgins and Zha. Latest data are updated with NBS. Seasonally adjusted.
Export	Billion RMB	$\Delta \log$	—
Rail Freight Volume	Million Tons	$\Delta \log$	Seasonally adjusted with holiday regressors.
Air Passenger Traffic	Million ppl	$\Delta \log$	—
Port Container Throughput	Million EPU	$\Delta \log$	—
Vehicle Sales	Thousand Units	$\Delta \log$	—

Electricity Production	Billion KWh	$\Delta\log$	Deducted from the year-to-date (YTD) accumulated series with even split for the first two months of a year. Seasonally adjusted.
Steel Production	Million Tons	$\Delta\log$	—
Cement Production	Million Tons	$\Delta\log$	—
Real Estate Developing Investment	Billion RMB	$\Delta\log$	—
Property Sales	Billion RMB	$\Delta\log$	—
Fiscal Revenue	Billion RMB	$\Delta\log$	—
Fiscal Expenditure	Billion RMB	$\Delta\log$	—
Foreign Direct Investment	Billion USD	$\Delta\log$	Deducted from the year-to-date (YTD) accumulated series. Seasonally adjusted.
Unemployment Rate	%	Δ	Registered unemployment rate before 2017 and surveyed unemployment rate after 2017.
Bank Lending Rate (1 Year)	%	Δ	.
Bank Deposit Rate (1 Year)	%	Δ	.
Interbank Repo Rate (7 Days)	%	Δ	.
Treasury Yield (1 Year)	%	Δ	Data before 2006:03 are from Shanghai Stock Exchange (SSE). Data after 2006:03 are from China Central Depository & Clearing Co (CCDC). Aggregated to monthly series by last values.
USD Exchange Rate	RMB Per USD	Δ	.
Effective Exchange Rate	Index	Δ	BIS Real Effective Exchange Rate (2020:01=100).
Money Supply M0	Billion RMB	$\Delta\log$	Seasonally adjusted with holiday regressors.
Money Supply M1	Billion RMB	$\Delta\log$	—

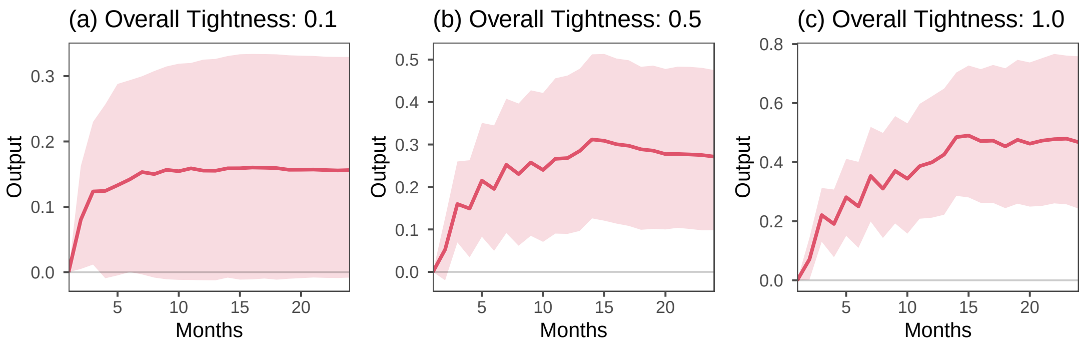
Money Supply M2	Billion RMB	$\Delta \log$	—
Bank Loans	Billion RMB	$\Delta \log$	—
Total Social Financing	Billion RMB	$\Delta \log$	Monthly TSF are available from 2015. Before 2015, quarterly observations are interpolated with bank loans. Seasonally adjusted.
Shanghai Stock Exchange Composite Index	Index	$\Delta \log$	.
Shenzhen Stock Exchange Component Index	Index	$\Delta \log$	.
Consumer Confidence Index	Index	Δ	.
Business Confidence Index	Index	Δ	Quarterly data interpolated to monthly.
Economic Leading Index	Index	Δ	CEIC leading index.
Industrial Enterprises: Product Sales Ratio	%	Δ	Seasonally adjusted.
Industrial Enterprises: Asset Liability Ratio	%	Δ	—
Industrial Enterprises: Total Profit Margin	%	Δ	Constructed by total profit (pre tax income) divided by total revenue. Seasonally adjusted.
Industrial Enterprises: Return on Asset	%	Δ	Constructed by total profit divided by total asset. Seasonally adjusted.
Industrial Enterprises: Inventory Turnover Ratio	%	Δ	Constructed by total cost of goods divided by inventory value. Seasonally adjusted.
Patent Applications	Units	$\Delta \log$	From Google Patents Public Data by IFI CLAIMS Patent Services and Google LLC.

Appendix C Prior Sensitivity

The prior distribution represents our beliefs or assumptions about the parameter before observing the data. The key hyperparameter in this study is λ, which controls the overall tightness of the model. A larger value of λ corresponds to a looser prior, meaning that the prior is less informative, more weight will be assigned to the data. Conversely, a smaller value of λ corresponds to a tighter prior, meaning that we assign relatively higher probability to a smaller range of parameter values before observing the data.

Figure C.1 conducts a sensitivity test using different values of λ. The results showed a less typical case, where the tighter the prior, the smoother the impulse response functions (IRFs) and the wider the credible interval. On the other hand, a looser prior results in more ragged IRFs but more precise estimates of the parameter. A tighter prior reduces the weight of the data, leading to a smoother posterior distribution. However, it is less typical that tighter priors result in wider credible intervals. This suggests that the prior setting may be at odds with the data, the peak of the prior distribution does not correspond to the probability mass revealed from the data. The median responses (the solid lines in the plots), though, generally point to the same direction.

Figure C.1: Variations in Prior Tightness



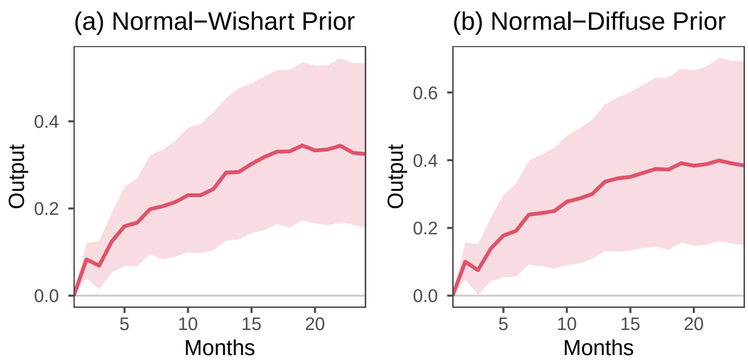
The Normal-Inverse-Wishart prior is commonly used in Bayesian analysis of vector autoregressive (VAR) models due to its simplicity and computational convenience. However, one of the criticisms of this prior is that it imposes a structure on the covariance matrix of the VAR coefficients, creating a dependence between the variance of the coefficients and the variance of the residuals. This structure may not always be appropriate, especially in cases where there is no theoretical justification for such a dependence.

To alleviate this concern, this section estimates the VAR model using a Normal-

Diffuse prior instead, which relaxes the intertwined structure between the variance of the coefficients and the variance of the residuals. The Normal-Diffuse prior places a normal distribution on the coefficients with a large variance, while placing a diffuse prior on the variance of the residuals. The choice of a Normal-Diffuse prior sacrifices an analytical solution, but Gibbs sampling can be used to estimate the posterior numerically.

The results in Figure C.2 show that the impulse response functions (IRFs) estimated from both priors are quite similar, indicating that our prior choice is not particularly restrictive in our case. This justifies the use of the conjugate prior as a computational tractable baseline choice.

Figure C.2: Normal-Inverse-Wishart vs Normal-Diffuse Prior



Appendix D IRFs from FAVAR

Figure D.1: Cumulative Responses to Demand Policy Shock

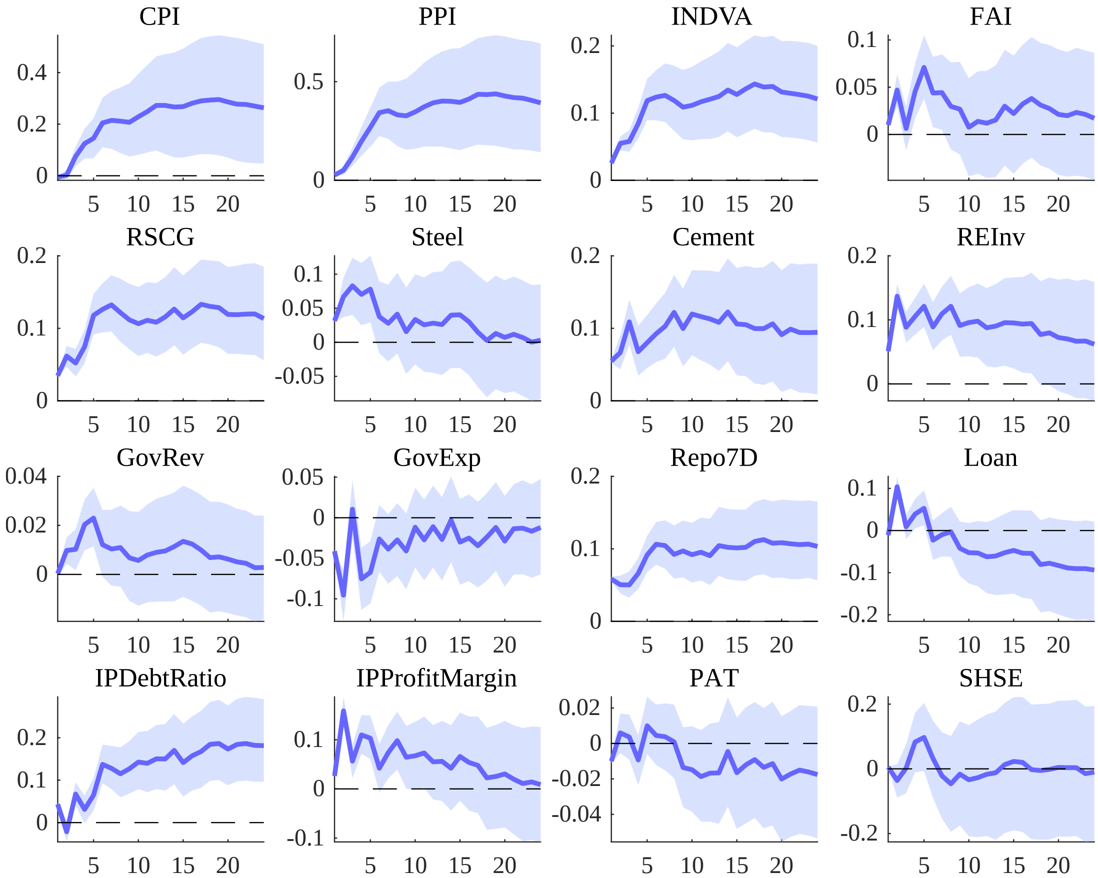


Figure D.2: Cumulative Responses to Supply Policy Shock

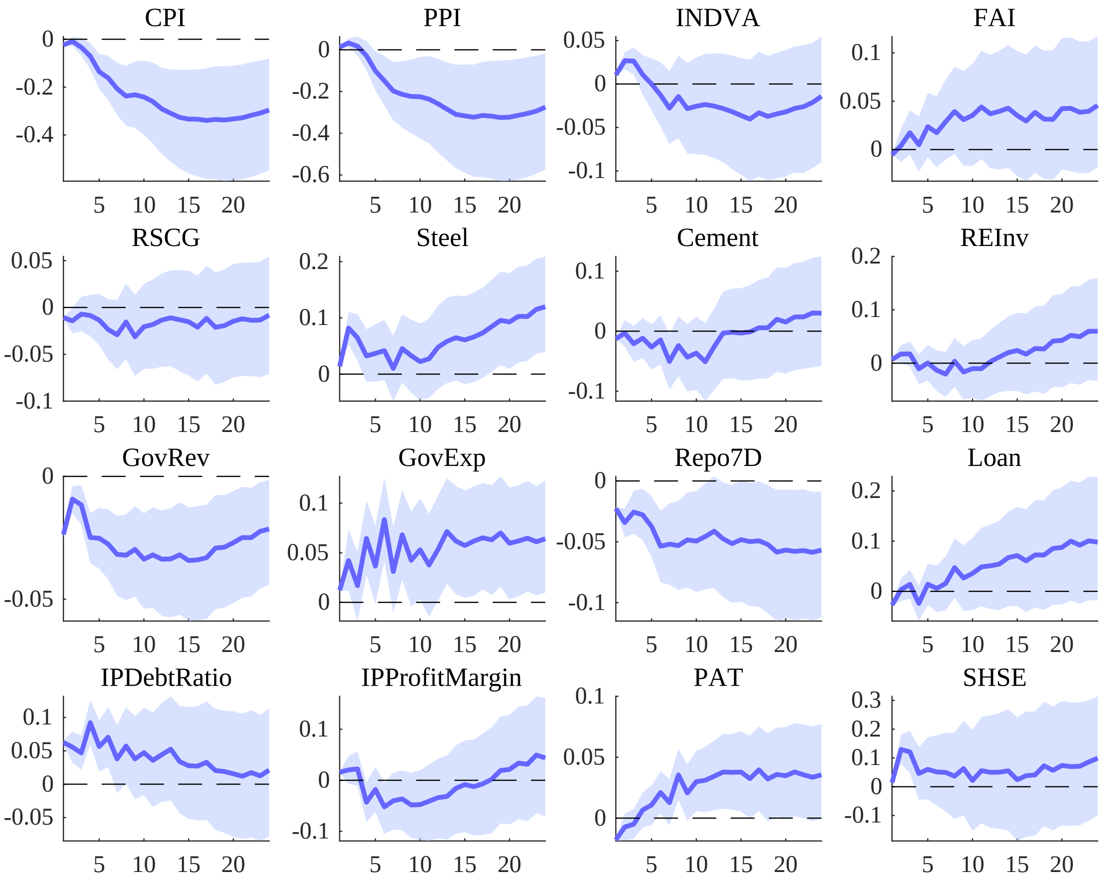


Figure D.3: Cumulative Responses to Negative Supply Shock, 2004-2012

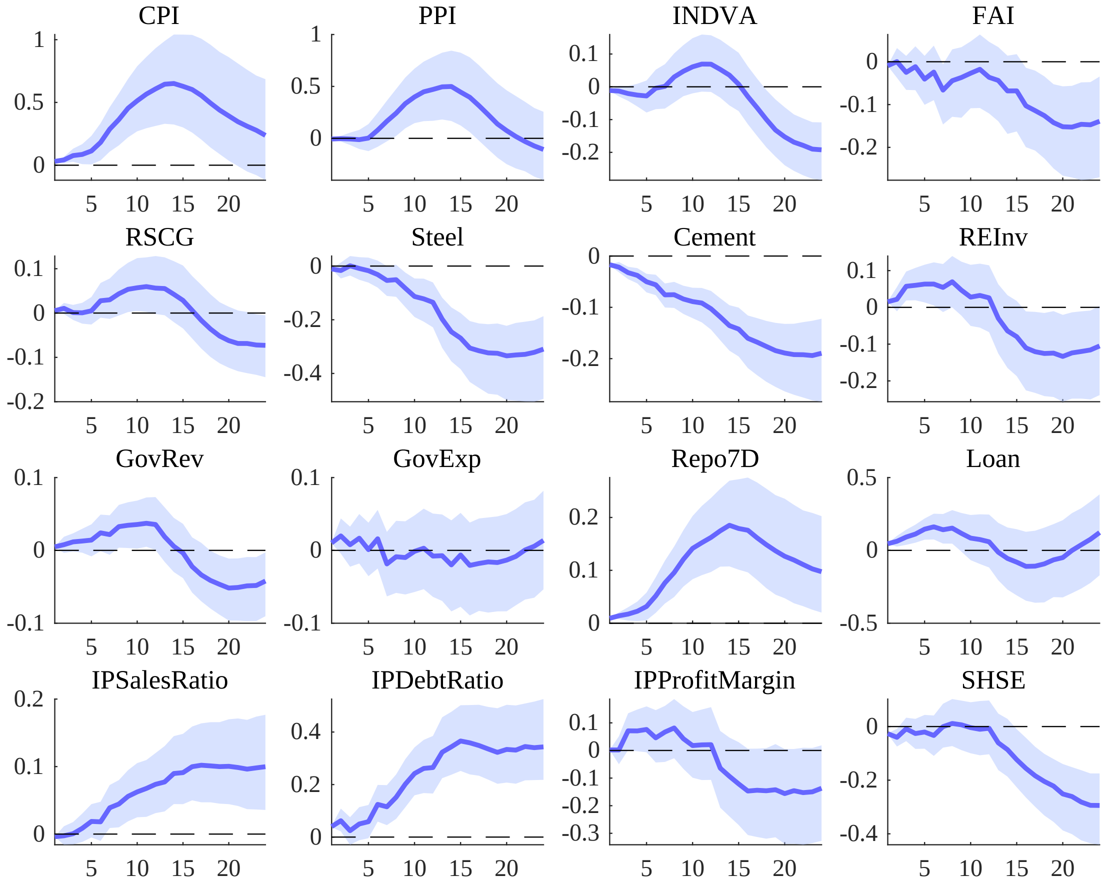


Figure D.4: Cumulative Responses to Negative Supply Shock, 2013-2019