Industry Impacts of US Unconventional Monetary Policy*

Eiji Goto

University of Missouri-St. Louis

26th October 2024

Abstract

Conventional monetary policy has been shown to create differential impacts on industry output. This paper looks at unconventional monetary policy to see its differential impacts on industries in the United States. Identification is achieved with zero and sign restrictions within a structural global vector autoregressive framework. The effects of unconventional monetary policy on output have substantial heterogeneity across industries. Furthermore, the effects on output and monetary policy transmission mechanisms are qualitatively similar to that of conventional monetary policy previously reported in the literature. These findings suggest a substitutability between conventional and unconventional monetary policies. Importantly, policymakers can use unconventional monetary policy and be reassured that impacts on specific industries are similar to those using conventional monetary policy.

JEL classification: E32; E52; G32

Keywords: Unconventional monetary policy; Industry output; Monetary policy transmission mechanisms

*Assistant Professor at the University of Missouri-St. Louis, 1 University Blvd. 408 SSB St. Louis, MO 63121, egoto@umsl.edu. I thank the editor and the two anonymous referees for the helpful comments to improve this paper. I am also thankful to Tara Sinclair, Dennis Jansen, Saroj Bhattarai, Michael Bradley, Frederick Joutz, Gillman Max, Claudia Sahm, and Roberto Samaniego for their comments and feedback. I thank participants at the Macro-International Seminar at the George Washington University, the 13th Economics Graduate Student Conference at Washington University in St. Louis, and the Georgetown Center for Economic Research Biennial Conference. Declarations of interest: none.

1 Introduction

After the financial crisis, the policy rates of many highly advanced economies reached the zero lower bound (ZLB) and central banks in those economies implemented unconventional monetary policy (henceforth unconventional policy). Unconventional policy influences the economy mainly through quantitative easing and forward guidance. While central banks focus on aggregate variables, investigating the disaggregated effects across industries provides new insights. First, differential impacts across industries directly influence the relative performance of industries. Second, the connection between the industry effects of unconventional policy and the financial structure of the industries has implications for the monetary policy transmission mechanisms. Third, knowing whether unconventional policy can be a substitute for conventional monetary policy (henceforth conventional policy) is beneficial for central bankers due to the steadily declining natural rate of interest (Holston et al., 2017) and a high likelihood of entering the ZLB. As an illustration, the recent outbreak of the novel Coronavirus disease (COVID-19) and the corresponding economic slowdown has led central banks in highly advanced economies to re-enter the ZLB.

In this paper, I estimate the impacts of unconventional policy on industry-level output in the US over the last decade using zero and sign restrictions. This paper also investigates whether the pattern of industry-level output responses and transmission mechanisms are similar to those found in the literature on conventional policy.

This paper contributes to the literature on several fronts. First, it provides the differential impacts of unconventional policy on industry output. It has been shown that conventional policy creates differential impacts on industry output (such as Dale and Haldane, 1995 and Ganley and Salmon, 1997), on regional output (such as Carlino and DeFina, 1998 and Arnold and Vrugt, 2002), and on household consumption (such as Kaplan et al., 2018 and Ampudia et al., 2018). The literature on unconventional policy focuses on the financial market effects (such as Gagnon et al., 2011; Krishnamurthy and Vissing-Jorgensen, 2011; and Neely, 2015) and aggregate effects (such as Gambacorta et al., 2014; Boeckx et al., 2017; and Bhattarai et al., 2021), however, the differential impacts of unconventional policy in the literature is scarce. This paper fills this gap in the literature and provides estimates of the effects of unconventional policy on industry output.

Second, this paper adds to the literature of industry studies in monetary policy (Dale and Haldane, 1995; Ganley and Salmon, 1997; and Dedola and Lippi, 2005). In the previous studies, the impacts of monetary policy are estimated on an industry-by-industry basis. This is necessary due to VAR models facing the curse of dimensionality. This paper, by exploiting the global VAR (GVAR) model and Bayesian methods, allows joint estimation of the industry impacts of unconventional policy, taking into account industry interactions.

Third, this paper explores the role of the transmission mechanisms of unconventional policy. One of the advantages of estimating the effects of monetary policy on industry output is to evaluate the potential transmission mechanisms: estimating the industry effects make it possible to associate the effect of monetary policy with the financial structure of the various industries (Dedola and Lippi, 2005 and Peersman and Smets, 2005), and thus infer the transmission mechanisms. This also allows investigation into the similarities and differences between unconventional and conventional policies in terms of industry-level impacts and monetary policy transmission mechanisms.

Identification within my structural Bayesian GVAR model is achieved with zero and sign restrictions. Given the unconventional policy shocks, I generate impulse response functions (henceforth response functions). I use the monthly industrial production index to estimate the model. To confirm the industry-level estimates, I construct a weighted response function from the industry response functions with a weight being the gross value added (GVA) share of the industry. The weighted response functions from all models are approximately the same as the aggregate manufacturing response functions.

I find that the industry-level output responses are heterogeneous across industries. For example, in response to a 1% increase in central bank total assets, the magnitude varies from -0.01% in food, beverage, and tobacco to 0.41% in motor and transportation industries. Generally, durable goods manufacturing industries, such as machinery, primary metal, and motor and transportation, are responsive due to the production structure relying heavily on investment and thus the inflow of funds helps to stimulate the industries. On the other hand, industries that are producing non-durable goods, such as food, beverage, and tobacco; chemical; and petroleum and coal product, respond weakly. This pattern of industry-level output responses is similar to the pattern of responses to conventional policy found in the literature (Dedola and Lippi, 2005).

Furthermore, I find that industries with a smaller leverage ratio, a larger short-term debt, and a smaller long-term debt ratio are associated with a larger output response to unconventional policy. This finding is consistent with the literature on conventional policy (such as Dedola and Lippi, 2005; Peersman and Smets, 2005, and Deng and Fang, 2022) and is consistent with the existence of a credit channel and an interest rate channel. Thus, the findings in this paper support the notion of ”substitutability” between conventional and unconventional policies (Debortoli et al., 2020 and Huber and Punzi, 2020) from an industry perspective.

The rest of this paper is organized as follows: Section 2 describes the data that are used, Section 3 outlines the methodology (including the model, identification, and estimation), Section 4 presents the main results, Section 5 investigates the relationship between output responses and the industry characteristics, Section 6 checks robustness, and finally Section 7 concludes.

2 Data

The data is of a monthly frequency and covers 2008M1-2015M12 based on when the Federal Reserve operates unconventional policy. I follow Gambacorta et al. (2014) and Bhattarai et al. (2021) to determine the beginning of the sample to be in 2008M1.[1] I use the industrial production index as industry output, the consumer price index (CPI) as price level, the central bank total assets, and stock market implied volatility. The data are seasonally adjusted except for the stock market implied volatility.

I plot industry output in Figure 1. The data is normalized so that 2010M1 is 100. Generally, industry output has an upward trend, while the rate of increase differs across industries: some industries grow fast, such as motor and transportation and computer and

[1]The beginning of the sample includes the phase of the Federal Reserve lowering the federal funds rate. However, the exclusion of the period does not alter the results as long as 2008M11, when the quantitative easing (QE) 1 is implemented, is included in the sample. The sample ends at 2015M12 because the Federal Reserve entered a tightening phase after that.

electronic product, while other industries grow slow, such as apparel and leather product and printing activities. I also plot the other variables used in this paper in Figure 2.[2]

[Figure 1 about here.]

[Figure 2 about here.]

The following is the complete list of industries examined in this paper: food, beverage, and tobacco; textile mills product; apparel and leather product; wood product; paper; printing activities; petroleum and coal product; chemical; plastic and rubber product; non-metallic mineral product; primary metal; fabricated metal product; machinery; computer and electronic product; electrical equipment etc; motor and transportation; furniture and related product; and other manufacturing. More details on the industry definitions are available in Table 1.

[Table 1 about here.]

Lastly, I use an input-output (IO) table to construct the GVAR model. Specifically, I use the IO table for generating the weights of how an industry is related to the remaining industries. For the IO table, I use the most recent data available at this time retrieved from the Bureau of Economic Analysis.[3]

3 Methodology

3.1 The Empirical Model

A GVAR model (Pesaran et al. 2004) is, broadly speaking, a panel expression of a vector autoregression (VAR) model. This model allows industry interactions by exploiting the fact that the individual industry dynamics are jointly considered. Additionally, this model incorporates the external information of the industry interactions from the IO table.

[2] I use the CBOE volatility index for stock market implied volatility.

[3] I use the IO table measured in 2017, however, the use of different years during the sample period (i.e. 2012) yields very similar results.

This GVAR specification follows Burriel and Galesi (2018). For each industry i, I model an ARX(p_i, q_i):

$$y_{i,t} = c_i + \sum_{j=1}^{p_i} A_{i,j} y_{i,t-j} + \sum_{j=0}^{q_i} B_{i,j} y^*_{i,t-j} + \sum_{j=0}^{q_i} C_{i,j} x_{t-j} + u_{i,t} \tag{1}$$

where c_i is an intercept; $A_{i,j}$, $B_{i,j}$, and $C_{i,j}$ are coefficient matrices; $u_{i,t}$ is white noise with nonsingular covariance matrix Σ_i; $y_{i,t}$ is industry i's output at time t; and $y^*_{i,t}$ is weighted average of remaining industry output $\forall j \neq i$ and is weakly exogenous:[4]

$$y^*_{i,t} = \sum_{j \neq i} w_{i,j} y_{j,t} \qquad\qquad \sum_{j \neq i} w_{i,j} = 1 \tag{2}$$

The weight, $w_{i,j}$, is assumed to be constant during the estimation periods. Traditionally bilateral trade flow is used (such as Vansteenkiste and Hiebert, 2011) since GVAR models are often used in the context of international spillover effects. However, since the focus is on industry-level interaction, I use the IO table for the weight.[5]

The vector x_t, common variable, is the same across industries and has the following VARX (p_x, q_x) specification:

$$x_t = c_x + \sum_{j=1}^{p_x} D_j x_{t-j} + \sum_{j=0}^{q_x} F_j \tilde{y}_{t-j} + u_{xt} \tag{3}$$

where c_x is a vector of intercepts, D_j and F_j are coefficient matrices, u_{xt} is white noise with nonsingular covariance matrix Σ_x, and $\tilde{y}_t = \sum_i w^*_i y_{i,t}$ is weakly exogenous and w^*_i is GVA share of industry i.

Next, I stack equations (1) and (3). Then a straightforward algebra constructs a structural GVAR model:

$$H_0 Z_t = h_0 + \sum_{j=1}^{p} H_j Z_{t-j} + e_t \tag{4}$$

[4]The assumption of weakly exogenous regressors is reasonable as an industry in the manufacturing sector accounts for a small fraction of the entire economy. However, to ensure that the potential endogeneity does not alter the results, I estimate a VAR (the industry output, the CPI, central bank total assets, and stock market volatility) for each industry separately from the same prior and generate response functions. The results are similar to the response functions generated from GVAR.

[5]Holly and Petrella (2012) use an IO table for the construction of the variable.

where $Z_t = (y_t', x_t')'$ includes the log of the industry output for all the industries, the log of the CPI, the log of central bank total assets, and stock market implied volatility in levels.

Assuming that H_0 is invertible. Then I obtain the reduced form GVAR (p) model:

$$Z_t = k_0 + \sum_{j=1}^{p} K_j Z_{t-j} + \nu_t \qquad \nu_t \sim \mathcal{N}(0, \Omega) \tag{5}$$

Once the reduced form GVAR is obtained, I then impose the identification in the next section and generate response functions.

The variables enter the model without taking the first difference as is standard in the literature (such as Gambacorta et al., 2014; Boeckx et al., 2017; and Christiano et al., 1999). I estimate the models in levels without imposing cointegration restrictions and thus I implicitly keep the long-run relationship of these variables in the model. It is known that, for the purpose of generating response functions, levels specification tends to be more robust than alternative specifications (such as Gospodinov et al., 2013). Additionally, incorporating a unit root prior, as described below in Section 3.3, provides another rationale for reasonably estimating the model in levels. However, a caveat is that under the level specification, a monetary policy shock is not restricted from having a permanent effect.

3.2 Identification

I apply the identification approach from Gambacorta et al. (2014). In the ZLB, the policy instrument is implicitly switched from the short-term nominal interest rate to quantitative easing. This identification exploits central bank total assets and stock market implied volatility to identify unconventional policy shock during the ZLB periods after the financial crisis (such as Gambacorta et al., 2014; Boeckx et al., 2017 and Bhattarai et al., 2021). The identification is a mixture of zero and sign restrictions.

The zero restriction states that a shock to central bank total assets does not have a contemporaneous impact on industry output and price level. In other words, unconventional policy has a lagged impact on output and price level. This zero restriction is a standard assumption in structural VAR analysis, as it enables the separation of a policy shock from other contemporaneous shocks, such as demand or supply shocks.

An unconventional policy shock in Gambacorta et al. (2014) is essentially a surprise increase in central bank total assets. However, a mere increase contains endogenous components. Here, stock market implied volatility plays a role as a financial market distress measure. The Federal Reserve is widely thought to endogenously respond to financial turmoil and economic uncertainty with unconventional policy. That is, an increase in financial market distress increases the central bank total assets. Then an exogenous component of the policy is a shock to the central bank total assets that decreases (or keeps steady) the stock market volatility. This is consistent with the notion in the literature that unconventional policy reduces financial market volatility and risk (such as Hattori et al., 2016; Krishnamurthy and Vissing-Jorgensen, 2011; Gagnon et al., 2011; and Mallick et al., 2017). Thus I only take this latter exogenous component of an increase in central bank total assets as the unconventional policy shock.

In order to generate the mixture of the sign and zero restrictions, I adapt the Givens rotation matrix as in Gambacorta et al. (2014). The complete description of the identification is in Appendix A.1 and A.3. The mixture of the zero and sign restrictions is imposed on the impact period. I also impose the same sign restriction for one period after the shock. However, I modify this assumption in the robustness check to examine how the results are affected. Table 2 summarizes the restrictions that are imposed.

[Table 2 about here.]

3.3 Estimation

To estimate the GVAR model, I follow the literature and estimate Equations (1) and (3) individually and obtain GVAR in Equation (5). This is because it is inevitable to face the curse of dimensionality due to the limited sample size and the number of parameters to be estimated.

I estimate each equation in Equations (1) and (3) using the Stochastic Search Variable Selection (SSVS) prior (George et al., 2008). I follow the application of the SSVS prior to the GVAR model in Cuaresma et al. (2016) and Feldkircher and Huber (2016).

For each ARX and VARX in Equations (1) and (3), I set the coefficient prior to the first own lag of each variable to be 1 and the remaining parameters to be zero. Unlike the Minnesota prior where estimates largely depend on a low number of hyperparameters, SSVS prior allows more flexibility and model uncertainty. The SSVS prior identifies promising subsets of identified parameters or selects a restricted VAR in an automatic, data-based fashion. Given that inference relies on posterior draws, I average out these restricted VARs. Consequently, irrelevant parameters are, on average, designed to shrink toward zero. This prior differs from standard priors by not imposing the same degree of cross-equation shrinkage commonly observed. Therefore, the flexibility of this prior is particularly beneficial in applications involving GVAR models, as demonstrated by Feldkircher and Huber (2016) and Cuaresma et al. (2016). A detailed explanation of the Bayesian estimation is in Appendix A.2. Due to the low sample size and the dimension of the GVAR, I impose $p_i = p_x = q_x = q_i = 3$.[6]

4 Results

I first provide the identified shocks in Section 4.1. Next, in Section 4.2, I show that the industry responsive functions approximately sum up to the aggregate manufacturing response function. In Section 4.3, I show that the industry-level output responses are heterogeneous. Finally, in Section 4.4 I briefly compare the findings with existing studies.

4.1 The identified shock

Before I explore the industry-level output responses, I present the dynamics of the identified shock and examine the characteristics of the identified shock along with the actions taken by the Federal Reserve. Figure 3 shows the time series of the median identified shock. The series is normalized so that its mean and standard deviation are zero and one, respectively.

[6]The previous studies include a small number of lags in large scale VARs. For example Gambacorta et al. (2014) include 2 lags for the panel VAR, Bhattarai et al. (2021) include 3 lags for the panel VAR, and Feldkircher and Huber (2016) include 1 lag for the GVAR. I also estimate the model with 12 lags since the data is of monthly frequency. Despite that the median response functions are similar to the benchmark results, the credible bands become wider. As a result, most industries become insignificant. These results are available upon request.

[Figure 3 about here.]

The identified shock captures unexpected components of the actions by the Federal Reserve relatively well. For example, the onset of QE1 and QE2 comes with positive spikes, which indicate that the actions by the Federal Reserve draw expansionary surprises to the economy. The ends of QE1 and QE2 come with reductions of the identified shock. The time series of the identified shock before and during QE3 are modest, while the central bank total assets dramatically rise, indicating that there are extensive endogenous and expected components.

4.2 Weighted Impulse Response Functions

First, I plot the weighted response function aggregated from industry response functions and the aggregate manufacturing response function from a traditional VAR on Figure 4, to show that the industry response functions approximately sum up to the aggregate response function. The aggregate manufacturing response functions are estimated using a VAR model. The system includes the aggregate manufacturing output, the CPI, central bank total assets, and stock market implied volatility. The same SSVS prior is employed for the estimation, and the identification is consistent with the benchmark zero and sign restrictions so that unconventional policy shocks have no contemporaneous impacts on the aggregate manufacturing output and the CPI as well as unconventional policy shock increases central bank's total assets and decreases (or maintains) stock market implied volatility for the first two horizons (h=0 and 1). If the industry response functions approximately sum up to the aggregate manufacturing response function, it is credible to argue the validity of the industry response functions. Using the gross value added share as a weight, the weighted response functions are calculated as follows:

$$WIRF_p = \sum_{i=1}^{I} weight_i * MIRF_{i,p} \tag{6}$$

where $WIRF_p$ represents the weighted response function at period $p = 1, \ldots, 24$,[7] $MIRF_{i,p}$ represents the median response functions for industry i at period p, and $I = 18$ is the total

[7] I plot the response function over a 24-period horizon.

number of industries.

Each industry response function is the average response from the entire sample period, from 2008M1 to 2015M12. Thus, I calculate the weighted response function using GVA-based weight from the sample period average. In Figure 4, the bold line represents the aggregate manufacturing response function and the dotted line represents the weighted response function. As is standard in the literature, the 68% Bayesian credible bands[8] are reported for the aggregate manufacturing response function.

[Figure 4 about here.]

Both weighted and aggregate manufacturing response functions are generated from the 1% increase in the central bank total assets. The 1% increase in central bank total assets is equivalent to an increase of approximately $20 billion. To interpret the size of the shock better, the size of QE1 is $1.75 trillion, QE2 is $600 billion, and QE3 is $40 billion per month.

The weighted response function is similar to the aggregate response function. Both increase and reach their maximum around 15 months after the shock. Over the period, the weighted response function is stronger than the aggregate manufacturing response function, though the weighted response function is mostly within the credible band of the aggregate manufacturing response function.

4.3 Industry results

Figure 5 shows the industry response functions. I report the 16% and 84% credible bands. The response functions are from the one standard deviation shock to the central bank total assets. The surprise increase in central bank total assets comes with a decrease in stock market implied volatility (due to the sign restriction) and an increase in the price level, consistent with the findings in the literature (such as Gambacorta et al., 2014; Bhattarai et al., 2021; and Boeckx et al., 2017).

[Figure 5 about here.]

[8] Credible band is an interval within which the estimate falls with the probability given.

With regard to the impacts on industry output, most of the industries respond positively to the unconventional policy shock but the magnitudes and significance of the positive responses vary by industries.

To compare the precise impacts of unconventional policy across industries, I calculate the monetary policy elasticity of output: the maximum percentage change in output in response to a 1% increase in central bank total assets. Table 3 summarizes the monetary policy elasticity of output. The elasticity varies from -0.01 in the food, beverage, and tobacco industry to 0.44 in the motor and transportation industry.

[Table 3 about here.]

Typically the responsive industries are in the durable goods manufacturing sector and the unresponsive industries are in the non-durable goods manufacturing sector. For example, all of the top five most responsive industries are durable goods producing industries and four out of the five least responsive industries are non-durable producing industries.[9]

4.4 Discussion

In the previous section, I find that unconventional policy stimulates the industry output heterogeneously. In this section, I briefly compare the results with the existing literature on conventional policy.

Several studies have examined industry impacts in the United States, including Dedola and Lippi (2005). They investigated the industry-level impacts of conventional monetary policy in five OECD countries, including the US, from 1975 to 1997, utilizing monthly frequency data. Their findings indicate that the motor vehicle, primary metal, machinery and equipment, and nonmetallic mineral product industries are responsive to policy changes, while the food, beverage, tobacco; paper; and printing industries exhibit weaker responses.

[9] A similar pattern emerges when employing alternative identifications and specifications, including: 1) Caldara and Herbst (2019) with 10-year Treasury futures in Rogers et al. (2018) as an instrument; 2) Cholesky decomposition utilizing the shadow rate according to Wu and Xia (2016); and 3) incorporating the 10-year Treasury yield in the model with additional sign restrictions such that the unconventional policy shock reduces the 10-year Treasury yield. For instance, specific durable goods-producing industries consistently exhibit a strong response, such as motor and transportation, primary metal, and computer and electronic products. Conversely, certain non-durable goods-producing industries consistently exhibit a weak response to the policy, including food, beverage, and tobacco; paper; printing activities; petroleum and coal products; chemicals; and other manufacturing.

From a slightly different perspective, Singh et al. (2022) explored the effects of monetary policy shocks on employment and hiring using a local projection method, covering both conventional and unconventional policy periods. Their results suggest that manufacturing and construction sectors exhibit stronger responses to tightening shocks relative to their service sector counterparts. They attribute these findings to the differences between the durable goods (manufacturing and construction) and nondurable goods (services) sectors, which aligns with the findings presented in this paper. However, a direct comparison of the results is not straightforward due to the differences in the degree of disaggregation and the outcome variables (labor market vs. output).

Several studies examine industry impacts in other countries in Europe and do not closely align with the findings in this paper. Ganley and Salmon (1997) explore the industry impacts of conventional policy in the UK using quarterly frequency data that spans from 1975 to 1991. They find that rubber and building material, furniture, electronic equipment, paper publishing, and leather respond strongly to the policy while food, beverage, and tobacco; machinery; textile; and motor vehicles respond weakly. Peersman and Smets (2005) investigate the industry impacts of conventional monetary policy in seven euro area countries using quarterly data that covers the period of 1980 to 1998. They find that transport equipment, fabricated metal, and basic metal are responsive to the policy while food, beverage, and tobacco; textile and apparel; and wood furniture are not responsive to the policy. While I find that the same industries respond strongly (such as fabricated metal product) and weakly (such as food, beverage, and tobacco), the pattern of responsiveness of industries generally do not closely match the pattern of responsiveness of industries in Ganley and Salmon (1997) and Peersman and Smets (2005).

Overall, comparisons with previous studies suggest that the industry impacts of unconventional and conventional policies are similar in the US. However, this may not be the case for other countries.

5 Effectiveness and industry characteristics

5.1 Industry characteristics

In this section, I investigate what industry characteristics are related to the effectiveness of unconventional policy. I construct the following five variables from the Compustat database that represent industry characteristics: firm size, leverage ratio, working capital ratio, short-term debt, and long-term debt ratio. Most variables are constructed by referring to Dedola and Lippi (2005). Since the Compustat database covers only publicly traded companies, the industry characteristics do not comprehensively represent the characteristics of the industries.

Specifically the industry characteristics are constructed by the following definitions:

- Firm size = the log of the number of employees
- Leverage ratio = $\dfrac{\text{Total liabilities}}{\text{Shareholders' equity}}$
- Working capital ratio = $\dfrac{\text{Current assets}}{\text{Current liabilities}}$
- Short-term debt = $\dfrac{\text{Current liabilities}}{\text{Total liabilities}}$
- Long-term debt ratio= $\dfrac{\text{Long-term debt}}{\text{Total assets}}$

The Compustat database contains annual frequency firm-level observations. In constructing the above variables, I utilize 2007 data to mitigate the potential endogenous influence of the financial crisis and unconventional policy on firm characteristics.[10] The variables above are constructed in the following order: For each firm, I construct the variables of interest, I allocate firms into industries based on the North American Industry Classification System (NAICS), and for each industry, I take the average and median of the above variables.

Firm size and leverage ratio are proxies for the borrowing capacity of an industry and represent the credit channel. An industry with larger firms or firms with higher leverage

[10] I thank the anonymous referee for this suggestion. The results remain highly comparable when utilizing the average and mean firm characteristics over the sample period spanning from 2008 to 2015.

ratios, on average, tends to possess more borrowing capacity than other industries with smaller firms or firms with lower leverage ratios. In the literature, the connection between firm size and monetary policy elasticity is closely investigated both empirically and theoretically (Gertler and Gilchrist, 1994; Ehrmann and Fratzscher, 2004; and Fisher, 1999). Also, large firms have access to direct and indirect financing. On the other hand, small firms usually only have access to indirect financing. Since credit supply helps small or low-leverage ratio firms increase their production, these firms tend to respond more strongly to policy.

The working capital ratio and short-term debt are proxies for channels on the supply side, mainly the interest rate channel: a change in the nominal interest rate alters the real interest rate and the user cost of capital, which alters production decisions. Working capital represents liquidity and short-term debt represents financing needs. These two variables are constructed using current liabilities. Since a change in the nominal interest rate affects current liabilities, these two variables are affected by the change in the policy rate. Thus, industries with lower working capital ratio and higher short-term debt are expected to respond strongly. However, since the policy rates are attached to the ZLB during the unconventional policy period, it is of interest to know to what extent the interest rate channel plays a role. One thing to note is that these channels are introduced as if they work independently, however, as shown in Bernanke and Gertler (1995), these channels are interrelated and are difficult to disentangle.

Long-term debt ratio is examined as unconventional policy aims to influence long-term interest rates. This implies that industries that possess debts with longer maturities tend to respond well to the policy. However, with regards to conventional policy, Deng and Fang (2022) show that firms with long-term maturity debt demonstrate a weaker response to the policy. Deng and Fang (2022) develop a heterogenous firm model where firms possess the following characteristics: 1) the ability to issue both short and long-term debts, 2) exposure to idiosyncratic productivity shocks that could result in defaults, and 3) the option to engage in investment activities through internal or external financing. In the presence of an expansionary conventional policy, firms with long-term maturity debt demonstrate a weaker response to the policy due to the necessity of allocating a substantial portion of their future cash flows toward debt servicing.

If we assume that unconventional policy transmission mechanisms are the same as conventional policy transmission mechanisms, industries that have smaller firm size, lower leverage ratio, lower working capital ratio, higher short-term debt, and higher long-term debt ratio are expected to respond strongly to the policy. Throughout this section, I show the results from the median industry characteristics, however, the average industry characteristics provide similar results.

5.2 Linear plot

To understand what industry characteristics are associated with higher output responses, I plot the linear relationship between industry characteristics and elasticity in Figure 6.[11] I plot the median industry characteristics against elasticity. I find that firm size is positive,[12] leverage ratio is negative, working capital ratio is positive, short-term debt is positive, and long-term debt ratio is negative.[13]

[Figure 6 about here.]

The negative sign of the leverage ratio and the positive sign of short-term debt align with the findings in Dedola and Lippi (2005). Similarly, the negative sign of the long-term debt ratio[14] is consistent with conventional monetary policy theory considering firm heterogeneity.

However, the result from the long-term debt ratio deviates from recent studies, such as Foley-Fisher et al., 2016 and Lakdawala and Moreland, 2021 which suggest that the effects of unconventional policy on stock prices are more pronounced for firms with long-term debt after controlling for various firm characteristics. This deviation may arise from

[11]This analysis does not provide statistical tests. However, regression analysis is not appropriate due to the sample (industry) size of 18.

[12]The positive relationship is likely to be affected by the outlier. Once I exclude the outlier the relationship becomes negative.

[13]Again, I find the same signs when I use alternative identifications and specifications of 1) Caldara and Herbst (2019) with 10-year Treasury futures in Rogers et al. (2018) as an instrument; 2) Cholesky decomposition utilizing the shadow rate according to Wu and Xia (2016); and 3) incorporating the 10-year Treasury yield in the model with additional sign restrictions such that the unconventional policy shock reduces the 10-year Treasury yield.

[14]I also find a negative relationship using the long-term debt to equity ratio: long-term debt over stockholder's equity.

omitted variables due to a limitation of the linear plot, the small sample size, aggregation of heterogeneous responses, differences between stock price and output, and other factors.

The observed signs of the leverage ratio and short-term debt in this exercise align with expectations, indicating the possible existence of credit and interest rate channels. The results suggest that the interest rate channel plays a role even though the policy rate is attached to the ZLB. This would imply that the real or expected interest rate still affects the production decisions of firms. One possibility is signaling theory, (such as Bauer and Rudebusch, 2013 and Bhattarai et al., 2015) that a central bank's promise to keep the interest rate lower in the future will lower the expected short-term real interest rates. This creates incentives for capital-intensive firms to invest in projects that involve borrowing. Thus, this signaling channel may cause the negative relationship between working capital and elasticity. Overall, the results I obtained here are consistent with the regression results found in Dedola and Lippi (2005) and the prediction in Deng and Fang (2022).

6 Robustness

In this section, I conduct four robustness analyses. Firstly, I modify the effective periods of the sign restriction. Secondly, I examine the sensitivity of the results by including the 10-year Treasury yield as an endogenous variable in the benchmark specification. Thirdly, I test the robustness of the industry order in the benchmark specification by employing a block recursive setup. Lastly, I investigate the robustness using the forward guidance shock constructed in Swanson (2021).

6.1 Changing the Sign Restriction Effective Periods

I change the periods that the sign restriction is effective. Previously, the sign restriction is imposed on the shock period (period 0) and the first period. To see how sensitive the results are, I impose the restriction until the end of the first quarter after the shock. In other words, I impose the same sign restriction on the shock period through the 3rd period after the shock. Table 4 summarizes the new identification.

[Table 4 about here.]

Figure 7 shows that changing the effective periods of the sign restrictions does not have much of an effect on the response functions. For comparison, I also include the response functions of the benchmark identification. The red line represents the median response functions of the benchmark identification, while the blue line represents the median response functions of this identification. Credible bands of both specifications are reported. The results are not largely affected by the new specification. Rather, the two results are very similar. Therefore, the finding is robust to the alternative effective period of the sign restrictions.

[Figure 7 about here.]

6.2 Including 10-year Treasury Yield as an Endogenous Variable

In this section, I re-estimate the benchmark model including the 10-year Treasury yield as an additional endogenous variable to ensure the robustness of the results. The benchmark specification, which excludes long-term asset yields, might potentially overlook transmissions to industries through long-term yields, as prior studies indicate that unconventional policies show strong impacts on long-term maturity yields (e.g., Krishnamurthy and Vissing-Jorgensen, 2011 and Bhattarai et al., 2021). The priors and identifications remain unchanged from the benchmark. Now, the endogenous vector Z_t includes the following variables in the specified order:

$$Z_t = \begin{pmatrix} ln(\text{Industry Output}_1) \\ \dots \\ ln(\text{Industry Output}_{18}) \\ ln(\text{Consumer Price Index}) \\ \text{10-year Treasury yield} \\ ln(\text{Central Bank Total Assets}) \\ \text{Stock Market Implied Volatility} \end{pmatrix}$$

.

Figure 8 illustrates the outcomes of this specification. As before, response functions from the benchmark case are also included. The red line denotes the median response functions from the benchmark specification, while the blue line represents those from this specification. Credible bands from both specifications are reported.

[Figure 8 about here.]

I find that the effects of this specification closely resemble those of the baseline specification. Minor discrepancies in the effects, such as weaker and more precise estimates regarding the apparel and leather product industry, are noted under this specification. Nonetheless, the impacts on most industries and the shapes of response functions closely mirror those of the benchmark results. Thus, the industry-level impacts of unconventional policy are insensitive to the inclusion of the long-term yield.[15]

6.3 A block-recursive setup

In this section, a block-recursive scheme is employed for the identification process, ensuring that the ordering of industries does not affect the results. One challenge encountered when specifying a structural VAR model under sequential identification is the determination of variable order. Due to the zero restriction, different arrangements of variables lead to varying effects of one variable on the others. For instance, during the shock period, the first variable is exclusively influenced by a shock to itself, the second variable is affected by shocks to the first and second variables, the third variable by shocks to the first, second, and third variables, and so on. Consequently, industries positioned earlier in the order are subject to fewer shocks during the shock period. The ordering of industries in the benchmark specification aligns with the industry classification presented in Table 1.

With the block-recursive setup, shocks to industries have an impact on all other industries during the shock period. However, unconventional policy shocks continue to exert lagged effects on industry output. I follow Wermuth (1992) and a positive covariance matrix, $\tilde{\Omega}$, can be decomposed as:

$$\tilde{\Omega} = \Psi^{-1} T (\Psi^{'})^{-1}.$$

[15] Similar results are obtained when incorporating the 10-year Treasury yield into the model with additional sign restrictions, wherein the unconventional policy shock reduces the 10-year Treasury maturity yield.

where Ψ represents an upper block-triangular matrix[16] and T denotes a symmetric positive definite diagonal block matrix. The symmetry and positive definiteness of matrix T lead to the following implications:

$$\tilde{\Omega} = \Psi^{-1} PP^{'} (\Psi^{'})^{-1} = \Psi^{-1} PIP^{'} (\Psi^{'})^{-1} = \Psi^{-1} PQQ^{'} P^{'} (\Psi^{'})^{-1}.$$

where matrix P represents a square root matrix of T, and matrix Q corresponds to the Given's rotation matrix as defined in Appendix A.1. By using these matrices, the expression $\Psi^{-1}P$ forms a block triangular matrix. Consequently, a shock to industries has contemporaneous impacts on other industries, while the unconventional policy shock exhibits a lagged impact on industry output.

Figure 9 illustrates that the imposition of the block-recursive setup has minimal impact on the response functions. In the majority of industries, the median response functions closely align with the benchmark response functions and fall within the credible bands derived from the benchmark specification. These findings indicate that the results remain robust when employing this particular specification.[17]

[Figure 9 about here.]

6.4 Forward guidance shock

The use of central bank total assets to identify unconventional policy shocks entails certain limitations as it is likely to overlook the forward guidance component of such policies. To address this concern, I employ the forward guidance shock developed in Swanson (2021) as a robustness check. Swanson (2021) constructs forward guidance shocks by extracting the principal components of the intraday changes in several asset prices during the FOMC

[16] Therefore, Ψ^{-1} is also an upper block-triangular matrix, which differs from the lower triangular matrix often used in standard recursive identification. To ensure consistency with this identification, relevant row blocks and column blocks of the estimated coefficient matrix, variance-covariance matrix, and the partition block of the endogenous vector in the reduced form GVAR are exchanged.

[17] In addition to the block-recursive setup, I conduct further analyses using two alternative specifications. Firstly, I flip the order of the industries under the benchmark specification. Secondly, I generate an orthogonal matrix, whose dimension corresponds to the number of industries, using the algorithm outlined in Rubio-Ramirez et al. (2010). This orthogonal matrix was then applied to the industry block of the Q matrix in Appendix A.1. I confirm that the results obtained from both of these alternative specifications remain robust and consistent with the findings from the benchmark specification.

announcements. Additionally, the author assumes that the forward guidance shock does not alter the current federal fund rates. Due to the limited 30-minute windows of the high-frequency data, the surprise component of the shock primarily captures the central bank announcements but may not effectively capture other macroeconomic shocks.

An issue raised in the literature concerning the use of high-frequency monetary policy shocks is that these measures can be predictable before announcements, with publicly available macroeconomic and financial market information (Bauer and Swanson, 2023). The use of forecastable high-frequency monetary policy shock measures tends to overstate the effects on macroeconomic variables, while the effects on financial variables remain similar. To ensure that the forward guidance shock is exogenous, I follow Bauer and Swanson (2023) and regress the forward guidance shock in Swanson (2021) on the same predictor regressors used in Bauer and Swanson (2023): nonfarm payrolls surprise, employment growth, S&P 500, yield curve slope, commodity prices, and treasury skewness.[18] I find that none of the regressors are significant at the 10% level, suggesting the appropriateness of the forward guidance shock for this analysis.

Since the forward guidance shock has already been identified, I employ a Bayesian proxy VAR approach in Caldara and Herbst (2019) within the framework of GVAR. In this approach, I consider m_t as the proxy or external instrument, and $e_{UMP,t}$ as the structural unconventional policy shock. The proxy satisfies the "relevance" condition (indicating a correlation between m_t and $e_{NUMP,t}$) and the "exogeneity" condition (indicating no correlation between m_t and non-monetary structural shocks denoted as $e_{NUMP,t}$). These conditions resemble the instrument variables method. The endogenous vector includes the cumulative sum of the forward guidance shock,[19] industry output, the CPI, and the excess bond premium in Gilchrist and Zakrajšek (2012).

One challenge when employing a variant of the proxy VAR is that as the dimension of the VAR increases, it becomes more difficult to ensure the exogeneity condition. Since the GVAR is relatively high dimensional, it is likely to face this problem. To address this issue,

[18] I thank the anonymous referee for this suggestion.

[19] I follow the methodology proposed by Caldara and Herbst (2019) and include the cumulative sum of the forward guidance shock. The authors assess the robustness of their estimation by employing the narrative approach of Romer and Romer (2004), where they incorporate the cumulative sum of the shock into their proxy VAR. However, I find similar response functions when I include the 10-year government bond yield instead of the cumulative sum of the forward guidance shock.

I adopt a locality approach commonly used in the GVAR literature (such as Dees et al., 2007 and Feldkircher and Huber, 2016). Specifically, after estimating equations 1 and 3, I apply the proxy VAR identification only to equation 3, the common equation.[20]

Figure 10 displays the response functions resulting from the forward guidance shock. Generally, the median response functions closely align with the benchmark response function. However, certain industries, including wood product, nonmetallic mineral product, and motor and transportation, fall outside the credible bands of the benchmark results. Although the two identification methods capture distinct aspects of the unconventional policy,[21] the response functions remain reasonably comparable. Overall, the benchmark results exhibit robustness when different measures of an unconventional policy shock are utilized.

[Figure 10 about here.]

7 Conclusion

This paper estimates the industry impacts of unconventional policy for the US using the structural Bayesian GVAR model with the zero and sign restrictions. The industry response functions reveal some interesting features. First, unconventional policy has heterogeneous impacts across industries. Among those responses, I find that unconventional policy strongly stimulates industries that produce durable goods. Such industries are known to be interest rate sensitive in the literature. Second, I find that smaller leverage ratio, larger short-term debt, and smaller long-term debt ratio are associated with higher industry output responses. The findings from this paper imply a similarity in the pattern of impacts and monetary policy transmission mechanisms between conventional and unconventional monetary policies.

Given the potential decline of the natural rate of interest in highly advanced countries (Holston et al., 2017), it is likely that the zero lower bound (ZLB) spreads to other countries

[20]Therefore, it is believed that monetary policy is conducted based on a combination of cumulative forward guidance shocks, the weighted average of industrial output, the Consumer Price Index (CPI), and the excess bond premium. This approach is reasonable as the Federal Reserve is unlikely to base its monetary policy solely on the reaction to individual components of industrial output.

[21]Indeed the correlation between the benchmark identification and Swanson (2021) is around 5%

and compels central bankers to adopt unconventional monetary policies. The findings presented in this paper offer some preliminary insights for countries that have not yet encountered the ZLB. However, considering the unique data and results observed in the US, as discussed in Section 4.4, further individualized research on the industry-specific impacts of unconventional monetary policies is warranted.

References

Ampudia, M., D. Georgarakos, J. Slacalek, O. Tristani, P. Vermeulen, and G. Violante (2018). Monetary policy and household inequality.

Arnold, I. J. and E. B. Vrugt (2002). Regional effects of monetary policy in the Netherlands. *International Journal of Business and Economics 1*(2), 123.

Bauer, M. D. and G. D. Rudebusch (2013). The signaling channel for federal reserve bond purchases. *International Journal of Central Banking, forthcoming*.

Bauer, M. D. and E. T. Swanson (2023). A reassessment of monetary policy surprises and high-frequency identification. *NBER Macroeconomics Annual 37*(1), 87–155.

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

Bhattarai, S., A. Chatterjee, and W. Y. Park (2021). Effects of us quantitative easing on emerging market economies. *Journal of Economic Dynamics and Control 122*, 104031.

Bhattarai, S., G. B. Eggertsson, and B. Gafarov (2015). Time consistency and the duration of government debt: A signalling theory of quantitative easing (No. w21336). Technical report, National Bureau of Economic Research.

Boeckx, J., M. Dossche, and G. Peersman (2017). Effectiveness and transmission of the ECB's balance sheet policies. *International Journal of Central Banking 13*(1), 297–333.

Burriel, P. and A. Galesi (2018). Uncovering the heterogeneous effects of ECB unconventional monetary policies across euro area countries. *European Economic Review 101*, 210–229.

Caldara, D. and E. Herbst (2019). Monetary policy, real activity, and credit spreads: Evidence from bayesian proxy svars. *American Economic Journal: Macroeconomics 11*(1), 157–192.

Carlino, G. and R. DeFina (1998). The differential regional effects of monetary policy. *The Review of Economics and Statistics 80*(4), 572–587.

Christiano, L. J., M. Eichenbaum, and C. L. Evans (1999). Monetary policy shocks: What have we learned and to what end? *Handbook of Macroeconomics 1*, 65–148.

Cuaresma, J. C., M. Feldkircher, and F. Huber (2016). Forecasting with global vector autoregressive models: A bayesian approach. *Journal of Applied Econometrics 31*(7), 1371–1391.

Dale, S. and A. G. Haldane (1995). Interest rates and the channels of monetary transmission: some sectoral estimates. *European Economic Review 39*(9), 1611–1626.

Debortoli, D., J. Galí, and L. Gambetti (2020). On the empirical (ir) relevance of the zero lower bound constraint. *NBER Macroeconomics Annual 34*(1), 141–170.

Dedola, L. and F. Lippi (2005). The monetary transmission mechanism: evidence from the industries of five OECD countries. *European Economic Review 49*(6), 1543–1569.

Dees, S., F. d. Mauro, M. H. Pesaran, and L. V. Smith (2007). Exploring the international linkages of the euro area: a global var analysis. *Journal of applied econometrics 22*(1), 1–38.

Deng, M. and M. Fang (2022). Debt maturity heterogeneity and investment responses to monetary policy. *European Economic Review 144*, 104095.

Ehrmann, M. and M. Fratzscher (2004). Taking stock: Monetary policy transmission to equity markets. *Journal of Money, Credit and Banking*, 719–737.

Feldkircher, M. and F. Huber (2016). The international transmission of us shocks—evidence from bayesian global vector autoregressions. *European Economic Review 81*, 167–188.

Fisher, J. D. (1999). Credit market imperfections and the heterogeneous response of firms to monetary shocks. *Journal of Money, Credit, and Banking*, 187–211.

Foley-Fisher, N., R. Ramcharan, and E. Yu (2016). The impact of unconventional monetary policy on firm financing constraints: Evidence from the maturity extension program. *Journal of Financial Economics 122*(2), 409–429.

Gagnon, J., M. Raskin, J. Remache, B. Sack, et al. (2011). The financial market effects of the Federal Reserve's large-scale asset purchases. *International Journal of central Banking 7*(1), 3–43.

Gambacorta, L., B. Hofmann, and G. Peersman (2014). The effectiveness of unconventional monetary policy at the zero lower bound: A cross-country analysis. *Journal of Money, Credit and Banking 46*(4), 615–642.

Ganley, J. and C. Salmon (1997). The industrial impact of monetary policy shocks: some stylised facts.

George, E. I., D. Sun, and S. Ni (2008). Bayesian stochastic search for var model restrictions. *Journal of Econometrics 142*(1), 553–580.

Gertler, M. and S. Gilchrist (1994). Monetary policy, business cycles, and the behavior of small manufacturing firms. *The Quarterly Journal of Economics 109*(2), 309–340.

Gilchrist, S. and E. Zakrajšek (2012). Credit spreads and business cycle fluctuations. *American Economic Review 102*(4), 1692–1720.

Gospodinov, N., A. M. Herrera, and E. Pesavento (2013). Unit roots, cointegration and pre-testing in var models. *Advances in Econometrics 32*, 81–115.

Hattori, M., A. Schrimpf, and V. Sushko (2016). The response of tail risk perceptions to unconventional monetary policy. *American Economic Journal: Macroeconomics 8*(2), 111–36.

Holly, S. and I. Petrella (2012). Factor demand linkages, technology shocks, and the business cycle. *The Review of Economics and Statistics 94*(4), 948–963.

Holston, K., T. Laubach, and J. C. Williams (2017). Measuring the natural rate of interest: International trends and determinants. *Journal of International Economics 108*, S59–S75.

Huber, F. and M. T. Punzi (2020). International housing markets, unconventional monetary policy, and the zero lower bound. *Macroeconomic Dynamics 24*(4), 774–806.

Kaplan, G., B. Moll, and G. L. Violante (2018). Monetary policy according to hank. *American Economic Review 108*(3), 697–743.

Krishnamurthy, A. and A. Vissing-Jorgensen (2011). The effects of quantitative easing on interest rates: channels and implications for policy (No. w17555). Technical report, National Bureau of Economic Research.

Lakdawala, A. and T. Moreland (2021). Monetary policy and firm heterogeneity: The role of leverage since the financial crisis. *Available at SSRN 3405420*.

Mallick, S., M. S. Mohanty, and F. Zampolli (2017). Market volatility, monetary policy and the term premium.

Neely, C. J. (2015). Unconventional monetary policy had large international effects. *Journal of Banking & Finance 52*, 101–111.

Peersman, G. and F. Smets (2005). The industry effects of monetary policy in the euro area. *The Economic Journal 115*(503), 319–342.

Pesaran, M. H., T. Schuermann, and S. M. Weiner (2004). Modeling regional interdependencies using a global error-correcting macroeconometric model. *Journal of Business & Economic Statistics 22*(2), 129–162.

Rogers, J. H., C. Scotti, and J. H. Wright (2018). Unconventional monetary policy and international risk premia. *Journal of Money, Credit and Banking 50*(8), 1827–1850.

Romer, C. D. and D. H. Romer (2004). A new measure of monetary shocks: Derivation and implications. *American economic review 94*(4), 1055–1084.

Rubio-Ramirez, J. F., D. F. Waggoner, and T. Zha (2010). Structural vector autoregressions: Theory of identification and algorithms for inference. *The Review of Economic Studies 77*(2), 665–696.

Singh, A., J. Suda, and A. Zervou (2022). Monetary policy, labor market, and sectoral heterogeneity. *AEA Papers and Proceedings 112*, 491–495.

Swanson, E. T. (2021). Measuring the effects of federal reserve forward guidance and asset purchases on financial markets. *Journal of Monetary Economics 118*, 32–53.

Vansteenkiste, I. and P. Hiebert (2011). Do house price developments spillover across euro area countries? evidence from a global VAR. *Journal of Housing Economics 20*(4), 299–314.

Wermuth, N. (1992). On block-recursive linear regression equations. *Brazilian Journal of Probability and Statistics*, 1–32.

Wu, J. C. and F. D. Xia (2016). Measuring the macroeconomic impact of monetary policy at the zero lower bound. *Journal of Money, Credit and Banking 48*(2-3), 253–291.

A Mathematical Appendix

A.1 Appendix: Complete description of Given's rotation matrix

The reduced form variance-covariance matrix, Ω, can be expressed as:

$$\Omega = BB' = BIB' = BQQ'B' \tag{7}$$

where B is a lower triangle matrix obtained by the Cholesky decomposition and Q is a Givens rotation matrix defined as:

$$Q = \begin{bmatrix} & 0 & 0 \\ I & \vdots & \vdots \\ & 0 & 0 \\ 0\dots0 & cos(\theta) & -sin(\theta) \\ 0\dots0 & sin(\theta) & cos(\theta) \end{bmatrix} \tag{8}$$

where $\theta \in [0, 2\pi]$.

A.2 Appendix: Complete description of Bayesian estimation

I have the following industry-level ARX:

$$y_{i,t} = c_i + \sum_{j=1}^{p_i} A_{i,j} y_{i,t-j} + \sum_{j=0}^{q_i} B_{i,j} y^*_{i,t-j} + \sum_{j=0}^{q_i} C_{i,j} x_{t-j} + u_{i,t}$$

Let $\Psi_i = (c_i, A_{i,1}, \ldots, A_{i,pi}, B_{i,0}, \ldots, B_{i,qi}, C_{i,0}, \ldots, C_{i,qi})$ and I denote the prior mean of Ψ_i to be $\underline{\Psi_i}$. The elements of $\underline{\Psi_i}$ take 1 if the parameter is associated with the first own lag and take 0 otherwise. The prior covariance matrix of Ψ_i, defined as V_{Ψ_i}, to be a diagonal matrix. The elements in V_{Ψ_i} take values based on hyperparameters. First, I set the prior variance of the intercept to 100. Second, I set the prior variance of i-th variable's own lag l to be λ_1^2/l^2. Third, I set the prior variance of the l th lag of variable j where $j \neq i$ to be $(\frac{\sigma_i * \lambda_2}{\sigma_j * l})^2$, where σ_j is the univariate OLS estimate of the standard deviation. Lastly, I set the prior variance of the exogenous variable, k, to be $(\frac{\sigma_i * \lambda_3}{\sigma_k * (l+1)})^2$. Here I set $\lambda_1 = \lambda_2 = \lambda_3 = 0.1$.

The elements of the prior coefficients, $\psi_{i,jk}$,follow weighted Gaussian distributions:

$$\psi_{i,jk}|\gamma_{i,jk} \sim (1-\gamma_{i,jk})\mathcal{N}(\underline{\psi_{i,jk}}, \kappa_{0,i,jk}) + \gamma_{i,jk}\mathcal{N}(\underline{\psi_{i,jk}}, \kappa_{1,i,jk})$$

Let $\kappa_{1,i,jk} = 10$ and $\kappa_{0,i,jk}$ to be the corresponding element of the Minnesota prior covariance matrix, V_{Ψ_i}.

As for Σ_i, I assume the inverse-Wishart prior:

$$\Sigma_i \sim \mathcal{IW}(S_{i,*}, n_i)$$

where $S_{i,*} = I$, and n is the number of variables in the system plus 2.

Now the posterior distributions are:

$$\Psi_i|\mathbf{y_i}, \mathbf{Z_i}, \gamma_i, \Sigma_i \sim \mathcal{N}(\bar{\Psi}_i, K_{\Psi_i}^{-1})$$

where

- $\mathbf{y_i} = vec(Y) \quad \text{and} \quad Y_i = [y_{i,1}, \cdots, y_{i,T}]$

- $\mathbf{Z}_{i,t} = Z_{i,t} \otimes I$ and $Z_i = [Z_{i,0}, \cdots, Z_{i,T-1}]$ with $Z_{i,t-1} = (1, y_{i,t-1}^{'}, \ldots, y_{i,t-pi}^{'}, y_{i,t}^{*'}, \ldots, y_{i,t-qi}^{*'}, x_t^{'}, \ldots, x_{t-qi}^{'})'$

- γ_i is a vector of $\gamma_{i,jk}$

- $K_{\Psi_i} = W_i^{-1} + Z_i Z_i' \otimes \Sigma_i^{-1}$ where W_i is diagonal with diagonal elements $(1-\gamma_{i,jk})\kappa_{0,i,jk} + \gamma_{i,jk}\kappa_{1,i,jk}$

- $\bar{\Psi}_i = K_{\Psi_i}^{-1}(W_i^{-1} vec(\underline{\Psi_i}) + (Z_i \otimes \Sigma_i^{-1})\mathbf{y_i})$

,

$$\Sigma_i | \mathbf{y_i}, \mathbf{Z_i}, \Psi_i \sim \mathcal{IW}(S_i, \tau_i)$$

where

- $S_i = S_{i*} + \sum_{t=1}^{T} (y_{i,t} - \mathbf{Z}_{i,t} vec(\Psi_i))(y_{i,t} - \mathbf{Z}_{i,t} vec(\Psi_i)))$

- $\tau_i = n_i + T$

, and

$$Prob(\gamma_{i,jk} = 1 | \psi_{i,jk}) = \frac{q_{i,jk}\phi(\psi_{i,jk}; 0, \kappa_{1,i,jk})}{q_{i,jk}\phi(\psi_{i,jk}; 0, \kappa_{1,i,jk}) + (1 - q_{i,jk})\phi(\psi_{i,jk}; 0, \kappa_{0,i,jk})}$$

where

- $Prob(\gamma_{i,jk} = 1 | \psi_{i,jk}) \propto q_{i,jk}\phi(\psi_{i,jk}; 0, \kappa_{1,i,jk})$

- $Prob(\gamma_{i,jk} = 0 | \psi_{i,jk}) \propto (1 - q_{i,jk})\phi(\psi_{i,jk}; 0, \kappa_{0,i,jk})$

- $\phi(\cdot; \mu, \sigma^2)$ denotes the density function of the normal distribution.

- $q_{i,jk} = 0.5$

I also estimate the common VARX equation in an analogous way.

A.3 Appendix: Algorithm of Generating Impulse Response Functions

A burn-in sample of 10,000 draws is discarded and then the following steps are taken to generate response functions.

Step 1: Draw parameters Ψ_i, Ψ_x, Σ_i and Σ_x

Step 2: Recover the reduced form GVAR model and compute the Cholesky decomposition of Ω.

Step 3: For each parameter draw of Ψ_i, Ψ_x, Σ_i and Σ_x, draw N random Given's rotation matrix, $Q^{i\in N}$ and calculate the N response functions.

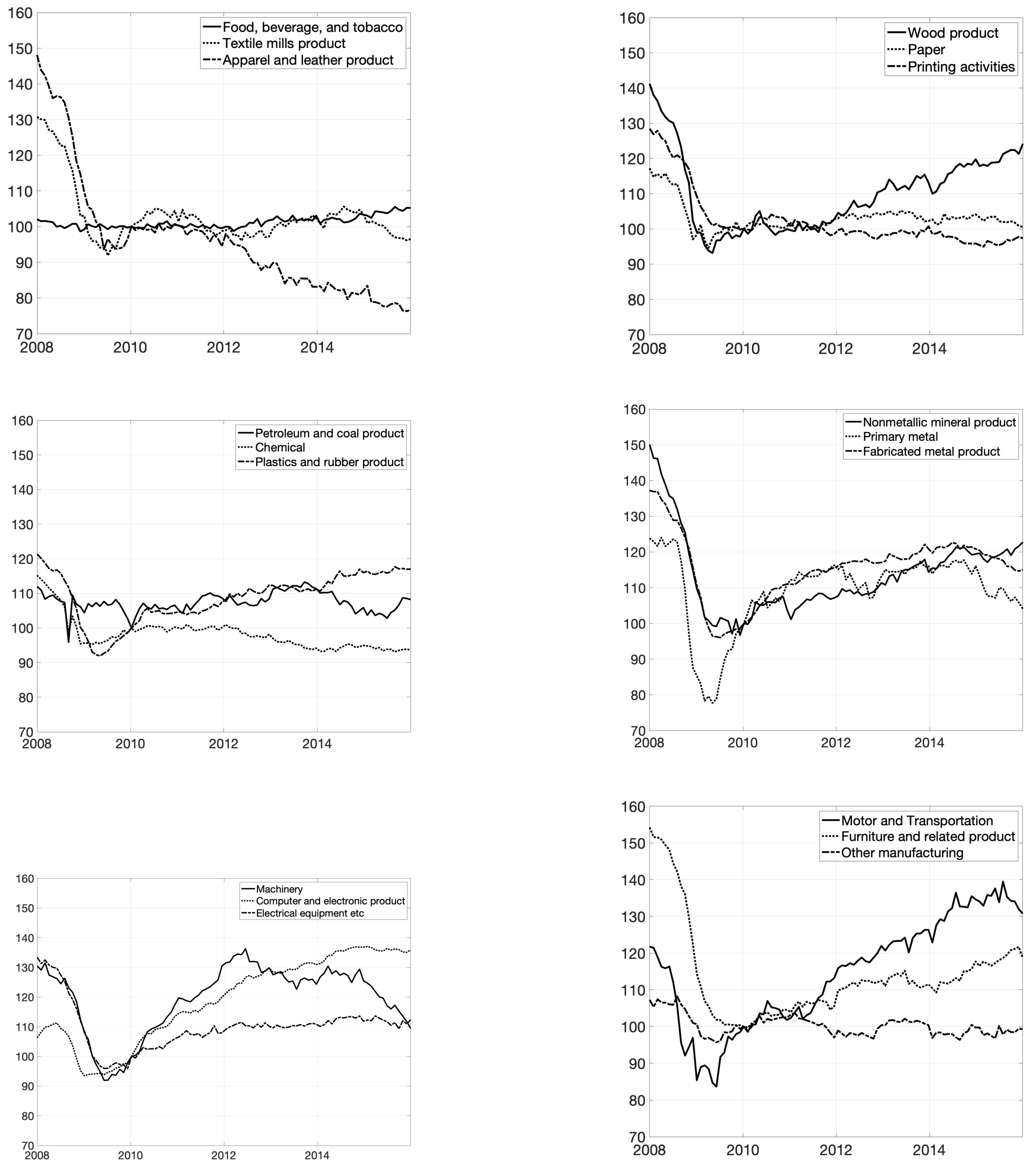
Step 4: If the response function satisfies the sign restriction on Table 2 in Section 3.2, keep it. Otherwise, discard the response function.

Step 5: Repeat steps 1, 2, 3, and 4 M times.

Here N = 50 and M = 2000. All of the successful response functions are sorted in descending order and the upper 84% and bottom 16% are reported as the Bayesian credible band. This credible band represents the statistical significance as well as modeling uncertainty since sign restriction from structural VAR models are not unique.

List of Figures

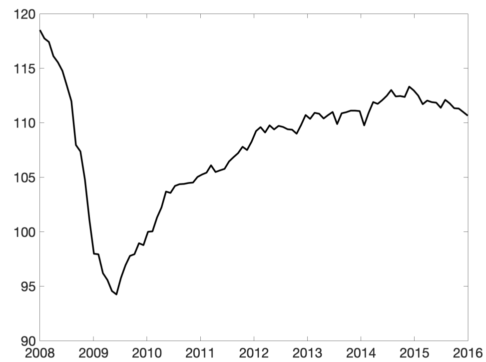
Figure 1: Industry output



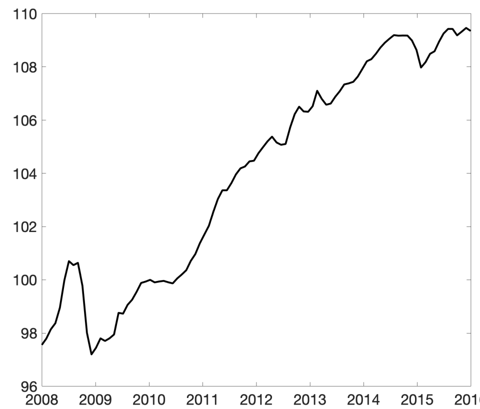
Note: All of the variables are normalized so that 2010M1=100.

Source: The Federal Reserve Board.

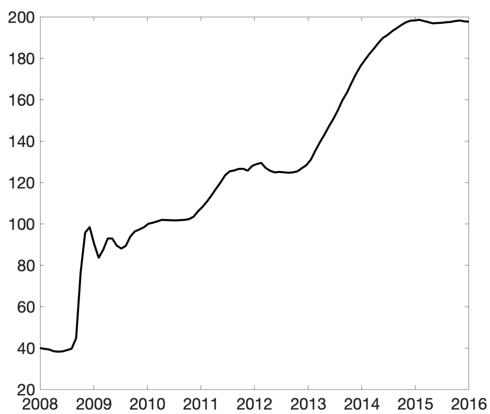
Figure 2: Data used in this paper



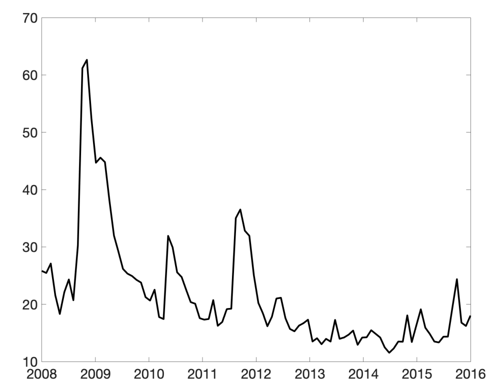
(a) Manufacturing Output



(b) Consumer Price Index



(c) Central Bank Total Assets

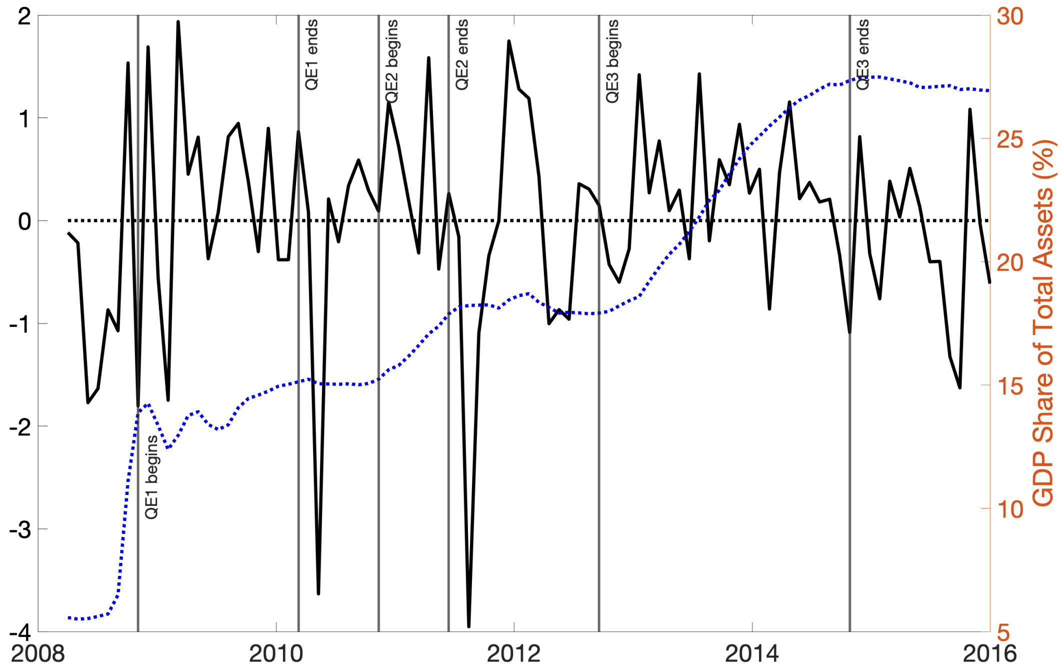


(d) Stock Market Implied Volatility

Note: Manufacturing Output, Consumer Price Index, and Central Bank Total Assets are normalized so that 2010M1=100.

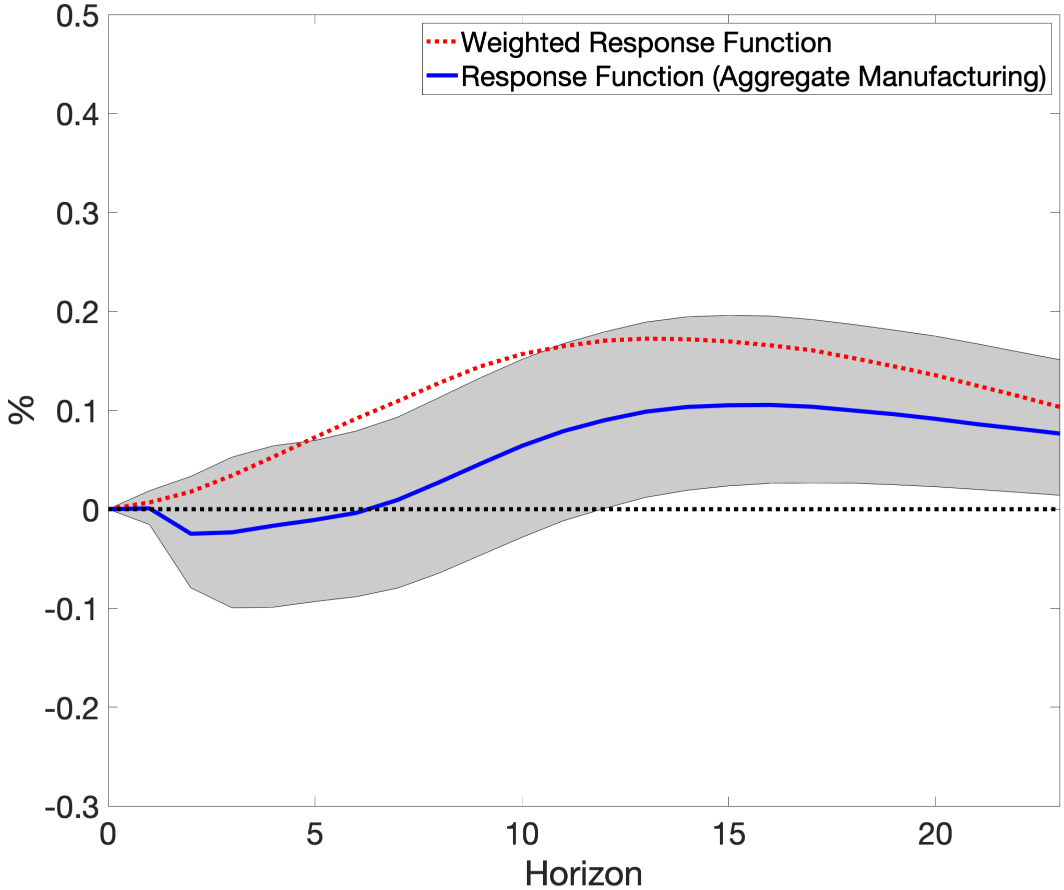
Source: Aggregate output: the Federal Reserve Board; Consumer price index: the Bureau of Labor Statistics; Central bank total assets (WALCL); Stock market implied volatility (VIXCLS)

Figure 3: The identified shocks



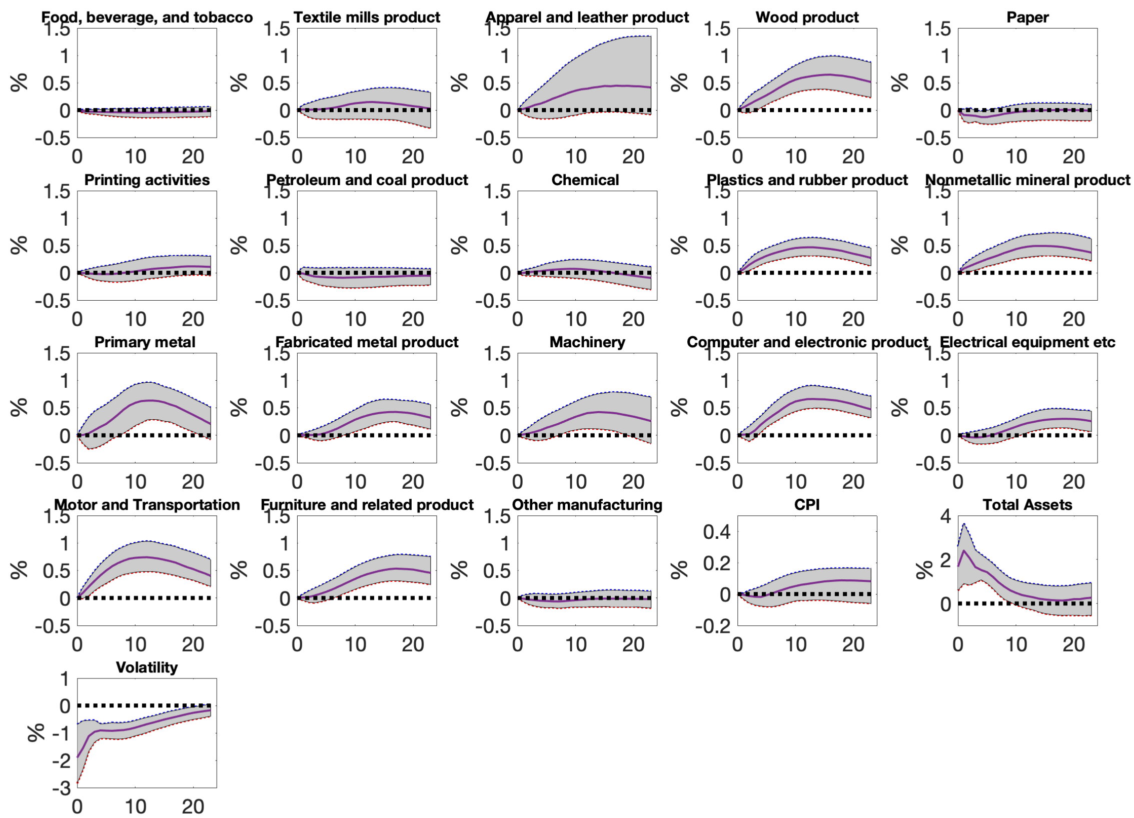
Note: The solid curves represent the median of the identified shocks from the structural GVAR model. The dotted curve represents the share of the central bank total assets of real GDP. I normalized the scale of the shocks so that the mean (as well as the sum) of the shock and the standard deviation of the shock are zero and one, respectively.

Figure 4: Weighted impulse response functions



Note: The median, 16^{th}, and 84^{th} Bayesian percentiles. Monthly horizon. The response function of aggregate manufacturing from the VAR model is attached for comparison. The traditional VAR includes the aggregate manufacturing output, the CPI, central bank total assets, and stock market implied volatility. The same SSVS prior is employed for the estimation, and the identification is consistent with the benchmark zero and sign restrictions.

Figure 5: Industry response functions



Note: The median, 16$^{\text{th}}$, and 84$^{\text{th}}$ Bayesian percentiles are reported. Monthly horizon.

Figure 6: Linear plot of industry characteristics and monetary policy elasticity of output

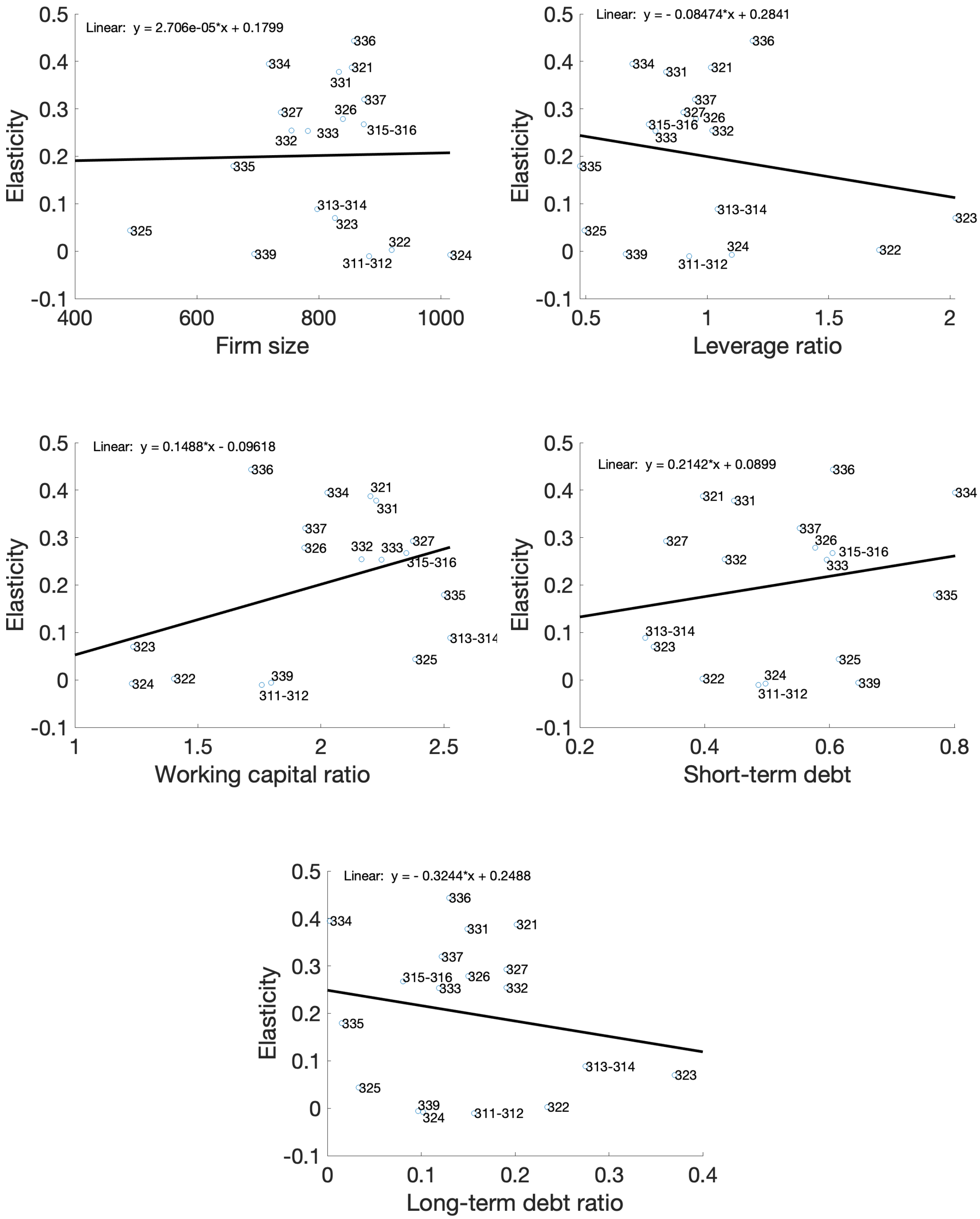
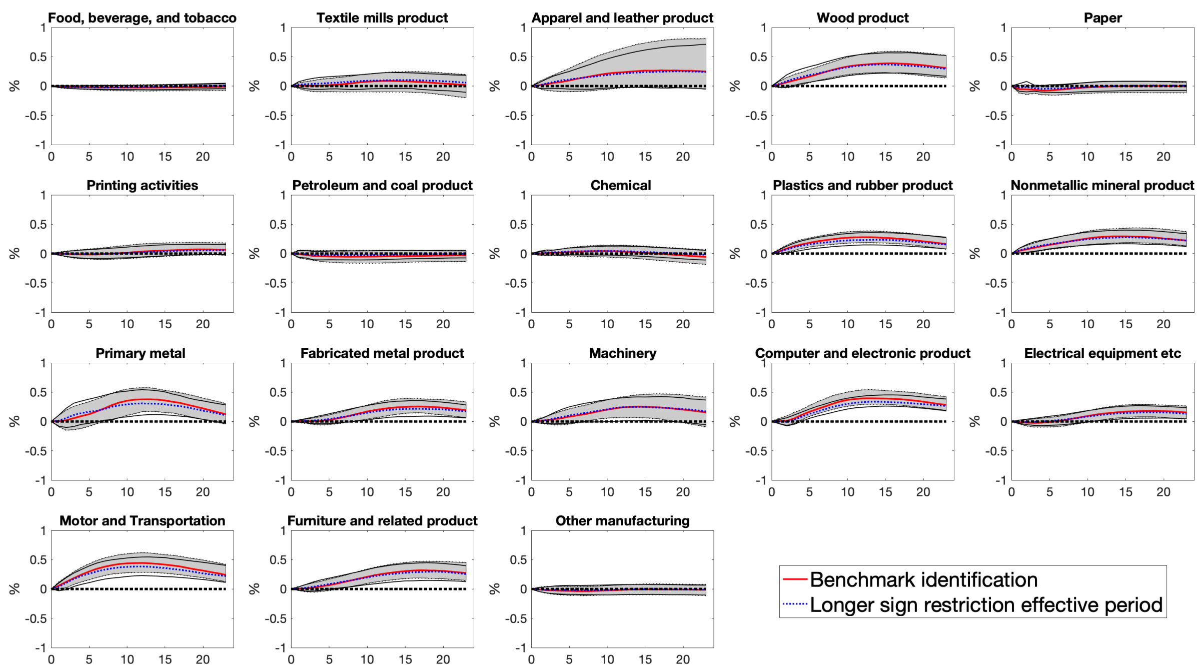
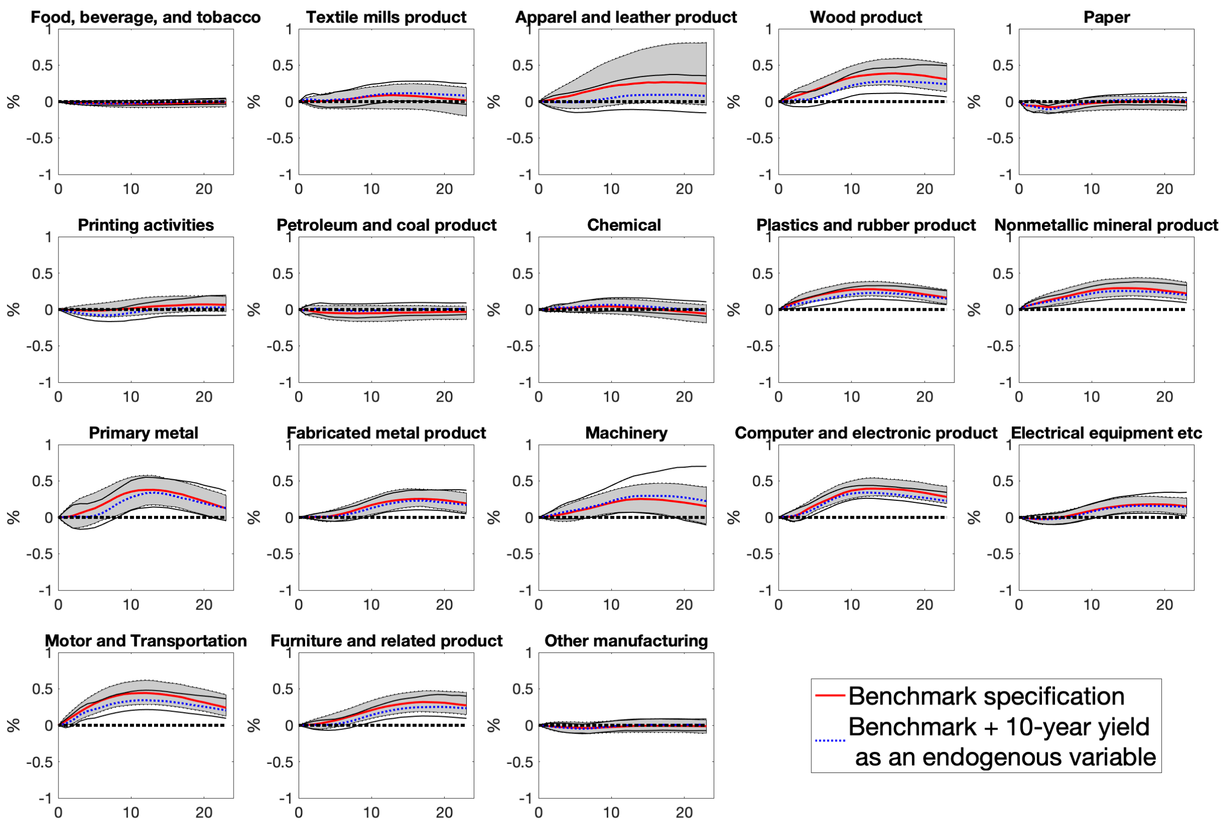


Figure 7: Industry impulse response functions with longer sign restrictions



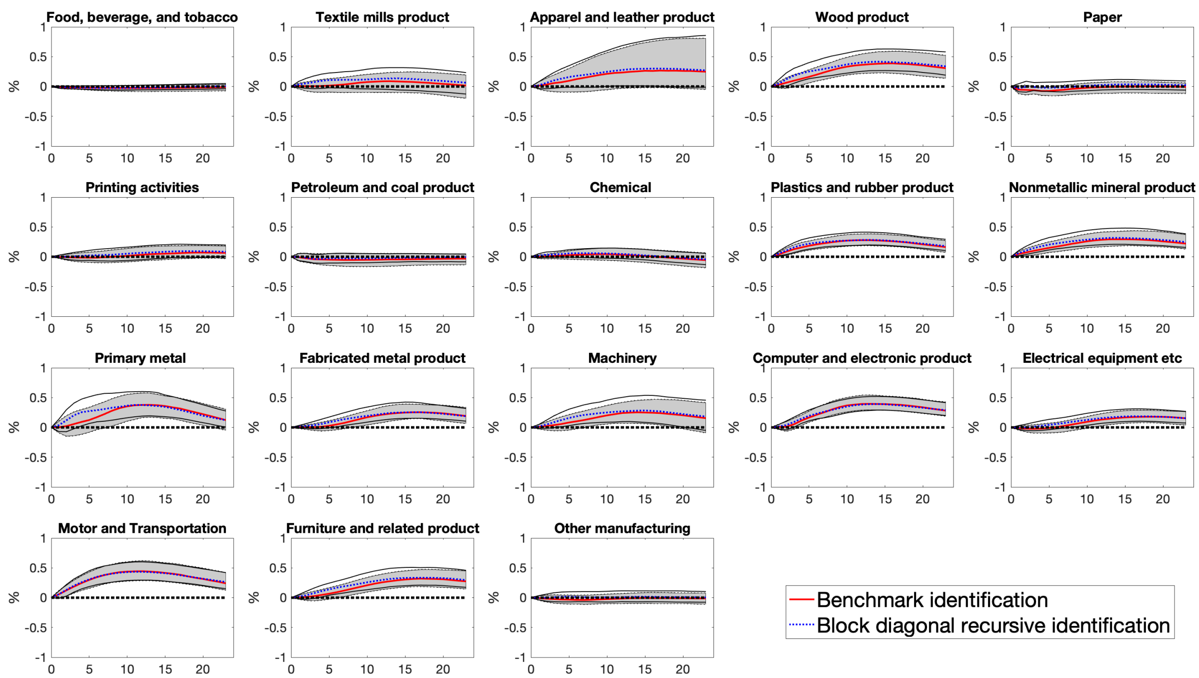
Note: The median, 16$^{\text{th}}$, and 84$^{\text{th}}$ Bayesian percentiles. Monthly horizon. The response functions from the benchmark identification is attached for comparison. The size of the shock is rescaled to be the size of shock from the benchmark identification.

Figure 8: Industry impulse response functions including 10-year Treasury yield as an endogenous variable



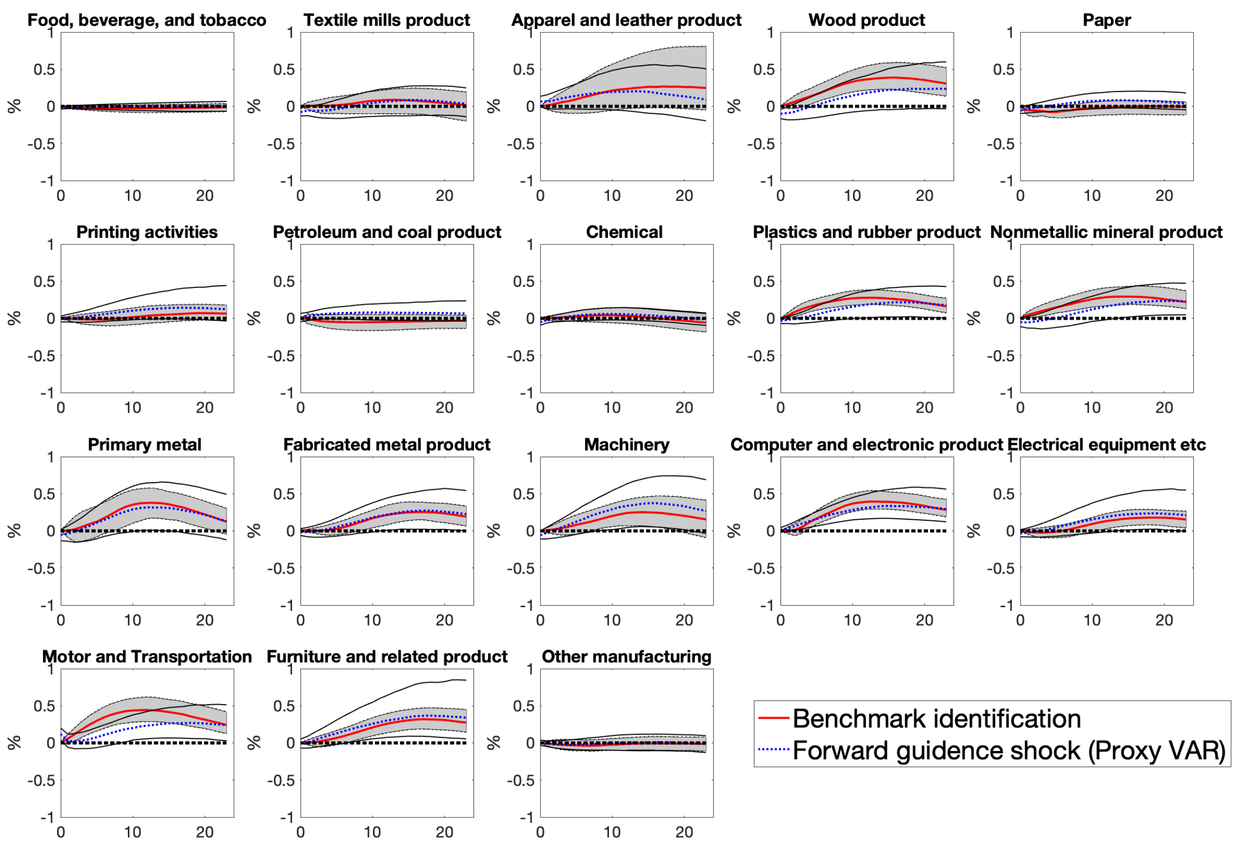
Note: The median, 16$^{\text{th}}$, and 84$^{\text{th}}$ Bayesian percentiles. Monthly horizon. The response functions from the benchmark specification is attached for comparison. The size of the shock is rescaled to be the size of shock from the benchmark specification.

Figure 9: Industry response functions (block recursive)



Note: The median, 16$^{\text{th}}$, and 84$^{\text{th}}$ Bayesian percentiles. Monthly horizon. The size of the shock is rescaled to be the size of the shock from the benchmark identification.

Figure 10: Industry response functions (forward guidance shock)



Note: The median, 16^{th}, and 84^{th} Bayesian percentiles. Monthly horizon. The size of the shock is rescaled to be the size of the shock from the benchmark identification.

List of Tables

Table 1: Industry definition

Industry	NAICS
Food, beverage, and tobacco	311-312
Textile mills product	313-314
Apparel and leather product	315-316
Wood product	321
Paper	322
Printing activities	323
Petroleum and coal product	324
Chemical	325
Plastic and rubber product	326
Nonmetallic mineral product	327
Primary metal	331
Fabricated metal product	332
Machinery	333
Computer and electronic product	334
Electrical equipment etc	335
Motor and transportation	336
Furniture and related product	337
Other manufacturing	339

Table 2: Sign restrictions of impulse response functions

	at period = 0	at period = 1
Industry Output_1	0	*
$\vdots$	$\vdots$	$\vdots$
Industry Output_{18}	0	*
Consumer Price Index	0	*
Central Bank Total Assets	>0	>0
Stock Market Implied Volatility	$\leq$0	$\leq$0

Table 3: Monetary policy elasticity of output

Industry	Elasticity	Industry	Elasticity
Food, beverage, and tobacco	-0.010	Nonmetallic mineral product	0.293
	(-0.070, 0.035)		(0.183, 0.424)
Textile mills product	0.088	Primary metal	0.378
	(-0.099, 0.235)		(0.174, 0.573)
Apparel and leather product	0.267	Fabricated metal product	0.254
	(-0.015, 0.774)		(0.152, 0.385)
Wood product	0.388	Machinery	0.253
	(0.223, 0.590)		(0.070, 0.452)
Paper	0.003	Computer and electronic product	0.395
	(-0.109, 0.075)		(0.296, 0.541)
Printing activities	0.070	Electrical equipment etc	0.179
	(-0.021, 0.186)		(0.082, 0.288)
Petroleum and coal product	-0.008	Motor and transportation	0.443
	(-0.072, 0.058)		(0.289, 0.617)
Chemical	0.043	Furniture and related product	0.320
	(-0.055, 0.140)		(0.188, 0.470)
Plastic and rubber product	0.278	Other manufacturing	-0.006
	(0.188, 0.384)		(-0.093, 0.083)
		Industry average	0.202
		Industry median	0.254

Note: Lower and upper values of a credible band in parenthesis. A credible band is an interval within which the estimate falls with the probability given. Elasticity is the maximum median impulse response function consistent with a 1% increase in central bank total assets. For example, for the Food, beverage, and tobacco industry, a 1% increase in central bank total assets increase the output by -0.01%. Credible bands are also transformed by the same amount as the elasticity is scaled.

Table 4: Sign restriction of impulse response function (robustness)

	at period = 0	at period = 1, 2 and 3
Industry Output_1	0	*
$\vdots$	$\vdots$	$\vdots$
Industry Output_{18}	0	*
Consumer price index	0	*
Central bank total assets	>0	>0
Stock market implied volatility	≤ 0	≤ 0