Industry Impacts of US Unconventional Monetary Policy*

Eiji Goto
University of Missouri-St. Louis

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Abstract

While conventional monetary policy has been shown to create differential impacts on industry output, how unconventional monetary policy affects industries is not yet known. This paper studies the effects of unconventional monetary policy on industry output in the United States. I employ both sign restrictions and high frequency data identifications within a structural global vector autoregressive framework. The effects 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 in the literature. These findings suggest a substitutability between conventional and unconventional monetary policies. Thus, unconventional monetary policy can be used as another tool in the policymakers' toolkit with similar industry impacts.

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*Assistant Professor at the University of Missouri-St. Louis, 1 University Blvd. 408 SSB St. Louis, MO 63121, egoto@umsl.edu. I am very thankful to Tara Sinclair, Saroj Bhattarai, Michael Bradley, Constantin Bürgi, Max Gillman, Dennis Jansen, Frederick Joutz, Xiaohan Ma, Claudia Sahm, Roberto Samaniego, and Toyoichiro Shirota 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, the 45th Eastern Economic Association Conference, the 3rd GW Student Research Conference in Economics 2019, the Georgetown Center for Economic Research Biennial Conference 2019, and the 2019 Pennsylvania Economic Association 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 they 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 effects across industries provides new insights. First, differential impacts across industries directly influence the relative performance of industries. Second, the connection between industry effects of unconventional policy and financial structure of the industry gives the implication of 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 forced 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 two alternative identification schemes. One is based on Quantitative Easing (QE). The other is based on use of High Frequency data (HF). These provide a comprehensive look at the measure the impacts of unconventional monetary policy. 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 (Dale and Haldane, 1995; Ganley and Salmon, 1997; and many others), on regional output (Carlino and DeFina, 1998 and Arnold and Vrugt, 2002), and on household consumption (Kaplan et al., 2018 and Ampudia et al., 2018). The literature of unconventional policy focuses on the financial market effects (Gagnon et al., 2011; Krishnamurthy and Vissing-Jorgensen, 2011; Neely, 2015) and aggregate effects (Gambacorta et al., 2014; Boeckx et al., 2017; Bhattarai et al., 2021; and many others), 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 applies two mainstream identifications of unconventional policy in the literature:

1. QE identification (e.g. Gambacorta et al., 2014)– identifies a policy shock using sign restrictions between central bank total assets and the financial market uncertainty.

2. HF identification (e.g. Gertler and Karadi, 2015) - focuses on the unexpected change in the bond prices around narrow intervals between the policy announcements.

These two identifications measure two different aspects of policy: the first identification measures the quantitative easing component and the second identification measures the forward guidance component of unconventional policy. The aggregate impacts of policy shocks from these identifications have been individually explored (Gambacorta et al., 2014; Peersman, 2011; Gertler and Karadi, 2015; Jarociński and Karadi, 2020; and many others), however, the quantitative and qualitative heterogeneous effects have not been explored and may differ between the two identifications. This paper evaluates the industry effects of unconventional policy by exploiting these two measures of policy shocks.

Third, this paper adds to the literature of industry studies in monetary policy (Dale and Haldane, 1995; Ganley and Salmon, 1997; Dedola and Lippi, 2005; and many others). In the prior literature, 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. In this paper, by exploiting the global VAR (GVAR) model and Bayesian methods, I estimate the industry impacts of unconventional policy jointly, taking into account the industry interactions.

Fourth, 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 this allows the inferences regarding the transmission mechanisms. This exercise also allows investigation as to the similarities and differences of unconventional and conventional policies in terms of industry level impacts and monetary policy transmission mechanisms.

I use structural Bayesian GVAR models with the two identification methods, the QE identification and HF identification, to identify unconventional policy shocks. Given the shocks, I generate impulse response functions (henceforth response functions). I use the monthly industrial production index to estimate the GVAR 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 both models are approximately the same as the aggregate manufacturing response functions, though there are differences when using the HF identification.

I find that the industry-level output responses are heterogeneous across industries. For example, in response to a 1% increase in central bank total asset from the QE identification, the magnitude varies from 0.01% in food, beverage, and tobacco to 0.53% in primary metal. In response to a 5 basis point increase in federal funds futures from the HF identification, the magnitude varies from 0.00% in food, beverage, and tobacco to 1.49% in machinery. 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 help to stimulate the industries. On the other hand, industries that are producing non-durable goods, such as food, beverage, and tobacco; chemical; and printing activities, respond weakly. This pattern of industry level output responses is similar across the two identifications, and 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 firm size and a lower working capital ratio are associated with a larger output response to unconventional policy. This finding is consistent with the literature on conventional policy (e.g. Dedola and Lippi, 2005 and Peersman and Smets, 2005) 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 response and the industry characteristics, Section 6 checks robustness, and finally Section 7 concludes.

2 Data

The data is of a monthly frequency. The data covers 2008M1-2015M12 based on when the Federal Reserve operates unconventional policy and when the federal funds rate is near zero and flat, representing the ZLB.

I apply two different identifications. For both identifications, I use industrial production index as industry output and consumer price index (CPI) as price level. In addition to these variables, I use central bank total assets and stock market implied volatility for the QE identification, and I use the 10-year Treasury yield, the S&P 500 index, and a credit spread (the excess bond premium from Gilchrist and Zakrajšek, 2012) for the HF identification. The industrial production index is obtained from the Federal Reserve Board. The consumer price index is retrieved from the Bureau of Labor Statistics, and all of the remaining data are retrieved from the FRED database.

For the HF identification, I use monetary policy surprises as constructed in Jarociński and Karadi (2020). The data is the change in the tick-by-tick three months federal funds future and S&P 500 index data. The change is from 10 minutes before to 20 minutes after the monetary policy announcement. These variables take zero the value if there are no announcements in the month. As discussed in Jarociński and Karadi (2020), the instruments provide the overall monetary policy stance and "timing surprises" of monetary policy decisions, which implies that the policy surprises can capture some forward guidance component of the unconventional policy. Including the HF identification to the analysis in addition to the QE identification provides a comprehensive analysis of unconventional policy.

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 electronic product, while other industries grow slow such as apparel and leather product and printing activities. I also plot the other data used in this paper in Figure 2.[1]

[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 Appendix 4.

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.[2]

3 Methodology

In this paper, I use a global VAR (GVAR) model and follow the identification methodology in Gambacorta et al. (2014) and Jarociński and Karadi (2020) to identify an unconventional policy shock, generate response functions, and assess the industry effects. Section 3.1 describes the models, Section 3.2 outlines the identifications, and Section 3.3 depicts the estimation.

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

[2] I use the IO table measured in 2017, however, the use of different years during the sample period (i.e. 2012) barely change the results.

3.1 The Empirical Model

A GVAR model (Pesaran et al. 2004) is, broadly speaking, a panel expression of vector autoregression (VAR) models. 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.

A general form of a GVAR model is:

$$y_{i,t} = v_i + A_i Y_{i,t-1} + W(L) y^*_{i,t} + C(L) x_t + u_{i,t} \qquad t = 1, .., T \tag{1}$$

where $W(L)$ and $C(L)$ represent matrix polynomials in the lag operator and $Y_{i,t-1}$ includes all of the $y_{i,t-1}$s. $y^*_{i,t}$ is a variable capturing contemporaneous information from the other industries:

$$y^*_{i,t} = \sum_{\substack{j=1 \\ j \neq i}}^{I} \omega_{i,j} y_{j,t}$$

where $\omega_{i,j}$ is the weight on industry j in the model for industry i. A typical weight used in the literature is the bilateral trade flow. In this paper, I use an IO table for constructing this weight.

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

$$x_t = c_x + \sum_{j=1}^{p_x} D_j x_{t-j} + \sum_{j=0}^{q_x} F_j \tilde{y}_{t-j} + u_{xt} \tag{2}$$

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 $\Sigma_{x,x}$, and $\tilde{y}_t = \sum_i w^*_i y_{i,t}$ where w^*_i is gross value added (GVA) share of industry i. This GVAR specification follows Burriel and Galesi (2018), whose framework is an extension of Pesaran et al. (2004). A detailed explanation of the GVAR specification is in Appendix A.2.

The variables enter the model without taking the first difference as is standard in the monetary policy literature (e.g. Gambacorta et al., 2014; Boeckx et al., 2017; Christiano et al., 1999; and many others). 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 (e.g. Gospodinov et al., 2013). However, a caveat is that under the level specification, a monetary policy shock may have a permanent effect.

For the QE identification, central bank total assets and stock market implied volatility are included to construct the unconventional policy shock. In the ZLB, the short-term nominal interest rate is no longer a monetary policy instrument. Central bank total assets and stock market implied volatility has been used to identify QE shocks during the ZLB periods after the financial crisis (e.g. Gambacorta et al., 2014; Boeckx et al., 2017 and Bhattarai et al., 2021). However, the use of central bank total assets as an instrument for unconventional policy entail some shortfalls[3], as it is likely to miss the forward guidance component of the unconventional policy. Hence, I also explore the HF identification.

For the HF identification, high frequency monetary policy shock, high frequency stock price, the 10-year Treasury yield, the S&P 500 index, the excess bond premium are included.

3.2 Identification

3.2.1 QE Identification

I apply the identification from Gambacorta et al. (2014). The identification is a mixture of zero and sign restrictions. The following equation summarizes the identification by showing the relationship of the reduced form error and structural error terms of the GVAR model (I omit the time subscript):

$$\underbrace{\begin{bmatrix} u_{\text{Industry Output}_1} \\ \vdots \\ u_{\text{Industry Output}_{18}} \\ u_{\text{CPI}} \\ u_{\text{Total Assets}} \\ u_{\text{Volatility}} \end{bmatrix}}_{\substack{\text{Reduced form error} \\ u_t}} = \begin{bmatrix} * & \dots & * & 0 & 0 \\ \vdots & \ddots & \vdots & \vdots & \vdots \\ * & \dots & * & 0 & 0 \\ * & \dots & * & 0 & 0 \\ * & \dots & * & + & + \\ * & \dots & * & -/0 & + \end{bmatrix} \underbrace{\begin{bmatrix} \epsilon_{\text{Industry Output}_1} \\ \vdots \\ \epsilon_{\text{Industry Output}_{18}} \\ \epsilon_{\text{CPI}} \\ \epsilon_{\text{Total Assets}} \\ \epsilon_{\text{Volatility}} \end{bmatrix}}_{\substack{\text{Structural error} \\ \epsilon_t}} \tag{3}$$

[3]Such as missing policy differentiation and composition effects.

where the components of ϵ_t are uncorrelated and have unit variance, $\Sigma_\epsilon = I$. The zero restriction states that a shock to central bank total assets does not have a contemporaneous impact on industry output and price. In other words, unconventional policy has at most a lagged impact on output and price. 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, a higher financial market distress increases central bank total assets. Then an exogenous component of policy is a shock to 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 uncertainty, volatility, and risk (e.g. Hattori et al., 2016; Krishnamurthy and Vissing-Jorgensen, 2011; Gagnon et al., 2011; Mallick et al., 2017; and many others). 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. The mixture of the zero and sign restrictions are 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 1 summarizes the restrictions that are imposed.[4]

[Table 1 about here.]

[4]The complementary restriction (a shock to stock market implied volatility increases central bank total assets and own variable) also are imposed so that the shock is fully identified. The importance of a fully identified sign restriction for inference is mentioned in Kilian and Lütkepohl (2017). However, response functions generated without this complementary restriction are qualitatively similar to the fully identified response functions.

3.2.2 HF Identification

I adopt the identification from Jarociński and Karadi (2020). To identify a policy shock, I use two high frequency data in the model: the change in the 3-month federal funds futures, and the change in the S&P 500 index between, both 10 minutes before and 20 minutes after of the monetary policy announcements. These announcement surprises are only affected by each other but are not affected by the other variables in the model. Given the narrow windows of the high frequency data, the surprise component of the shock captures the central bank announcements but is not likely to capture other macroeconomic shocks.

In order to identify unconventional policy shock, I set up the following equation:

$$\begin{bmatrix} m_t \\ x_t \end{bmatrix} = \sum_{j=1}^{p} \begin{bmatrix} 0 & 0 \\ A^j_{xm} & A^j_{xx} \end{bmatrix} \begin{bmatrix} m_{t-j} \\ x_{t-j} \end{bmatrix} + \begin{bmatrix} 0 \\ c_x \end{bmatrix} + \begin{bmatrix} u^m_t \\ u^x_t \end{bmatrix}, \qquad \begin{bmatrix} u^m_t \\ u^x_t \end{bmatrix} \sim \mathcal{N}(0, \Omega) \tag{4}$$

where m_t is a vector of high frequency variables, notably the change in federal funds futures and the S&P 500 index, x_t is other monthly variables including the 10-year Treasury yield, the S&P 500, industry output, the CPI, and the excess bond premium. Based on the assumption of the high frequency data, m_t does not depend on variables in x_t, while x_t does depend on variables in m_t.

This setup is an alternative approach to external instruments identifications (e.g. Stock and Watson, 2012; Gertler and Karadi, 2015; Mertens and Ravn, 2013; Gortz et al., 2021, and Caldara and Kamps, 2017). Since the two approaches generate asymptotically indifferent response functions up to a scaling factor (Plagborg-Møller and Wolf, 2021), I choose the setup in equation (4) due to the compatibility with the Bayesian inference.

The setup in equation (4) shows that monetary policy surprise, the change in federal funds futures, is located on the top row of the system. Thus the order of the variables does not matter in this identification despite the use of the Cholesky decomposition; this identification does not require imposing zero restrictions on any of the variables in the system, and the monetary policy surprise can contemporaneously affect all of the variables in the system.[5]

[5] Jarociński and Karadi (2020) further impose sign restriction on the high frequency variables to decompose announcement surprises into the central bank information component and monetary policy component. This paper is focused on identifying the general announcement effect of unconventional policy and does

3.3 Estimation

I estimate the GVAR model and generate response functions using the independent Gaussian-inverse Wishart prior. This prior is more flexible than other Bayesian priors and is useful for estimating models with small sample sizes by setting tight parameter distributions. However, it is computationally more demanding than other Bayesian methods and requires a Markov Chain Monte Carlo (MCMC) algorithm. The estimation includes 2 lags of the endogenous variables. I follow the Bayesian method of Kilian and Lütkepohl (2017) and Koop et al. (2010). One of the gains of estimating a Bayesian VAR is to circumvent problems with over-parameterization with the GVAR model. Another gain of estimating a Bayesian VAR is to overcome the problems of the broader confidence bands and uninformative response functions that plague the frequentist approach (Kilian and Lütkepohl, 2017). A detailed explanation of the Bayesian estimation and how I generated response functions is in Appendix A.3.

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 Shocks

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

[Figure 3 about here.]

not decompose announcement surprises.

Regarding the shock from the QE identification, the identified shock captures unexpected components of the actions by the Federal Reserve relatively well. For example, the onset of QE1 and QE2 come with positive spikes, which indicate that the actions by the Federal Reserve draw surprisingly expansionary shocks to the economy. The ends of QE1 and QE2 come with reductions of the identified shock. Contrarily, with regard to the identified shock from the HF identification, most of the announcement activities are clustered around the QE1 announcements. This finding is likely to be due to lower volatility of the federal funds rate during the ZLB.

The identified shocks do not necessarily coincide with the actions taken by the Federal Reserve. The time series of the identified shocks before and during QE3 are modest, while the central bank total assets dramatically rise, indicating that there are extensive endogenous and expected components. It is also possible that economic agents are more familiar and attentive to the actions led by the Federal Reserve after experiencing QE1 and QE2. Overall, the dynamics of the two identified shocks are clearly different from one another.

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. 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:

$$WIRF_p = \sum_{i=1}^{I} weight_i * MIRF_{i,p} \tag{5}$$

where $WIRF_p$ represents the weighted response function at period $p = 1, \ldots, 24$,[6] $MIRF_{i,p}$ represents the median response functions for industry i at period p, and $I = 18$ is the total

[6] 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[7] and the dotted line represents the weighted response function. The 68% Bayesian credible bands[8] are reported for the aggregate manufacturing response function as is standard in the literature.

[Figure 4 about here.]

Both the QE identification and the HF identification have shocks that lead to increases in output. From here on, to compare the results from the two identifications, I multiply -1 with the response functions from the HF identification. I do this because the QE identification represents an accommodative policy, while the HF identification represents a tightening policy. In terms of magnitudes, the QE identification is in line with the literature (such as Gambacorta et al., 2014; Bhattarai et al., 2021; Boeckx et al., 2017, and many others) and the HF identification is also in line with the findings in the literature utilizing high frequency data (Jarociński and Karadi, 2020 and Gertler and Karadi, 2015).

Both weighted and aggregate manufacturing response functions are generated from the same size of shocks. The one standard deviation shock to central bank total assets in the QE identification increases the central bank total assets by 2.06%. This is equivalent to an increase of approximately $40 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 HF identification is normalized so that there is a 5 basis point decrease in federal funds futures, which translates to a 7.8 basis point decrease in the 10-year Treasury yield on average.

The weighted response function from the QE identification is similar to the aggregate response function. Both increase and reach their maximum around 10 to 15 months after the shock. Over the period, the weighted response function is slightly weaker than the

[7]The aggregate manufacturing response functions are estimated using a VAR model. For the QE identification, the system includes the aggregate manufacturing, CPI, central bank total assets, and stock market implied volatility. For the HF identification, the system includes the high frequency monetary policy surprise, high frequency S&P 500 index, 10-year treasurey yield, S&P 500, the aggregate manufacturing, CPI, and excess bond premium.

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

aggregate manufacturing response function, though the weighted response function is within the credible band of the aggregate manufacturing response function.

On the contrary, the weighted response function from the HF identification takes a different path than the aggregate response function. In response to the shock, the weighted response function immediately reaches its maximum after three months and slowly goes back to zero, while the aggregate response function slowly increases and reaches its maximum at the end of the horizon. Potential explanations for these deviations are estimation uncertainty and differences in the model. In spite of those differences, they end up reaching a similar level at the end. While there are some deviations, the weighted response functions reasonably tracks the aggregate response functions.

4.3 Industry Results

Figures 5 and 6 show the industry response functions from the QE identification and HF identification, respectively. I report the 16% and 84% credible bands. As mentioned before the response functions are from the one standard deviation shock to central bank total assets for the QE identification and a 5 basis point decrease in federal funds futures. With regards to the QE identification, 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; Boeckx et al., 2017, and many others). With regards to the HF identification, the decrease in monetary policy surprise increases the high frequency S&P 500, decreases the Treasury yield, increases the CPI, increases the S&P 500, and slightly decreases the excess bond premium, also consistent with the findings in the literature (Jarociński and Karadi, 2020 and Gertler and Karadi, 2015).

With regard to the impacts on industry output, I find that 16 out of 18 industries respond significantly positive for the QE identification and that 15 out of 18 industries respond significantly positive for the HF identification.

[Figure 5 about here.]

[Figure 6 about here.]

The magnitudes 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 the change in the respective monetary policy instruments.[9] Table 2 summarizes the monetary policy elasticity of output. The elasticity varies from 0.02 to 0.53 for the QE identification and from 0.00 to 1.494 for the HF identification.

[Table 2 about here.]

Even though the nature of the two identifications differ, they are similar when it comes to the degree of responsiveness. The top five responsive industries from the two identification have four overlaps: wood product, primary metal, machinery, and computer and electric product industries. The least five responsive industries from the two identification has also have four overlaps: food beverage and tobacco, printing activities, chemical, and other manufacturing. Typically the responsive industries are in the durable goods manufacturing sector and the unresponsive industries are in the non-durable goods manufacturing sector.

The persistence of response functions from the two identifications is somewhat different. With regard to the QE identification, most of the industries increase their production and reach their maximum about 10 periods after the shock and then slowly decline. However, with the HF identification, production reaches its maximum a few months after the shock and then slowly go back up to zero. This might be caused by the central bank total assets potentially influencing output as long as the effect still exists, while the high frequency surprise terms disappear in the period after the shock.

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 of conventional policy.

[9]For the QE identification, the change in monetary policy instrument is a 1% increase in central bank total assets and for the HF identification, the change in monetary policy instrument is a 5 basis point decrease in federal funds futures.

Several studies examine industry impacts in other countires in Europe. 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).

The differences of industry responsiveness between the above studies and this paper may be a result of different countries being studied; the above studies focused on euro area countries while this paper studied the US. It is possible that the same industries have different industry characteristics in the US and in countries in the euro area, which would lead to different responsiveness. In order to compare the industry responses in this paper to literature that also examines the US, I look to Dedola and Lippi (2005). They study the industry impacts of conventional policy in the five OECD countries, which includes the US, over the period of 1975 to 1997 using monthly frequency data. They find that motor vehicle, primary metal, machine and equipment, and nonmetallic mineral product are responsive while food, beverage, tobacco; paper; and printing respond poorly. This pattern of industry level output responses matches the pattern I find in this paper quite well. This indicates that the industry impacts of unconventional policy and conventional policy are similar in the US, however, this might not be the case for other countries.

5 Effectiveness and Industry Characteristics

5.1 Industry Characteristics

In the previous section, I find that the pattern of industry level output responses to unconventional policy is similar between the two identifications and to that of conventional policy in the US. In this section, I investigate what industry characteristics are related to the effectiveness of unconventional policy. I construct the following four variables from the Compustat database that represent industry characteristics: firm size, leverage ratio, working capital ratio, and short-term debt. These 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 = 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 $= \dfrac{\text{Current Liabilities}}{\text{Total Liabilities}}$

The Compustat database contains annual frequency firm-level observations. I construct the above variables over the sample period used in this paper. The variables above are constructed in the following order: I deflate the nominal variables using the GDP deflator, for each firm and each year I construct the variables of interest, for each firm I take the average of each variable over the sample period, 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 borrowing capacity of an industry and represent the credit channel. An industry with larger firms or firms with higher leverage ratios, on average, tend 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 (Gertler and Gilchrist, 1994 and Ehrmann and Fratzscher, 2004) and theoretically (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 need. 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.

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, and higher short-term debt are expected to respond strongly to the policy. Throughout this section, I show the results from the average industry characteristics, however, the median 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 on Figure 7.[10] I plot the average industry characteristics against elasticity from both identifications. I find

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

that firm size and the working capital ratio have negative correlations with the responsiveness to policy in both identifications, which is consistent with the findings in Dedola and Lippi (2005). Also the QE identification further indicates a negative correlation of the leverage ratio, and a positive correlation of short-term debt, with the elasticity. However, the HF identification finds the opposite signs. These plots are small samples and not much should be take from it. Overall, firm size and working capital show the expected signs from this exercise, which indicate the possible existence of the credit and interest rate channels.

[Figure 7 about here.]

5.3 Industry Characteristics Weighted Response Function

To support the previous findings, I construct an industry characteristic weighted response function. That is, I generate several weighted response functions with the weight being the industry characteristics. The weighted response function tends to be more responsive if responsive industries have higher values of the industry characteristics. Alternatively, the weighted response function tends to be less responsive if responsive industries have lower values of the industry characteristics. By generating the weighted response function, I visually obtain the association of the monetary policy responsiveness and industry characteristics. I construct the industry characteristic weighted response function using the following formula:

$$WIRF_p = \sum_i \left(\frac{\text{industry characteristics}_i}{\sum_i \text{industry characteristics}_i}\right) * MIRF_{ip} \tag{6}$$

Figure 8 shows the industry characteristics weighted response functions. For comparison, I plot an equally weighted response function.[11] Consistent with the previous section, the results show that firm size and working capital ratio weights make the weighted response functions weaker. With regards to the QE identification, short-term debts lead to a stronger estimated effect while leverage ratio leads to a weaker effect. This is consistent with the prediction in Section 5. Similarly to the previous section, we do not find this pattern from the HF identification.

[11]Since there are 18 industries, the weight is $\frac{1}{18}$.

[Figure 8 about here.]

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). I find that monetary policy transmission mechanisms of conventional and unconventional policies do not differ.

6 Robustness

In this section, I conduct a series of robustness analyses.

6.1 Changing the Sign Restriction Effective Periods

To study the effect of unconventional policy, an accurate identification is key. The results should not be radically altered by the choice of the effective periods of sign restriction. Therefore, I change the periods that the sign restriction is effective on the QE identification. 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 3 summarizes the new identification.

[Table 3 about here.]

Figure 9 shows the response functions of this identification. For a 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, imposing the sign restriction as shown on Table 1 in Section 3.2 is sufficient to generate an ideal unconventional policy shock.

[Figure 9 about here.]

6.2 QE identification with Long-term Interest Rate

In this section, I use a long-term asset yield to identify an unconventional policy shock following Bhattarai et al. (2021). The idea is that unconventional policies operated in the US focus on long-term asset purchases. In Section 3.2, I used the identification in Gambacorta et al. (2014), which is a broad measure of unconventional policy. Here, I extend the identification and observe how the use of a long-term asset yield changes the results from the benchmark identification. The new identification includes long-term interest rate in the GVAR framework.

One of the purposes of unconventional policy is to reduce long-term interest rates through the purchase of assets. This identification allows the unconventional policy shock to be more specific to the policy. Now the endogenous vector y_t contains:

$$y_t = \begin{bmatrix} ln(\text{Industry Output}_{1,t}) \\ \vdots \\ ln(\text{Industry Output}_{18,t}) \\ ln(\text{CPI}_t) \\ \text{Long-Term Yield}_t \\ ln(\text{Total Assets}_t) \\ \text{Volatility}_t \end{bmatrix} \tag{7}$$

where Long yield$_t$ is the 10-year government bond yield. I impose an additional sign restriction on top of the benchmark identification so that a shock to central bank total assets decrease the long-term interest rate. One caveat of this identification is that it may not capture the policies not intending to reduce the long-term asset yield: such as direct lending to banks. The following is the identification:[12]

[12]Again, I omit the time subscript

$$
\underbrace{\begin{bmatrix} u_{\text{Industry Output}_1} \\ \vdots \\ u_{\text{Industry Output}_{18}} \\ u_{\text{CPI}} \\ u_{\text{Long-Term Yield}} \\ u_{\text{Total Assets}} \\ u_{\text{Volatility}} \end{bmatrix}}_{\substack{\text{Reduced form error} \\ u_t}} = \begin{bmatrix} * & \cdots & * & 0 & 0 \\ \vdots & \ddots & \vdots & \vdots & \vdots \\ * & \cdots & * & 0 & 0 \\ * & \cdots & * & 0 & 0 \\ * & \cdots & * & - & 0 \\ * & \cdots & * & + & + \\ * & \cdots & * & -/0 & + \end{bmatrix} \underbrace{\begin{bmatrix} \epsilon_{\text{Industry Output}_1} \\ \vdots \\ \epsilon_{\text{Industry Output}_{18}} \\ \epsilon_{\text{CPI}} \\ \epsilon_{\text{Long-Term Yield}} \\ \epsilon_{\text{Total Assets}} \\ \epsilon_{\text{Volatility}} \end{bmatrix}}_{\substack{\text{Structural error} \\ \epsilon_t}} \tag{8}
$$

Figure 10 shows the results of this identification. For a comparison, I also include the response functions from the benchmark identification. As before, the red line represents the median response functions from the benchmark identification, while the blue line represents the median response functions from this identification. Credible bands from both specifications are reported.

[Figure 10 about here.]

I find that the impacts from this identification are generally weaker than the impacts from the benchmark identification, but the shapes of the response functions do not vary much between the two specifications. This indicates that the refinement of the identification causes a quantitative level shift of the response functions, but the qualitative impacts of unconventional policy are not radically altered.

6.3 Changing the order of the industries

An issue with specifying a structural GVAR model is the order of variables. Due to the zero restriction of the QE identification, different orders of the variables changes how one variable affects the other variables. For example, in the shock period, the first variable is only affected by a shock to the first variable, the second variable is affected by shocks to the first and second variables, the third variable is affected by shocks to the first, second, and third variables, etc. Thus the earlier an industry is in the order, the less shocks that industry is affected by in the shock period. Note that this problem does not happen when the HF identification is used, as the monetary policy shock affects all of the variables contemporaneously.

The order of industries from the benchmark specification is reported in Table 4. Since it is impractical to test all possible combinations, I estimate the model by flipping the order of the industries. Figure 11 shows the results. The results from this specification are almost identical to the benchmark. The results from the wood and printing activities show some deviations between the different specifications, however, the median response functions are within the credible bands given from the benchmark QE identification.

[Figure 11 about here.]

6.4 HF Identification with 1-Year Treasury Yield

In the analysis of the HF identification, I include the 10-year Treasury yield so that the high frequency announcement surprises can have real impacts during the ZLB. However, Jarociński and Karadi (2020) instead use the 1-year Treasury yield. Therefore, in this section I use the 1-year Treasury yield instead of the 10-year Treasury yield and compare the results.

Figure 12 reports the results. The results from this specification moderately alters the response functions. For almost all of the industries, the impacts become weaker. This suggests some struggles of the model transmitting the policy shock to the real economy through the 1-year Treasury yield during ZLB. Similarly to the findings in Section 6.2, this specification generates a level shift of the response functions, however, the qualitative impacts of unconventional policy are not drastically altered.

[Figure 12 about here.]

7 Conclusion

This paper estimates the industry impacts of unconventional policy for the US using structural Bayesian GVAR model. The monetary policy shocks are constructed using the QE and HF identifications. 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 the industries that produce durable goods, which are known to be interest rate sensitive in the literature. Second, the pattern of industry responses are similar between the QE and HF identifications. Though the two identifications measure different aspects of unconventional policy, industry level output responses are quite similar. Third, I find that smaller firm size and lower working capital are associated with higher industry output responses. The findings from this paper imply a similarity of 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 ZLB spreads to other countries and requires other central bankers to implement an unconventional policy. The results obtained in this paper provide some bottom line predictions for countries that have not yet experienced the ZLB and aid central bankers in creating an unconventional policy.

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A Mathematical Appendix

A.1 Appendix: Complete Description of Identification

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

$$\Omega = BB' = BIB' = BQQ'B' \tag{9}$$

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

$$Q = \begin{bmatrix} & 0 & 0 \\ I & \vdots & \vdots \\ & 0 & 0 \\ 0\dots0 & cos(\theta) & -sin(\theta) \\ 0\dots0 & sin(\theta) & cos(\theta) \end{bmatrix} \tag{10}$$

where $\theta \in [0, 2\pi]$. The above definition can generate the relationship between reduced form error and structural form error terms:

$$
\underbrace{\begin{bmatrix} u_{\text{Industry output}_1} \\ \vdots \\ u_{\text{Industry output}_{18}} \\ u_{\text{CPI}} \\ u_{\text{Total Assets}} \\ u_{\text{Volatility}} \end{bmatrix}}_{\substack{\text{Reduced form error} \\ u_t}} = \begin{bmatrix} * & \dots & * & 0 & 0 \\ \vdots & \ddots & \vdots & \vdots & \vdots \\ * & \dots & * & 0 & 0 \\ * & \dots & * & 0 & 0 \\ * & \dots & * & + & + \\ * & \dots & * & -/0 & + \end{bmatrix} \underbrace{\begin{bmatrix} \epsilon_{\text{Industry output}_1} \\ \vdots \\ \epsilon_{\text{Industry output}_{18}} \\ \epsilon_{\text{CPI}} \\ \epsilon_{\text{Total Assets}} \\ \epsilon_{\text{Volatility}} \end{bmatrix}}_{\substack{\text{Structural error} \\ \epsilon_t}} \tag{8 revisited}
$$

A.2 Complete Description of GVAR Specification

For each industry i, I model a VARX(p_i, q_i):

$$
y_{i,t} = c_i + \sum_{j=1}^{p_i} A_{i,j} y_{i,t-j} + \sum_{j=0}^{q_i} B_{i,j} y^*_{i,t-j} + \sum_{j=0}^{q_i} C_{i,j} x_{t-j} + u_{i,t} \tag{11}
$$

where c_i is a vector of intercepts; $A_{i,j}$, $B_{i,j}$, and $C_{i,j}$ are coefficient matrices; $u_{i,t}$ is white noise with nonsingular covariance matrix $\Sigma_{i,i}$; $y_{i,t}$ consists of domestic variables (i.e. a vector of output industry i at time t); $y^*_{i,t}$ contains the remaining industry variables (i.e. a vector that consists of industry output except for industry i); and $y^*_{i,t}$ is constructed as a weighted average of domestic variables $\forall j \neq i$:

$$
y^*_{i,t} = \sum_{j \neq i} w_{i,j} y_{j,t} \qquad\qquad \sum_{j \neq i} w_{i,j} = 1 \tag{12}
$$

The weight, $w_{i,j}$, is assumed to be constant during the estimation periods. Traditionally bilateral trade flow is used (e.g. Vansteenkiste and Hiebert, 2011 and Galesi and Lombardi, 2009) since GVAR models are often used for assessing international spillover effects. However, since the focus is on industry level interaction, I use the 2017 IO table for the weight.[13]

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

[13] Holly and Petrella (2012) and Vansteenkiste (2007) use an IO table for the construction of a foreign variable.

$$x_t = c_x + \sum_{j=1}^{p_x} D_j x_{t-j} + \sum_{j=0}^{q_x} F_j \tilde{y}_{t-j} + u_{xt} \tag{13}$$

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 $\Sigma_{x,x}$, and $\tilde{y}_t = \sum_i w_i^* y_{i,t}$ and w_i^* is GVA share of industry i.

Given the specifications of equation (11) and exploiting the fact that $y_{i,t}^* = W_i y_t$, where W_i is a link matrix based on the IO table and $y_t = [y'_{1,t}, y'_{2,t}, ..., y'_{I,t}]'$, equation (11) can be transformed to:

$$G_{i,0} y_{i,t} = c_i + \sum_{j=1}^{p_i} G_{i,j} y_{i,t-j} + \sum_{j=0}^{q_i} C_{i,j} x_{t-j} + u_{i,t} \tag{14}$$

where $G_{i,0} = (I - B_{i,0} W_i)$ and $G_{i,j} = (A_{i,j} + B_{i,j} W_i)$. Now we stack all of the industries together to get:

$$G_0 y_t = c + \sum_{j=1}^{p} G_j y_{t-j} + \sum_{j=0}^{q} C_j x_{t-j} + u_t \tag{15}$$

Likewise, using the fact that $\tilde{y}_t = W^* y_t$, where W^* is a link matrix based on the industry GVA share, equation (13) becomes:

$$x_t = c_x + \sum_{j=1}^{p_x} D_j x_{t-j} + \sum_{j=0}^{q_x} F_j W^* y_{t-j} + u_{xt} \tag{16}$$

By combining equations (15) and (16), we can construct a structural global VAR model:

$$H_0 Z_t = h_0 + \sum_{j=1}^{p} H_j Z_{t-j} + e_t \tag{17}$$

where $Z_t = (y'_t, x'_t)'$, $H_0 = \begin{bmatrix} G_0 & -C_0 \\ -FW^* & I \end{bmatrix}$, $h_0 = \begin{bmatrix} c \\ c_x \end{bmatrix}$, $H_j = \begin{bmatrix} G_j & C_j \\ F_j W^* & D_j \end{bmatrix}$, and $e_t = \begin{bmatrix} u_t \\ u_{xt} \end{bmatrix}$. Finally, e_t has the variance-covariance matrix $\Sigma = \begin{bmatrix} \Sigma_{i,j} & \Sigma_{i,x} \\ \Sigma_{x,i} & \Sigma_{x,x} \end{bmatrix}$

Assuming that H_0 is invertible. Then we obtain the reduced form global VAR (p)

model:

$$Z_t = k_0 + \sum_{j=1}^{p} K_j Z_{t-j} + \nu_t \qquad \nu_t \sim \mathcal{N}(0, \Omega) \tag{18}$$

where $k_0 = H_0^{-1}h_0$, $K_j = H_0^{-1}H_j$, $\nu_t = H_0^{-1}e_t$, and $\Omega = H_0^{-1}\Sigma H_0^{-1'}$.

To estimate the model, I impose $p_i = p_x = q_x = q_i = 2$. Hypothetically, directly estimating equation (18) is ideal, however, given the limited sample size and the number of the parameters to be estimated, it is inevitable to face the curse of dimensionality. To circumvent this problem, I follow the conventional way to estimate a GVAR: estimate the domestic equation (11) and the common equation (13) individually using OLS. This is the prior for the coefficient matrix.

A.3 Appendix: Complete Description of Bayesian Estimation

A.4 QE identification

First, I impose the priors of $vec(K)$ and Ω to be independent and they follow the independent Gaussian-inverse Wishart distribution. The joint pdf is:

$$g(vec(K), \Omega) = g_{vec(K)}(vec(K)) * g_{\Omega}(\Omega)$$

The distributions for $vec(K)$ and Ω are:

$$vec(K) \sim \mathcal{N}(vec(K^*), V_{vec(K)})$$

and

$$\Omega \sim \mathcal{IW}(S_*, n)$$

where K^* is the OLS estimates, $S_* = I$, and n is the number of variables in the system plus 1. For the prior variance of the coefficients parameter, $V_{vec(K)}$, I impose the Minnesota prior. This enables the prior distribution to be tight and that is necessary to overcome the curse of dimensionarity with the GVAR model. First, I set the prior variance of the intercept to be infinity and the prior variance of the j, k^{th} elements of K_i to be:

$$v_{jk,i} = \begin{cases} (\lambda/i)^2 & \text{if j=k} \\ (\lambda\alpha\sigma_j/i\sigma_k)^2 & \text{if j}\neq\text{ k} \end{cases} \tag{19}$$

where $\lambda = 0.3$ and $\alpha = 0.05$. σ_j and σ_k are obtained from equation by equation OLS estimates of the VAR model. Then $V_{vec(K)}$ is:

$$V_{vec(K)} = \begin{bmatrix} \infty & & & & & & & & & & & & \\ & \ddots & & & & & & & & & & & \\ & & \infty & & & & & & & & & & \\ & & & v_{1,1,1} & & & & & \mathbf{0} & & & & \\ & & & & \ddots & & & & & & & & \\ & & & & & v_{n-1,1,1} & & & & & & & \\ & & & & & & v_{1,2,1} & & & & & & \\ & & & & & & & \ddots & & & & & \\ & & & & & & & & v_{n-1,2,1} & & & & \\ & & & & & & & & & \ddots & & & \\ & & & \mathbf{0} & & & & & & & v_{1,1,2} & & \\ & & & & & & & & & & & \ddots & \\ & & & & & & & & & & & & v_{n-1,n-1,2} \end{bmatrix}$$

Now, the posterior distributions are:

$$vec(K)|\Omega, \mathbf{y} \sim \mathcal{N}(vec(\bar{K}), \bar{\Omega}_{vec(K)})$$

and

$$\Omega|vec(K), \mathbf{y} \sim \mathcal{IW}(S, \tau)$$

where

$$\mathbf{y} = vec(Y) \quad \text{and} \quad Y = [y_1, \cdots, y_T],$$

$$vec(\bar{K}) = [V_{vec(K)}^{-1} + (ZZ' \otimes \Omega^{-1})]^{-1}[V_{vec(K)}^{-1} vec(K^*) + (Z \otimes \Omega^{-1})\mathbf{y}],$$

$$\bar{\Omega}_{vec(K)} = [V_{vec(K)}^{-1} + (ZZ' \otimes \Omega^{-1})]^{-1},$$

$$S = S_* + \sum_{t=1}^{T}(y_t - \mathbf{Z}_t vec(K))(y_t - \mathbf{Z}_t vec(K))',$$

and

$$\tau = T + n.$$

Moreover, Ω is the OLS estimate, $\mathbf{Z}_t = Z_t \otimes I$ and $Z = [Z_0, \cdots, Z_{T-1}]$ with $Z_{t-1} = (1, y'_{t-1}, y'_{t-2})'$.

Here the posterior distribution of $vec(K)$ is conditional on Ω and the posterior distribution of Ω is conditional on $vec(K)$. Therefore, the Gibbs sampler is required to draw sample parameters from the joint posterior distribution. A burn-in sample of 20,000 draw is discarded following the literature[14] and then the following steps are taken to generate response functions.

Step 1: Draw reduced form parameters $K_i^{*r}s$ and Ω^{*r} and compute the Cholesky decomposition of Ω^{*r}.

Step 2: For each $K_i^{*r}s$ and Ω^{*r}, draw N random Given's rotation matrix, $Q^{i \in N}$. For each combination of $K_i^{*r}s$, Ω^{*r}, and Q^i, calculate the response function.

Step 3: If the response function satisfies the sign restriction on Table 1 in Section 3.2, keep it. Otherwise, discard the response function.

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

Here N = 1000 and M = 1000. All of the successful response functions are sorted in a 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.

A.5 High Frequency Data Identification

The equation (4) can be expressed as the following matrix notation:

$$\begin{bmatrix} M & X \end{bmatrix} = W \begin{bmatrix} 0 & A \end{bmatrix} + \begin{bmatrix} U^M & U^X \end{bmatrix} \qquad \begin{bmatrix} U^M & U^X \end{bmatrix} \sim \mathcal{N}(0, \Omega)$$

[14] I also calculate the Geweke convergence criteria (Geweke et al., 1991) and almost all of the parameters converged before 4,000 draws.

where $M = (m_1, \ldots, m_T)'$, $X = (x_1, \ldots, x_T)'$, $W = (m_{t-1}, x_{t-1}, m_{t-2}, x_{t-2}, 1)'$, $B = (A^1_{xm} A^1_{xx} A^2_{xm} A^2_{xx} c_x)'$, $U^M = (u^m_1, \ldots, u^m_T)'$, and $U^X = (u^x_1, \ldots, u^x_T)'$

First, I impose the priors of $vec(B)$ and Ω to be independent and they follow the independent Gaussian-inverse Wishart distribution. The joint pdf is:

$$g(vec(B), \Omega) = g_{vec(B)}(vec(B)) * g_{\Omega}(\Omega)$$

The distributions for B and Ω are:

$$vec(B) \sim \mathcal{N}(vec(B^*), V_{vec(B)})$$

and

$$\Omega \sim \mathcal{IW}(S_*, n)$$

where B^* is the OLS estimates, S_* is the diagonal element of Ω, and n is the number of variables in the system plus 2. For the prior variance of the coefficients parameter, $V_{vec(B)}$, I impose the Minnesota prior in the previous section.[15]

Given the prior specification, the posterior distributions are:

$$vec(B)|\Omega, \mathbf{X}, \mathbf{M} \sim \mathcal{N}(vec(\bar{B}), \bar{\Omega}_{vec(B)})$$

and

$$\Omega|vec(B), \mathbf{X}, \mathbf{M} \sim \mathcal{IW}(S, \tau)$$

where

$$vec(\bar{B}) = [V^{-1}_{vec(B)} + (\Omega^{-1}_{XX.1} \otimes W'W)]^{-1}[V^{-1}_{vec(K)} vec(B^*) + (\Omega^{-1}_{XX.1} \otimes W')vec(X + M\Omega^{-1}_{MM}\Omega_{MY})],$$

$$\bar{\Omega}_{vec(B)} = [V^{-1}_{vec(B)} + (\Omega^{-1}_{XX.1} \otimes W'W)]^{-1},$$

$$S = S_* + (\begin{bmatrix} M & X \end{bmatrix} - W \begin{bmatrix} 0 & A \end{bmatrix})'(\begin{bmatrix} M & X \end{bmatrix} - W \begin{bmatrix} 0 & A \end{bmatrix}),$$

[15] $\lambda = 0.1$ and $\alpha = 0.3$ are imposed

and

$$\tau = T + n.$$

where $\Omega = \begin{bmatrix} \Omega_{MM} & \Omega_{MX} \\ \Omega_{XM} & \Omega_{XX} \end{bmatrix}$ and $\Omega_{XX.1} = \Omega_{XX} - \Omega_{XM}\Omega_{MM}^{-1}\Omega_{MX}$.

The Gibbs sampler draws sample parameters from the joint posterior distribution. A burn-in sample of 100,000 draw is discarded and then the following steps are taken to generate response functions.

Step 1: Draw reduced form parameters $B_i^{*r}s$ and Ω^{*r}, compute the Cholesky decomposition of Ω^{*r}, and calculate the response function.

Step 2: Repeat step 1 M times. Here M = 2000. All of the response functions are sorted in a descending order and the upper 84% and bottom 16% are reported as the Bayesian credible band.

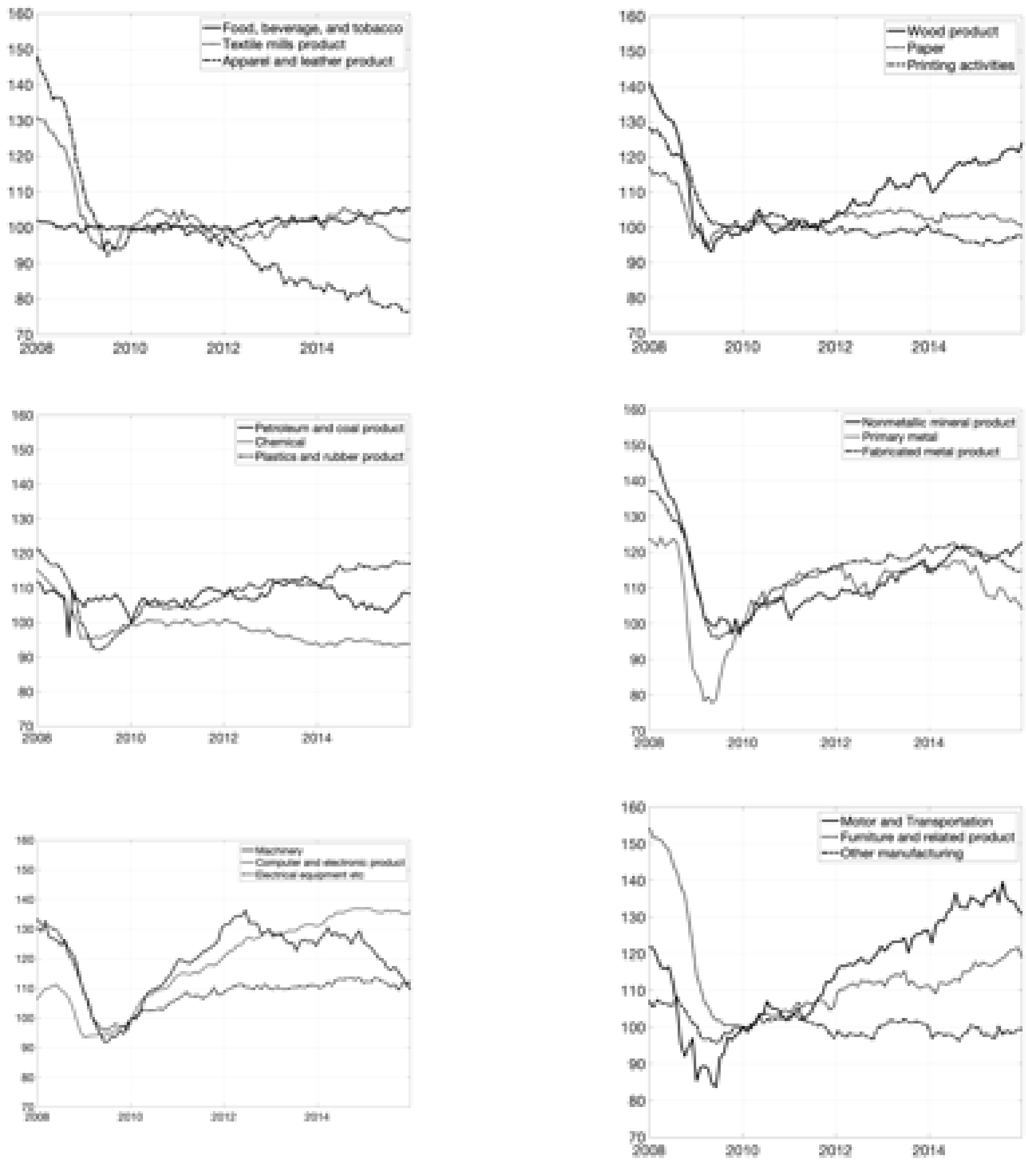
B Appendix Figures

C Appendix: Tables

[Table 4 about here.]

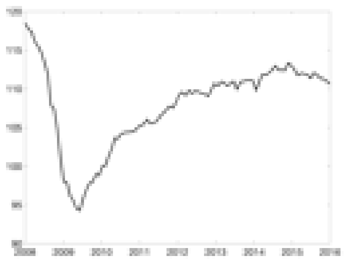
List of Figures

Figure 1: Industry Output

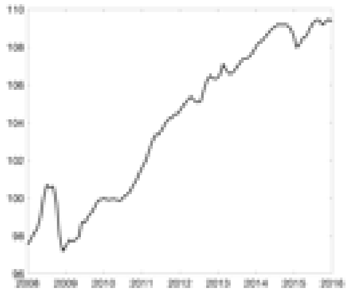


Note: All of the variables are normalized so that 2010M1=100.
Source: The Federal Reserve Board.

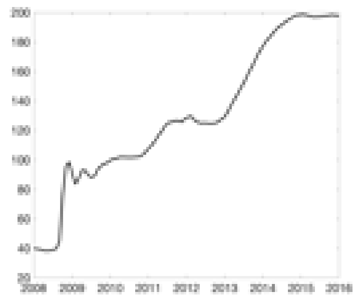
Figure 2: Data Used in This Paper



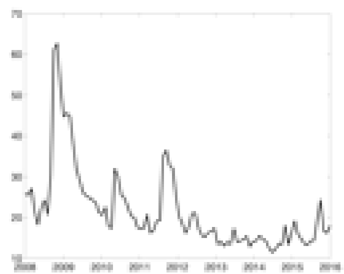
(a) Manufacturing Output



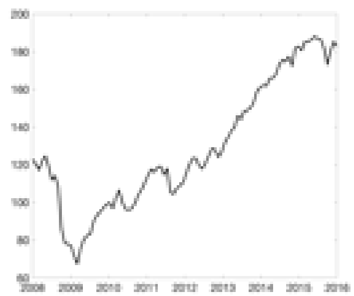
(b) Consumer Price Index



(c) Central Bank Total Assets

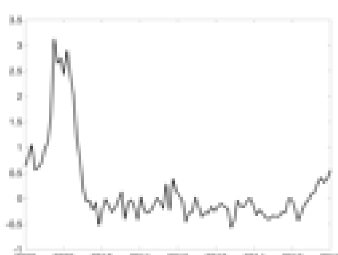


(d) Stock Market Implied Volatility

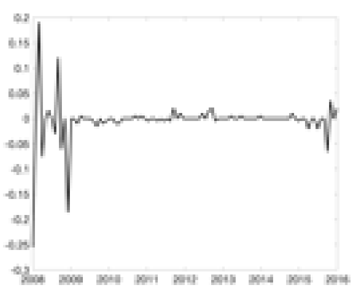


(e) S&P 500

(f) 10-Year Treasury Yield



(g) Excess Bond Premium



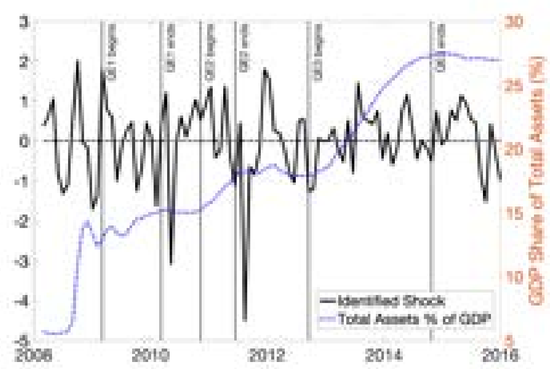
(h) Monetary Policy Surprises

(i) S&P 500 Surprises

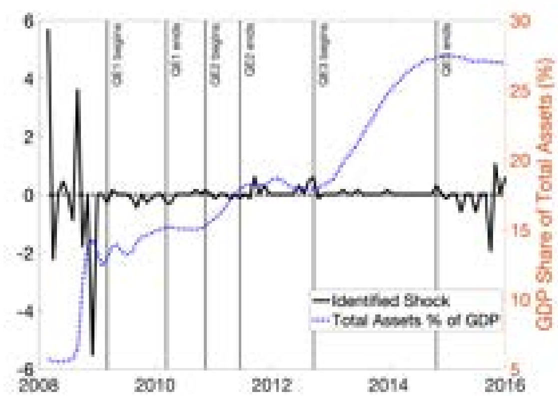
Note: Manufacturing Output, Consumer Price Index, Central Bank Total Assets, and S&P 500 are normalized so that 2010M1=100.

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), 10-year Treasury yield (IRLTLT01USM156N): the FRED database; Excess bond premium: Gilchrist and Zakrajšek (2012); Monetary Policy Surprises, S&P 500 Surprises, and S&P 500: Jarociński and Karadi (2020).

Figure 3: The Identified Shocks



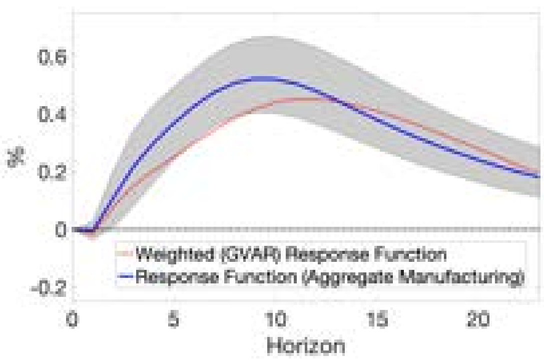
(a) QE Identification



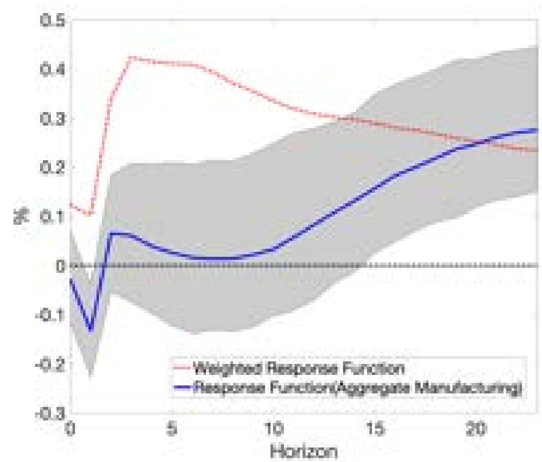
(b) High Frequency Data Identification

Note: The solid curves represent the median of the identified shocks from the structural GVAR model. The dotted curve represents the share of 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



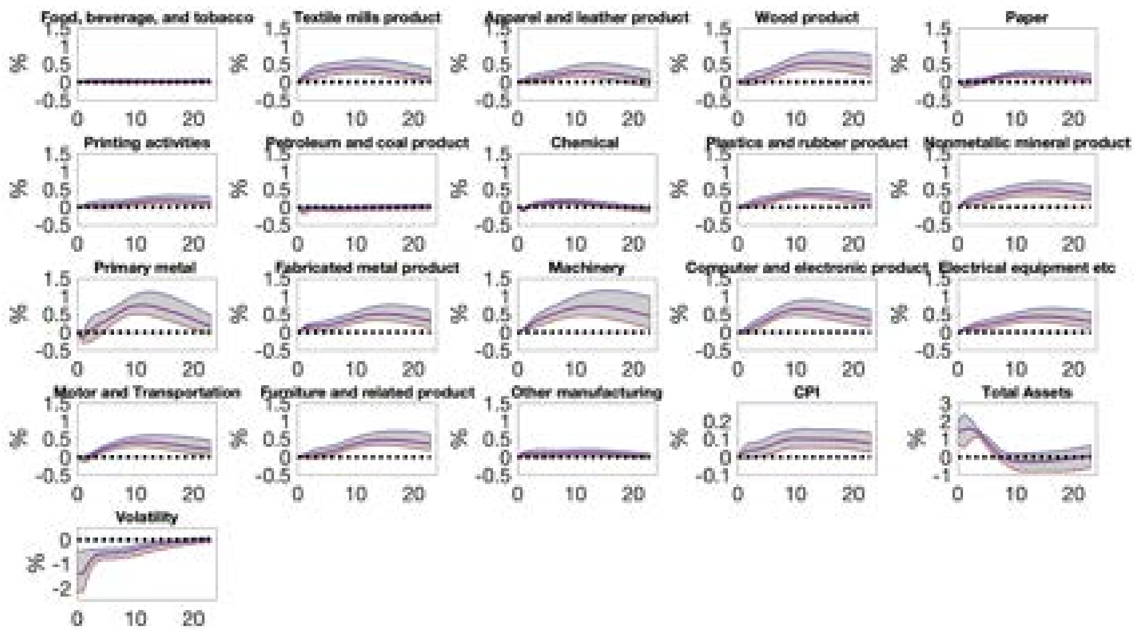
(a) QE Identification



(b) High Frequency Data Identification

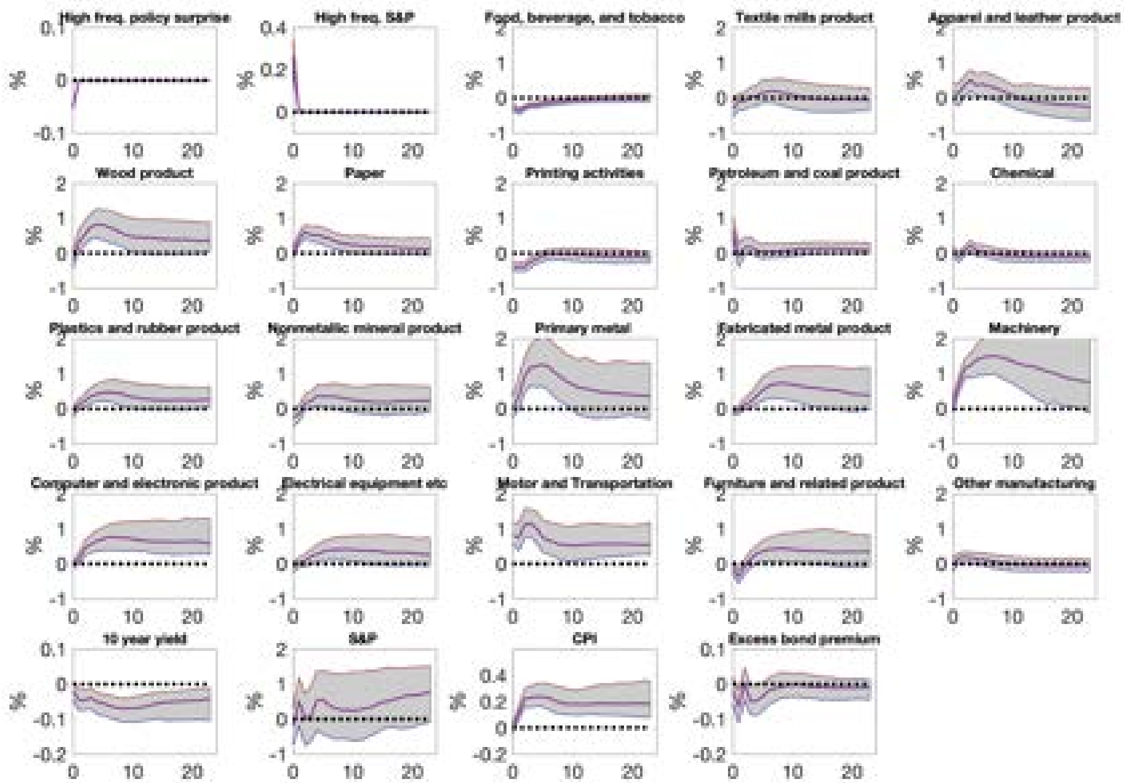
Note: The Median, 16$^{\text{th}}$, and 84$^{\text{th}}$ Bayesian percentiles. Monthly horizon. The response function of aggregate manufacturing from the VAR model is attached for comparison. To compare the results from the two identification easier, I multiply -1 with the response functions from the HF identification.

Figure 5: Industry Response Functions (QE Identification)



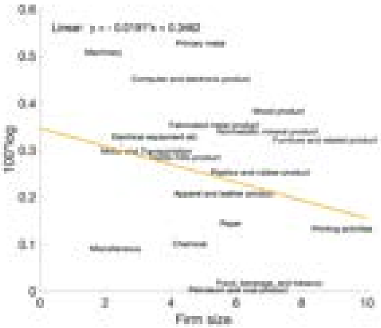
Note: The Median, 16th, and 84th Bayesian percentiles are reported. Monthly horizon.

Figure 6: Industry Response Functions (High Frequency Data Identification)

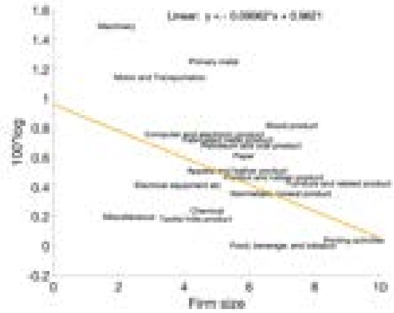


Note: The Median, 16^{th}, and 84^{th} Bayesian percentiles are reported. Monthly horizon. To compare the results from the two identification easier, I multiply -1 with the response functions.

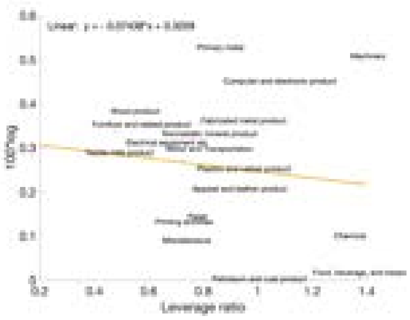
Figure 7: Linear Plot of Industry Characteristics and Monetary Policy Elasticity of Output



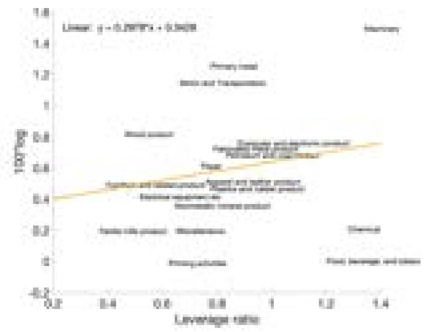
Firm Size, QE Identification



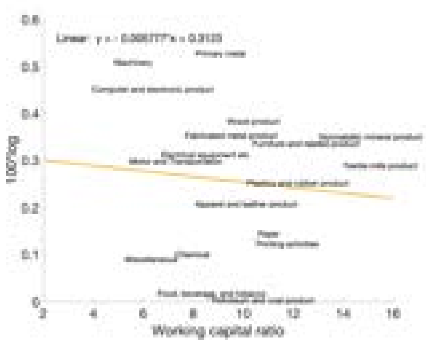
Firm Size, HF Identification



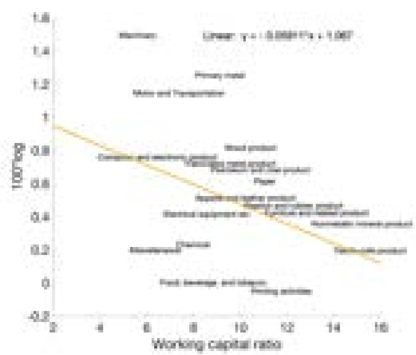
Leverage Ratio, QE Identification



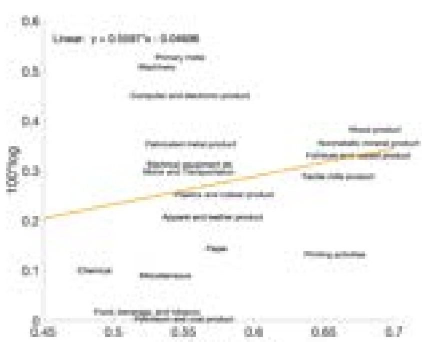
Leverage Ratio, HF Identification



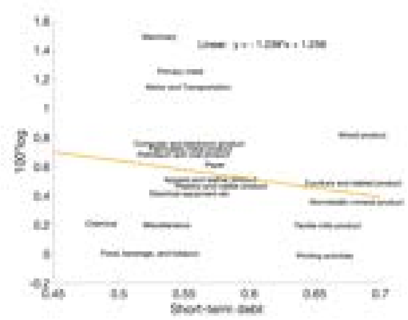
Working Capital Ratio, QE Identification



Working Capital Ratio, HF Identification

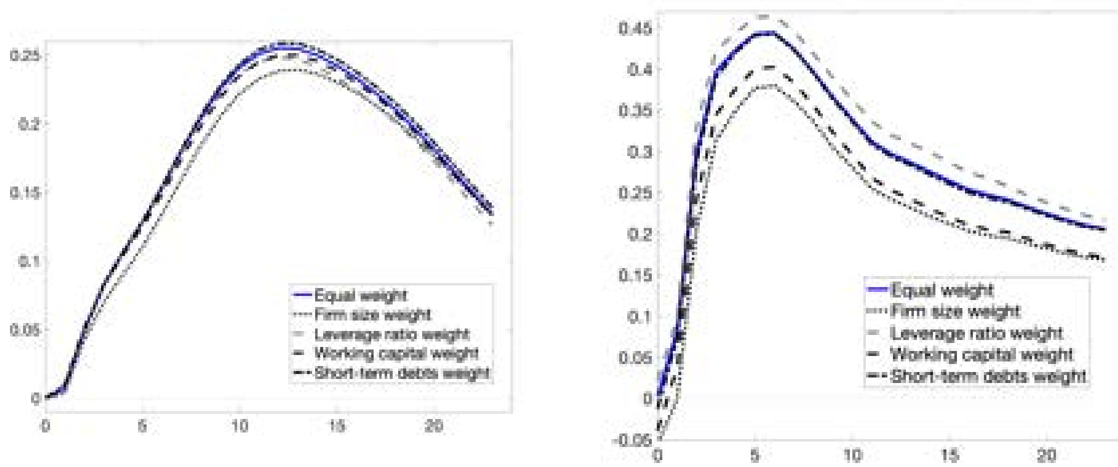


Short-Term Debt, QE Identification



Short-Term Debt, HF Identification

Figure 8: Industry Characteristics Weighted Impulse Response Functions

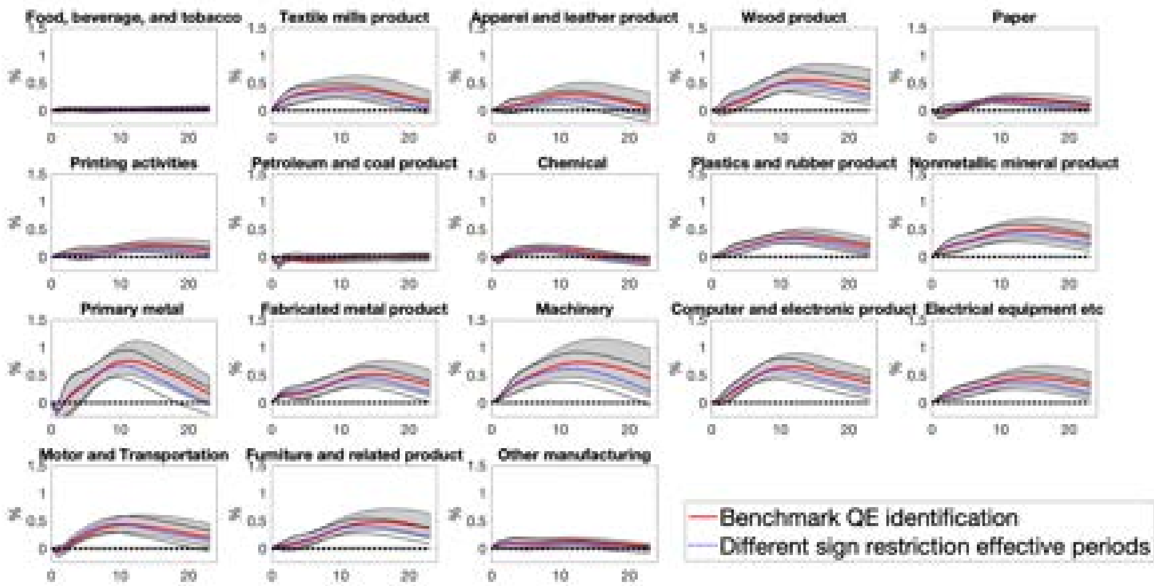


QE identification

HF identification

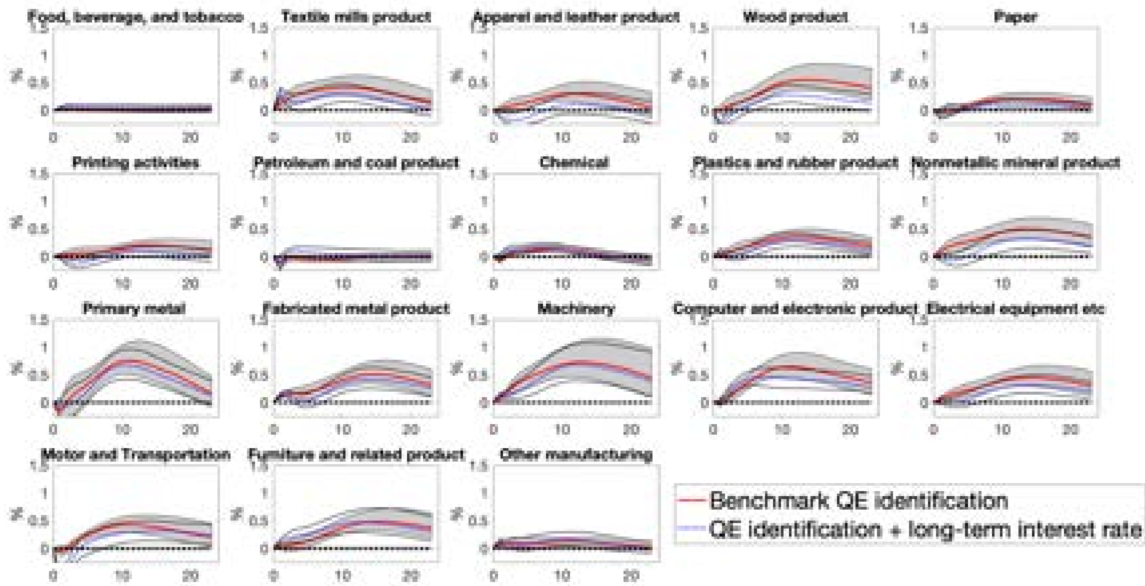
Note: Monthly horizon. Weight is constructed based on $\frac{\text{industry characteristics}_i}{\sum_i \text{industry characteristics}_i}$ for each industry i. To compare the results from the two identification easier, I multiply -1 with the response functions from the HF identification.

Figure 9: Industry Impulse Response Functions with Longer Sign Restrictions



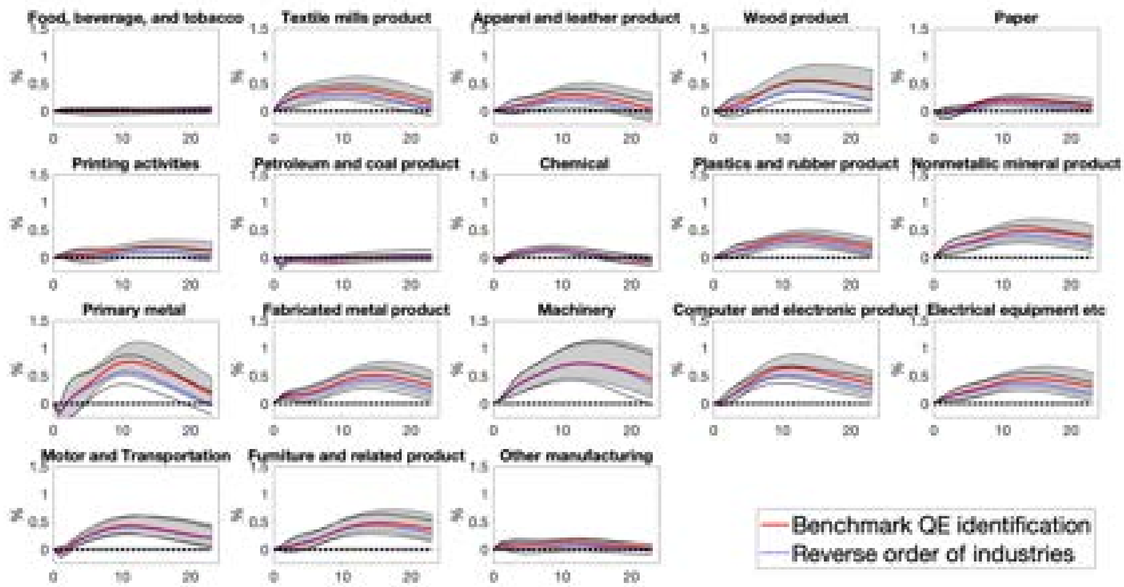
Note: The Median, 16^{th}, and 84^{th} Bayesian percentiles. Monthly horizon. The response functions from the benchmark QE identification is attached for comparison. The size of the shock is rescaled to be the size of shock from the benchmark QE identification.

Figure 10: Industry Impulse Response Functions with Long-Term Interest Rate



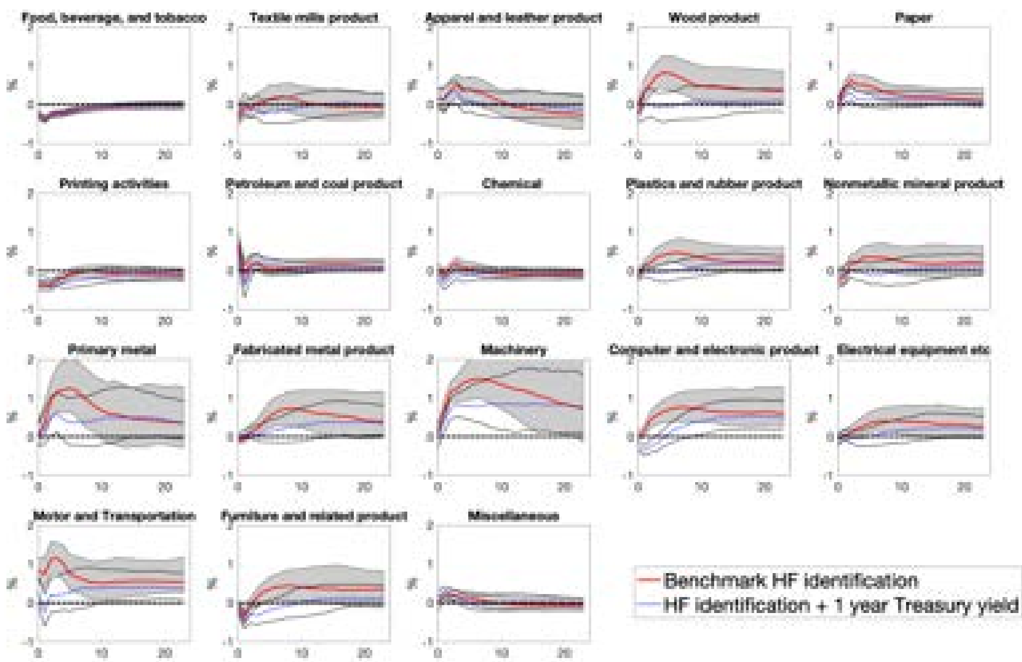
Note: The Median, 16th, and 84th Bayesian percentiles. Monthly horizon. The response functions from the benchmark QE identification is attached for comparison. The size of the shock is rescaled to be the size of shock from the benchmark identification.

Figure 11: Industry Response Functions (Reverse Order of Industries)



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

Figure 12: Industry Response Functions (High Frequency Data Identification with 1-Year Treasury Yield)



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 shock from the benchmark identification. To compare the results from the two identification easier, I multiply -1 with the response functions from the HF identification.

List of Tables

Table 1: Sign Restrictions of Impulse Response Functions

	at period = 0	at period = 1
Industry Output	0	*
Consumer Price Index	0	*
Central Bank Total Assets	>0	>0
Stock Market Implied Volatility	$\leq$0	$\leq$0

Table 2: Monetary Policy Elasticity of Output

Industry	Elasticity QE	Elasticity High Freq.	Industry	Elasticity QE	Elasticity High Freq.
Food, beverage, and tobacco	0.018	0.004	Nonmetallic mineral product	0.339	0.357
	(-0.003, 0.043)	(-0.119, 0.089)		(0.220, 0.484)	(0.101, 0.646)
Textile mills product	0.289	0.195	Primary metal	0.527	1.254
	(0.181, 0.425)	(-0.142, 0.534)		(0.356, 0.758)	(0.643, 2.017)
Apparel and leather product	0.208	0.513	Fabricated metal product	0.354	0.722
	(0.115, 0.339)	(0.199, 0.793)		(0.232, 0.526)	(0.293, 1.164)
Wood product	0.383	0.818	Machinery	0.508	1.494
	(0.253, 0.572)	(0.427, 1.257)		(0.314, 0.782)	(0.981, 2.237)
Paper	0.144	0.614	Computer and electronic product	0.451	0.760
	(0.100, 0.211)	(0.434, 0.813)		(0.323, 0.617)	(0.386, 1.153)
Printing activities	0.133	0.011	Electrical equipment etc	0.313	0.415
	(0.075, 0.218)	(-0.131, 0.189)		(0.201, 0.464)	(0.104, 0.764)
Petroleum and coal product	0.003	0.682	Motor and transportation	0.298	1.146
	(-0.043, 0.040)	(0.427, 0.996)		(0.204, 0.409)	(0.779, 1.547)
Chemical	0.101	0.207	Furniture and related product	0.336	0.446
	(0.064, 0.142)	(0.046, 0.345)		(0.230, 0.498)	(0.060, 0.854)
Plastic and rubber product	0.253	0.467	Other manufacturing	0.091	0.198
	(0.185, 0.341)	(0.207, 0.814)		(0.042, 0.144)	(0.046, 0.345)
			Industry average	0.26	0.57
			Industry median	0.29	0.49

Note: Lower and upper values of credible band in parenthesis. Credible band is an interval within which the estimate falls with the probablity given. For the QE identification, elasticity is the maximum median impulse response function consistent with a 1% increase in central bank total asset and for HF identification, elasticity is the maximum median impulse response function consistent with a 5 basis point decrease in federal funds futures. For example, for the paper industry, a 1% increase in central bank total assets increase the output by 0.144% with the QE identification and a 5 basis point decrease in federal funds futures increases the output by 0.614% with the HF identification. Credible bands are also transformed by the same amount as the elasticity is scaled.

Table 3: Sign Restriction (Robustness) of Impulse Response Function

	at period = 0	at period = 1, 2 and 3
Industry Output	0	*
Consumer Price Index	0	*
Central Bank Total Assets	>0	>0
Stock Market Implied Volatility	≤0	≤0

Table 4: 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