# Industry Impacts of US Unconventional Monetary Policy

*By* Eiji Goto*

*This paper studies the effects of unconventional monetary policy on industry output in the United States. I use structural Bayesian vector autoregressive and global vector autoregressive models with zero and sign restrictions to identify an unconventional monetary policy shock. The effects on output have substantial heterogeneity across industries and are qualitatively similar to conventional monetary policy in the literature. Furthermore, regression analysis indicates similar monetary policy transmission mechanisms between unconventional and conventional monetary policies. These findings suggest a substitutability between conventional and unconventional monetary policies from an industry perspective.*
*JEL: E32; E52; G32*
*Keywords: Unconventional monetary policy; Industry output; Monetary policy transmission mechanisms*

## I. 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 through quantitative easing, credit easing, yield curve control, forward guidance, negative interest rate policy, etc. 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, by associating industry effects of unconventional policy with the financial structure of the industry, we can learn more about 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 decline of the natural rate of interest (Holston, Laubach and Williams, 2017*a*) and a high likelihood of entering the ZLB. As an illustration, the recent outbreak of the

* 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, 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.

novel Coronavirus disease (COVID-19) and the corresponding economic slowdown forces 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. This paper also investigates whether the pattern of industry output responses and transmission mechanisms are similar to the literature of conventional policy.

This paper provides several contributions to the literature. First, it provides the differential impacts of unconventional policy on industry output. In conventional policy literature, it has been shown that conventional policy creates differential impacts on industry output (Dale and Haldane, 1995; Ganley and Salmon, 1997; Alam and Waheed, 2006; and many others), on regional output (Carlino and DeFina, 1998 and Arnold and Vrugt, 2002), and on household consumption (Kaplan, Moll and Violante, 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, Hofmann and Peersman, 2014; Boeckx, Dossche and Peersman, 2017; Bhattarai, Chatterjee and Park, 2015; and many others), however, the differential impacts of unconventional policy in the literature is scarce. This paper fills this gap in the literature and examines the effects of unconventional policy on industry output.

Second, this paper adds joint consideration to the literature of industry studies in monetary policy (Dale and Haldane, 1995; Ganley and Salmon, 1997; Ibrahim, 2005; Dedola and Lippi, 2005; and many others). In the literature, the impacts of monetary policy are estimated on an industry by industry basis or, at most, on a few industry basis, due to VAR models facing the curse of dimensionality. Thus, joint consideration has not been widely explored. In this chapter, by exploiting the gloval VAR (GVAR) model and the Bayesian method, I estimate the industry impacts of unconventional policy jointly taking into account the industry interaction.

Third, this paper explores the role of transmission mechanisms of unconventional policy. One of the advantages of estimating the effects of monetary policy on industry output is to evaluate potential transmission mechanisms: estimating the effects make it possible to associate the effect of the monetary policy with the industry characteristics of financial structure (Dedola and Lippi, 2005 and Peersman and Smets, 2005). I apply this approach to understand the transmission mechanisms. This exercise enables us to investigate to what extent unconventional and conventional policies are similar in terms of not only industry level impacts but also monetary policy transmission mechanisms.

I use structural Bayesian VAR and GVAR models with zero and sign restrictions as in Gambacorta, Hofmann and Peersman (2014) to identify an unconventional policy shock. Given the shock, I generate impulse response functions (henceforth response functions). I use monthly industrial production index to estimate the VAR model for each industry and to jointly estimate the GVAR model for all industries. To confirm the industry level estimates, I construct a weighted response function from the industry response functions with a weight being the gross domestic product (GDP) share of the industry. The weighted response functions from both models are approximately the same as the aggregate manufacturing response functions, indicating either model can capture the dynamics of industry level response functions well.

I find that the industry-level output responses are heterogeneous across industries. For example, the magnitude varies from 0.01% in food, beverage, and tobacco to 0.72% in machinery, in response to a 1% increase in the central bank total asset. 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; petroleum and coal product; and printing activities, respond weakly. This pattern of industry level output responses is similar to the pattern of conventional policy found in the literature (Dedola and Lippi, 2005). The above findings are also retained when the GVAR model is used. However, analyses with a finer industry definition would benefit from a joint consideration.

Furthermore, I find that industries with a smaller firm size, lower working capital, and higher short-term debt are associated with a larger output response to unconventional policy. This finding is consistent with the literature of industry study in conventional policy (e.g. Dedola and Lippi, 2005 and Peersman and Smets, 2005) and implies the existence of credit channel and interest rate channel. The findings in this paper support the notion of "substitutability" between conventional and unconventional policies (Debortoli, Galí and Gambetti, 2020) in terms of an industry perspective.

In the robustness analysis, I estimate the industry impacts of unconventional policy with a coarser industry definition. While the results become less striking, the above findings are generally preserved.

The rest of this paper is organized as follows: Section II describes the datasets that are used, Section III outlines the methodology (including the model, identification, and estimation), Section IV presents the main results, Section V investigates the relationship between output response and the industry characteristics, Section VI checks robustness, and finally Section VII concludes.

## II. Data

The data is of a monthly frequency. The dataset covers 2008M1-2015M12 and I choose this range based on when the Federal Researve operates unconventional policy and when the policy rates are near zero and flat, representing the ZLB.

I use the following four variables: industry output, consumer price index (CPI), central bank total assets, and stock market implied volatility. These variables, excluding stock market implied volatility, are seasonally adjusted. The industry output is industrial production index and is obtained from the Federal Reserve Board. The consumer price index is retrieved from the Bureau of Labor Statistics, and central bank total assets and stock market implied volatility are retrieved from the FRED database.

I plot industry output on Figure 1. The data is normalized so that 2010M1 is 100. Generally, the industry output has an upward trend while the rate of increase seems different: 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 aggregate manufacturing output, consumer price index, central bank total assets, and stock market implied volatility in Figure 2.[1]

To combat the financial crisis, the Federal Reserve implemented unconventional policies and increased their total assets in an unprecedented degree; they more than quadrupled their size of assets. These substantial increases in central bank total assets are correlated with the increase in aggregate output. In this paper, I investigate whether unconventional policy contributes to this rise in aggregate output and whether there exists any heterogeneity in industry output.

Lastly, the following is the complete list of industries examined in this chapter: 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; nonmetallic 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 C1.

I use an input-output (IO) table to construct the GVAR model. Specifically, I use the data for generating the weight of the foreign variable defined in the next section. For the IO table, I use the most recent data available at this time retrieved from the Bureau of Economic Analysis.[2]

## III. Methodology

In this paper, I use structural VAR and GVAR models and follow the identification methodology in Gambacorta, Hofmann and Peersman (2014) to identify an unconventional policy shock, generate response functions, and assess the industry effects. Section III.A describes the models, Section III.B states the identification, and Section III.C depicts the estimation.

### *A. The Empirical Model*

In this section, I describe the two frameworks. The first model is a VAR model that limits industry interactions outlined in Section III.A. The second model is a

[1] I use CBOE volatility index for stock market implied volatility.
[2] I use the 2017 data: https://www.bea.gov/industry/input-output-accounts-data.

global VAR (GVAR) model that allows industry interactions outlined in Section III.A.

Vector Autoregression. — I estimate the following VAR ($p$) model for each industry:

$$y_t = \nu + \sum_{i=1}^{p} A_i y_{t-i} + u_t \qquad t = 1, .., T \tag{1}$$

where $p$ is the number of lags, $y_t$ is a column vector of endogenous variables, $\nu$ is a column vector of intercept terms, $A_i$s are coefficient matrices, and $u_t$ is white noise with nonsingular covariance matrix $\Sigma_u$. In this chapter, $y_t$ consists of the following variables: log of industry output, log of consumer price index, log of central bank total assets, and level of stock market implied volatility. In this paper, I regard this specification as a benchmark.

Global Vector Autoregression. — The VAR model in the previous section does not allow for industry interactions. Thus, I estimate a global VAR (GVAR) model to take into account the industry interactions.

A GVAR model is a panel expression of VARs (Pesaran, Schuermann and Weiner, 2004). A general form of a GVAR model is:

$$y_{i,t} = v_i + A_i Y_{i,t-1} + W(L) y^*_{i,t} + u_{i,t} \qquad t = 1, .., T \tag{2}$$

where $W(L)$ represents a matrix polynomial in the lag operator and $Y_{i,t-1}$ includes all of the $y_{i,t-1}$s and lags of all of the industries $i$. $y^*_{i,t}$ is a foreign variable capturing 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 bilateral trade flow. In this chapter, I use an IO table for constructing the weight of the foreign variable. I setup a GVAR model following Burriel and Galesi (2018) whose framework is an extension of Pesaran, Schuermann and Weiner (2004). A detailed explanation of the GVAR specification is in Appendix A.A2.

For both VAR and GVAR specifications, the variables enter the model without taking the first difference as is standard in monetary policy literature (e.g. Gambacorta, Hofmann and Peersman, 2014; Boeckx, Dossche and Peersman, 2017;

Christiano, Eichenbaum and Evans, 1999; Ibrahim, 2005; 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 impulse response functions, levels specification tends to be more robust than alternative specifications (e.g. Gospodinov, Herrera and Pesavento, 2013). However, a caveat is that under level specification, a monetary policy shock may lead to a permanent effect.

The variables in those models are intended to capture the dynamics of macroeconomics and to identify an unconventional policy shock. As is standard in the monetary policy literature, industry output and CPI are in the system to ensure the macroeconomic and industry dynamics. Central bank total assets are included as a monetary policy instrument because short-term nominal interest rate is no longer an instrument under the ZLB. Central bank total assets are a general measure of unconventional policy. However, this obviously has some shortfalls. First, it does not differentiate the policies. For example, the Federal Reserve's QE1 is mainly to purchase the mortgage-backed securities and agency securities, but the policies after QE2 are to purchase the long-term securities. Those differences are not captured and are expressed as a mere increase in total assets. Thus, the results cannot discern how and by how much each specific policy affected the output.

Second, it cannot cover the policies which intend to change the composition of the central bank total assets. For example, operation twist by the Federal Reserve is not captured in this framework. This policy is to purchase long-term securities and sell the same amount of short-term securities. The net increase in the assets is zero and thus the effect is not represented in the instrument.

Third, it cannot explicitly include the forward guidance component. This identification comes from the literature of event study and shows that unconventional policy has an effect on mitigating financial market distress. However, the frequency in the VAR framework in this paper is significantly lower than in those event studies.

Finally, stock market implied volatility is in the framework to represent financial market turmoil. The variable is used to disentangle the exogenous innovation to central bank total assets from the endogenous response to financial market distress. Details of the identification is discussed in the next section.

### *B. Identification*

I follow the identification of the unconventional policy shock from Gambacorta, Hofmann and Peersman (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 VAR model (I omit the time subscript):

$$
(3) \qquad \underbrace{\begin{bmatrix} u_{\text{Industry output}} \\ u_{\text{CPI}} \\ u_{\text{Total Assets}} \\ u_{\text{Volatility}} \end{bmatrix}}_{\substack{\text{Reduced form error} \\ u_t}} = \begin{bmatrix} * & * & 0 & 0 \\ * & * & 0 & 0 \\ * & * & + & + \\ * & * & -/0 & + \end{bmatrix} \underbrace{\begin{bmatrix} \epsilon_{\text{Industry output}} \\ \epsilon_{\text{CPI}} \\ \epsilon_{\text{Total Assets}} \\ \epsilon_{\text{Volatility}} \end{bmatrix}}_{\substack{\text{Structural error} \\ \epsilon_t}}
$$

where the components of $\epsilon_t$ are uncorrelated and have unit variance, $\Sigma_\epsilon = I_4$. The zero restriction states that a shock to the 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. This assumption enables the separation of an unconventional policy shock from other contemporaneous shocks, such as demand or supply shocks.

To identify an unconventional policy shock, I apply a short-run sign restriction. An unconventional policy shock is essentially a surprise increase in central bank total assets. However, a mere increase contains some endogenous components. To separate these components from an increase in central bank total assets, stock market implied volatility plays a role as a financial market distress measure. I exclude the case of an increase in central bank total assets when the stock market implied volatility increases. This translates that the Federal Reserve endogenously responds to financial turmoil and economic uncertainty by unconventional policy. This component is a reverse causality of unconventional policy: a higher financial market distress increases the central bank total assets.

An exogenous component is a shock to the central bank total assets that decreases (or keeps steady) the stock market volatility. This notion is consistent with the literature that unconventional policy reduces the financial market uncertainty, volatility, and risks (e.g. Hattori, Schrimpf and Sushko, 2016; Krishnamurthy and Vissing-Jorgensen, 2011; Gagnon et al., 2011; Mallick, Mohanty and Zampolli, 2017; and many others). I then only take the latter component of an increase in central bank total assets and call it as an unconventional policy shock. Without the stock market implied volatility term, one could not differentiate these two distinct effects. Lastly, shocks to central bank assets and stock market volatility increase their own variables.

In order to generate the mixture of the sign and zero restrictions, I adapt the Givens rotation matrix as in Gambacorta, Hofmann and Peersman (2014). The complete description of the identification is in Appendix A.A1. The mixture of the zero and sign restriction is imposed on the impact period. I also impose the same sign restriction the 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.[3] I apply the same identification on the GVAR model.

### C. Estimation

I estimate both VAR and GVAR models and general 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 endogenous variables by following Gambacorta, Hofmann and Peersman (2014). I follow the Bayesian method of Kilian and Lütkepohl (2017) and Koop, Korobilis et al. (2010). One of the gains of estimating Bayesian VAR is to circumvent problems with overparameterization, especially with the GVAR model. Another gain of estimating Bayesian VAR is to overcome the problems of the frequentest approach of the broader confidence bands and uninformative response functions (Kilian and Lütkepohl, 2017). A detailed explanation of the Bayesian estimation and how I generated response functions for the VAR model is in Appendix A.A3 and the explanation for the GVAR model is in Appendix A.A4.

## IV. Results

In this section, I first provide the aggregate manufacturing results in Section IV.A. Next, in Section IV.B, I show that the industry responsive functions approximately sum up to the aggregate manufacturing response function and that the industry level output responses are heterogeneous. Finally, in Section IV.C, I briefly compare the findings with the existing studies.

### A. Aggregate Manufacturing Results

Before I explore the results of response functions, 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 from the structural VAR model when aggregate manufacturing is used for output. The identified shock is normalized so that the mean and standard deviation of the shock are zero and one, respectively.

The time series of 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

[3] The complementary restriction (a shock to VOL increases AT 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).

Reserve draw surprisingly expansionary shocks to the economy. The ends of QE1 and QE2 come with reductions of the identified shock.

The identified shock does not necessarily coincide with the dynamics of central bank total assets. On one hand, a sharp rise in central bank total assets in October of 2008 comes with a large increase in the identified shock. However, the time series of the identified shock during QE3 is modest, while central bank total assets dramatically rise, indicating that there are extensive endogenous and expected components. It is possible that economic agents are more familiar and attentive to the actions led by the Federal Reserve after experiencing QE1 and QE2. Overall, the identified shock is consistent with the actions taken by the Federal Reserve.

Figure 4 shows the response functions generated by the VAR model and represents a one standard deviation shock to the central bank total assets on aggregate manufacturing output, CPI, central bank total asset, and stock market implied volatility. The 68% Bayesian credible bands[4] are reported as is standard in the literature. The results show that unconventional policy has statistically positive impacts on both output and CPI. Impacts on central bank total assets are positive and impacts on stock market volatility are negative at the first period and slowly revert back to zero: these observations are in line with the literature of empirical unconventional policy (such as Gambacorta, Hofmann and Peersman, 2014; Bhattarai, Chatterjee and Park, 2015; Boeckx, Dossche and Peersman, 2017, and many others). Figure 4 shows that the effects on aggregate output and price are long lasting and stay significantly positive until the last period.

I find that a one standard deviation shock is a 2.06% increase in central bank total assets. 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.

Now, I investigate whether the results are in line with the studies in the empirical literature of unconventional policy. Table 2 summarizes the results from other studies. The table reports the maximum value of the median response function of output from a one standard deviation shock to the central bank total assets. While there are several similarities of the methodologies to these studies, such as identification (Gambacorta, Hofmann and Peersman, 2014) and estimation (Boeckx, Dossche and Peersman, 2017), generally the response to the shock is slightly larger than in those studies. The impacts tend to be stronger if studies use industrial production as output instead interpolated GDP, since manufacturing is more responsive to monetary policy than to aggregate GDP. Thus, it is possible that the impact from this paper is larger since this paper uses industrial production as output. While the estimation method, identification, countries, and sample periods are different, the result is not dramatically different from those studies.

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

### B. Industry Results

First, I plot the weighted response functions from both VAR and GVAR models and the aggregate manufacturing response function on Figure 5 to ensure that the industry response functions approximately sum up to the aggregate response function. One of the purposes of this paper is to uncover the heterogeneous responses to the unconventional policy shock. 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, since the output comovements across industries and the role of spillover are sufficiently small. Using the gross value added share as a weight, the weighted response functions are calculated by following:

$$WIRF_p = \sum_{i=1}^{I} weight_i * MIRF_{ip} \tag{4}$$

where $WIRF_p$ represents the weighted response function at period $p \in 24$[5], $MIRF_{ip}$ represents the median response functions for industry $i$ at period $p \in 24$, and $I$ is the total number of industries. Each industry response function is the average response from the entire sample period. Thus, I calculate the weighted response function using weight from the sample period average. To calculate the weight, I first calculate the average gross value added (GVA) of the sample period for each industry. Then, I sum up the average GVA across industries and I denote it as total GVA. Finally, I calculate the weight as the average GVA of industry $i$ over total GVA. In Figure 5, the bold line represents the aggregate response function and the dotted line represents the weighted response function. I also report the credible bands of the aggregate response functions in the figure.

The weighted response function is similar to the aggregate response function but not identical. Over the period, the weighted response functions are lower than the aggregate manufacturing response function. The potential explanations of these deviations are estimation uncertainty and/or statistical measurement error between aggregate manufacturing output and sum of the industry output. The impacts of the GVAR model last longer than the impacts of the VAR model. This difference might be a result of spillover effect. While there are some deviations, the deviation is not large and is generally within the credible band. Therefore, the weighted response functions overall match the aggregate manufacturing result.

Figure 6 shows the industry response functions from the VAR model. I report the 16% and 84% credible bands. I find that 17 out of 18 industries are statistically significant and positive. Figure 7 shows the industry response functions from the GVAR model. I find that 16 out of 18 industries are statistically significant and positive. In terms of providing positive impacts, the unconventional policy works

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

well.

In Figure 7, in addition to the response functions from the GVAR model, I also plot the response functions from the VAR model to directly compare the impacts between the two models. To compare the impacts from two different models, I rescale the size of the shocks to be the same. Compared to the individual industry level estimation, some industries increase their production, some industries do not change production, and other industries decrease their production. While the results from the two models do not dramatically differ, it may be beneficial to estimate the impacts using a joint model at this industry definition. As mentioned before, response functions from the GVAR model tends to be longer lasting than the response functions from the VAR model. This may be due to spillover effects between industries.

The magnitude of the positive responses varies 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 by one percentage change in central bank total assets. Table 3 summarizes the monetary policy elasticity of output. The elasticity varies from 0.01 to 0.72 from the VAR model and 0.00 to 0.54 from the GVAR model. For three industries from the VAR model and seven industries from the GVAR model, the elasticities exceed the credible band of the aggregate manufacturing. Likewise, for eight industries from the VAR model and six industries from the GVAR model, the elasticities fall below the credible band given by the aggregate manufacturing. These results imply that unconventional policy creates heterogeneous impacts on industry output.

### *C. 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.

This paper finds that durable goods producers such as machinery, primary metal, and transportation respond strongly while non-durable goods producers such as food, beverage, and tobacco; paper; and petroleum respond weakly. Industries that produce durable goods tend to be interest rate sensitive because the industries tend to be capital intensive and consumption of those goods rely on loan payments. Despite that the fluctuation of interest rate is minimal during the ZLB, I find that industries in durable goods manufacturing are more responsive to unconventional policy than industries in non-durable goods manufacturing.

Now, I compare these results with the existing studies that examine the industry impacts of conventional policy. Ganley and Salmon (1997) explore the industry impacts of conventional policy in the UK using the 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 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 my paper studied the US. It is possible that the same industries have different industry characteristics in the US and in countries in 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 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.

## V. Effectiveness and Industry Characteristics

### *A. Industry Characteristics*

In the previous section, I find that the pattern of industry level output responses to unconventional policy is similar to that of conventional policy in the US. In this chapter, I investigate what industry characteristics are related to the effectiveness of unconventional policy. I construct the following four variables that represent industry characteristics from the Compustat database: 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 industry-level explanatory variables 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 credit channel. An industry with larger firms or higher leverage ratio firms, on average, tend to possess more borrowing capacities than other industries with smaller firms or lower leverage ratio firms. In the literature, the connection between firm size and monetary policy elasticity is closely investigated 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, while small firms have access to indirect financing, direct financing is usually not an option. Since credit supply helps small or low leverage ratio firms increase their production, these firms tend to respond to the policy strongly.

Working capital ratio and short-term debt are proxies for channels on the supply side, mainly interest rate channel, change in the nominal interest rate alters the real interest rate and user cost of capital, which alters production decisions. Working capital represents liquidity and short-term debt represents financing need of an industry. These two variables are constructed using current liabilities. Since a change in nominal interest rate affects the current liabilities, these two variables are affected by the change in policy rate. Thus, industries with lower working capital ratio and higher short-term debt are expected to respond strongly. Since the policy rates are attached to the ZLB during unconventional policy period, it is of interest to know to what extent 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 I 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 to the policy strongly. Throughout this section, I show the results from the average industry characteristics, however, the median industry characteristics provide similar results.

### B. 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 8. I plot the average industry characteristics against elasticity from both VAR and GVAR models. I find that correlation of elasticity against firm size is negative, leverage is not clear, working capital is negative, and short term debt is not clear. From here, firm size and working capital show the expected signs, which indicate the possible existence of the credit and interest rate channels.

### C. 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 responsive if responsive industries have higher values of the industry characteristics. Alternatively, the weighted response function tends to be unresponsive 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:[6]

$$WIRF_p = \sum_i \left(\frac{max(\text{industry characteristics}_i, 0)}{\sum_i max(\text{industry characteristics}_i, 0)}\right) * MIRF_{ip} \tag{5}$$

Figure 9 shows results from the VAR and GVAR models. For comparison, I plot an equally weighted response function.[7] The results show that the leverage ratio and short-term debt weights make the weighted response functions stronger while the firm size and working capital ratio weights make the weighted response function weaker. The results of the leverage ratio does not satisfy the prediction as the weighted response function is stronger than the benchmark, however, the other industry characteristics satisfy the prediction.

### D. Regression Analysis

Despite that the linear plot and weighted impulse response functions provide the existence of the relationship between some of the industry characteristics and monetary policy elasticity of output, they do not provide statistical tests. In

[6]I use max function in order to calculate the weight, since some of the industry characteristics take negative values and thus the constructed weight can take negative values.

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

this section, I run regressions to indicate the association between the industry characteristics and monetary policy responsiveness. In this paper, I analyze only 18 industries and this is the sample size, which obviously is a limitation of the analysis. I estimate the following equation:

$$\begin{aligned}\text{Elastiticy}_i = \beta_0 + \beta_1 \text{firm size}_i + \beta_2 \text{leverage ratio}_i \\ + \beta_3 \text{working capital ratio}_i + \beta_4 \text{short-term debt}_i + e_i\end{aligned}$$

where $i \in 18$ is industry, $\beta$s are the coefficients and $e_i$ is the error terms. Table 4 shows the results. The equation is estimated using the robust standard errors. Columns (1) and (2) show the results when maximum elasticity is a dependent variable while columns (3) and (4) show the results when the last period of the elasticity is a dependent variable. The results are overall consistent with the previous analyses. A smaller firm size, a lower working capital, and a larger short-term debt are associated with a higher industry level output response. This indicates the existence of credit and interest rate channels within unconventional policy. However, coefficients of leverage is positive, which is not consistent with being a proxy for borrowing capacity. However, Peersman and Smets (2005) argue that industries with higher leverage ratio tend to face difficulty making new loans. It is possible that this aspect of leverage ratio causes the positive results.

Based on the results, it seems that the interest rate channel plays a role, even though the policy rate is attached to the ZLB. This implies that real or expected interest rate still affects the production decisions of firms. One possibility is that signaling theory, (such as Bauer and Rudebusch, 2013 and Bhattarai, Eggertsson and Gafarov, 2015), a central bank's promise to keep the interest rate lower towards the future, lowers the expected short-term real interest rates. This creates incentive for capital intensive firms to invest in projects that involve money borrowing. Thus, this signaling channel may cause the negative relationship between working capital and elasticity and the positive relationship between short-term debt and elasticity.

Overall, the results I obtained here are consistent with the regression results found in Dedola and Lippi (2005). Thus, I do not find any evidence that monetary policy transmission mechanisms of conventional and unconventional policies differ.

## VI. Robustness

In this section, I conduct two sets of robustness analyses. First, I estimate the model using alternative identifications, and second I estimate the impacts of unconventional policy with a coarser industry definition.

### *A. Alternative Identifications*

Changing the Sign Restriction Effective Periods. — In this section, I change the periods that the sign restriction is effective. To study the effect of unconventional policy, an accurate identification is a key part and the results should not be radically altered by the choice of the effective periods of sign restriction. 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 5 summarizes the new identification. I impose this identification on the benchmark VAR model.

Figure 10 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 almost identical. Therefore, imposing the sign restriction as shown on Table 1 in Section III.B is sufficient to generate an ideal unconventional policy shock.

Unconventional Policy Shock with Long-term Interest Rate. — In this section, because unconventional policies operated in the US focus on long-term asset purchases, I use a long-term asset yield to identify an unconventional policy shock following Bhattarai, Chatterjee and Park (2015). In Section III.B, I use the identification in Gambacorta, Hofmann and Peersman (2014), which is a broad measure of unconventional policy. However, in this section, I change 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 VAR framework. I retrieve the 10-year government bond yield from the FRED database. 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:

$$y_t = \begin{bmatrix} ln(\text{Industry output}_t) \\ ln(\text{CPI}_t) \\ \text{Long yield}_t \\ ln(\text{Total Assets}_t) \\ \text{Volatility}_t \end{bmatrix} \tag{6}$$

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 (again, I omit the time subscript):

$$(7) \qquad \underbrace{\begin{bmatrix} u_{\text{Industry output}} \\ u_{\text{CPI}} \\ u_{\text{Long yield}} \\ u_{\text{Total Assets}} \\ u_{\text{Volatility}} \end{bmatrix}}_{\substack{\text{Reduced form error} \\ u_t}} = \begin{bmatrix} * & * & 0 & 0 & 0 \\ * & * & 0 & 0 & 0 \\ * & * & * & - & * \\ * & * & * & + & + \\ * & * & * & -/0 & + \end{bmatrix} \underbrace{\begin{bmatrix} \epsilon_{\text{Industry output}} \\ \epsilon_{\text{CPI}} \\ \epsilon_{\text{Long yield}} \\ \epsilon_{\text{Total Assets}} \\ \epsilon_{\text{Volatility}} \end{bmatrix}}_{\substack{\text{Structural error} \\ \epsilon_t}}$$

Figure 11 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.

I find that the impacts from this identification are generally stronger than the impacts from the benchmark identification, however, 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, however, the qualitative impacts of unconventional policy do not seem to change.

### *B. Coarser Industry Definition*

In Section IV, I find that the industry level output responses are heterogeneous and find that monetary policy elasticity of output is negatively related to firm size and working capital and is positively related to short-term debt. In this section, I use a coarser industry definition (such as agriculture, construction, etc) to conduct the same analysis. Due to the data availability, I use quarterly frequency data. The dataset covers 2008Q1-2017Q4.[8] The industry output data is real value added and is obtained from the Bureau of Economic Analysis. I plot industry output on Appendix B1. The quarterly frequency is not as suitable for analyzing monetary policy as monthly frequency (Gambacorta, Hofmann and Peersman, 2014; and Bhattarai, Chatterjee and Park, 2015).[9] The quarterly data and limited ZLB period provide a small sample period of 40.

The following is the complete list of industries examined: agriculture, manufacturing (includes utilities and mining), construction, trade (sum of wholesale

[8]I utilize a longer time span in this exercise than in the previous exercise because the quarterly frequency dramatically reduces the sample size and it is difficult to estimate the GVAR model if the same time span is used.

[9]They use the interpolation method (Chow and Lin, 1971) to generate a monthly GDP. However, in order to implement this method, relevant monthly frequency data for each industry's output is required. As correlations between the reference series and industry output vary across industries, it would be difficult to conduct interpolation in this paper.

and retail trade), transportation and information, financial activities (includes real estate), professional service, education and healthcare, leisure (sum of arts, entertainment, and recreation and accommodation and food), other services, and government. More details of the industry definitions are available in Appendix C2.

I estimate the model following the same methodology as in Section III, except I only impose the sign restriction on the shock period due to the dataset being of quarterly frequency.[10] Figure 12 and 13 present the industry response functions from the VAR model and GVAR model, respectively. The impacts are overall heterogeneous. Appendix C3 summarizes the monetary policy elasticity of output. The elasticity varies from 0.00 to 0.10 in the VAR model and 0.01 to 0.14 in the GVAR model. For five industries in the VAR model and six industries in the GVAR model, the elasticities exceed the credible band of the aggregate. Likewise, for three industries in the VAR model and one industry in the GVAR model, the elasticities fall below the credible band given by the aggregate. Usually, cyclical industries, such as construction and trade, respond strongly while agriculture and education and healthcare respond weakly. In general, the impacts look less heterogeneous than the industries within manufacturing. It is possible that the industry aggregation averages out the heterogeneous impacts from the finer industry definition.

Due to the problem with the sample size, the credible bands of the GVAR model are wider that those in the VAR model. However, median response functions from the GVAR model closely follow the median response functions from the VAR model. This suggests that under the coarser industry definition, joint estimation may not be as necessary because the industry level comovement and spillover effects are sufficiently small. However, there are some industries (e.g. manufacturing and construction) that respond stronger in the GVAR model than in the individual industry estimation.

Lastly, Figure 14 displays linear plots of the average industry characteristics against elasticity from both the VAR and GVAR models. I exclude government from the analysis due to data availability. I find that a smaller firm size and lower working capital are associated with higher output responses. Again, leverage ratio does not provide a clear result. Also, the correlation between short-term debt and elasticity is negative, which is not consistent with the main results.

Overall, the findings of the coarser definition are less striking. However, the results are overall consistent with the findings in Section IV.

## VII. Conclusion

This paper estimates the industry impacts of unconventional policy for the US using structural Bayesian VAR and GVAR models. The industry response

[10]Changing the imposition of the sign restriction to one quarter does not change the results qualitatively.

functions reveal some interesting features. First, unconventional policy stimulates industries heterogeneously. Among those responses, I find that unconventional policy strongly stimulates the industries that produce durable goods, which is known to be interest rate sensitive in the literature. Second, the pattern of industry responses are similar between the VAR and GVAR models, however, the finer the industry definition the more important joint consideration is. Third, I find that smaller firm size, lower working capital, and a higher short-term debt 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, Laubach and Williams, 2017*b*), 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 ZLB and aid central bankers in creating an unconventional policy. Lastly, this paper did not assess impacts across policies. This would be a great topic for future research.

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 | ≤0 | ≤0 |

Table 2—: Sign Restrictions of Impulse Response Functions

| Authors | Country | Estimate | | Sample period |
|---|---|---|---|---|
| | | Output in % | 1 standard deviation shock in % | |
| This paper | US | 0.52 | 2.06 | 2008-2015 |
| Gambacorta, Hofmann and Peersman (2014) | US | 0.10 | 2.70 | 2008-2011 |
| | UK | 0.12 | 4.50 | 2008-2011 |
| | Japan | 0.10 | 1.20 | 2008-2011 |
| | EU | 0.10 | 2.40 | 2008-2011 |
| Bhattarai, Chatterjee and Park (2015) | US | 0.40 | 2.00 | 2008-2014 |
| Boeckx, Dossche and Peersman (2017) | EU | 0.10 | 1.50 | 2007-2014 |
| Burriel and Galesi (2018) | EU | 0.08 | 1.00 | 2007-2015 |
| Schenkelberg and Watzka (2013) | Japan | 0.40 | 7.00 | 1995-2010 |
| Peersman (2011) | EU | 0.40 | 1.75 | 1999-2009 |
| Average | | 0.20 | 2.67 | |
| Median | | 0.10 | 2.00 | |

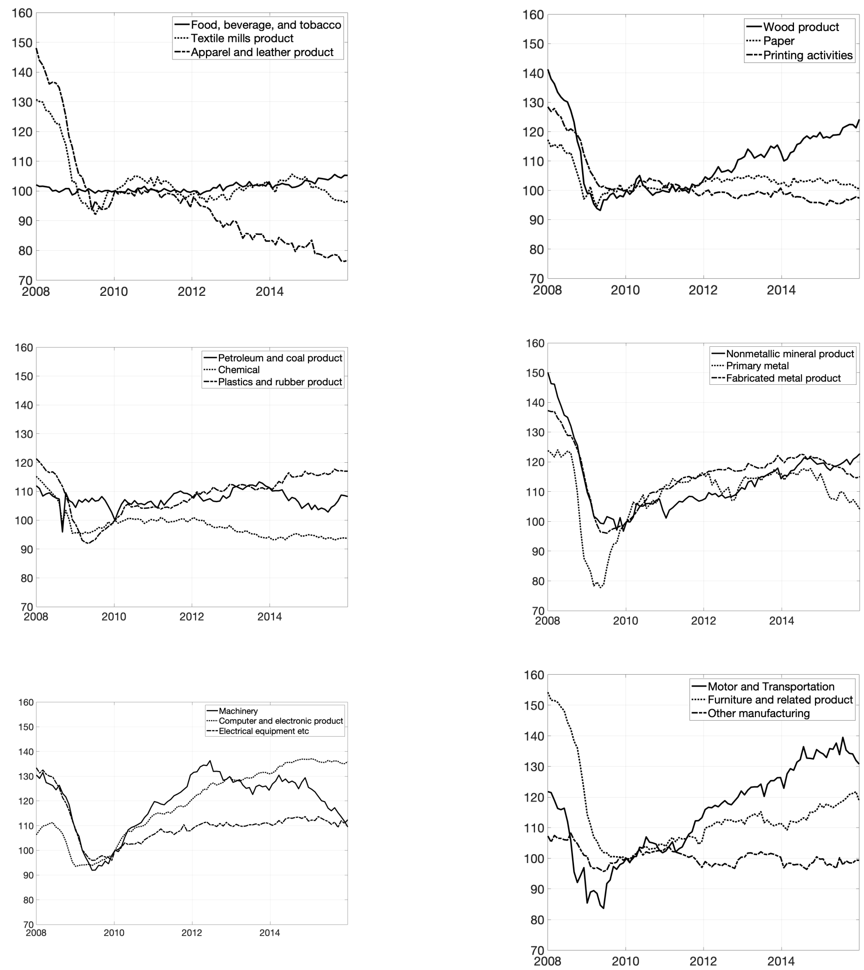
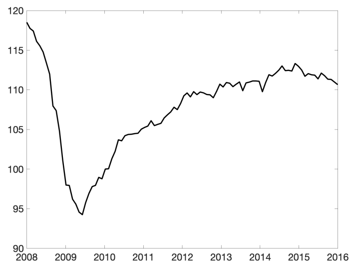


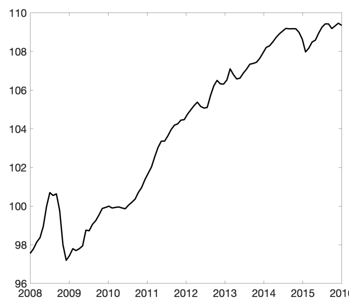

Figure 1. : Industry Output

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

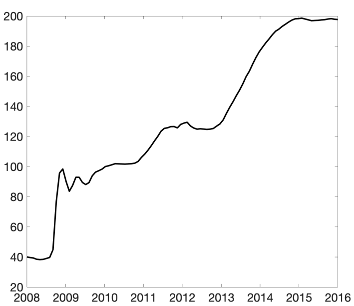
*Source:* The Federal Reserve Board.



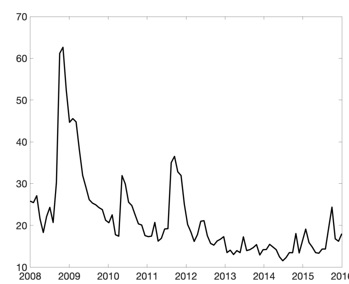

(a) Manufacturing output




(b) Consumer price index




(c) Central bank total assets




(d) Stock market implied volatility

Figure 2. : Manufacturing Output, Consumer Price Index, Central Bank Total Assets, and Stock Market Implied Volatility

*Note:* All of the variables except stock market implied volatility 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: the FRED database; Stock market implied volatility: the FRED database.

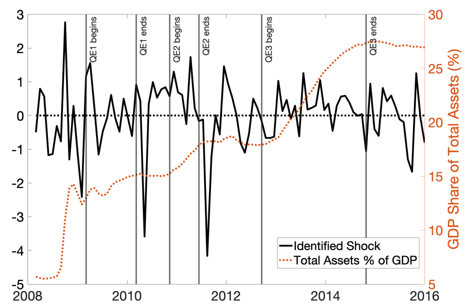



Figure 3. : Identified Shock

*Note:* The solid curve represents the median of the identified shock from the structural VAR model when aggregate manufacturing output is used. The dotted curve represents the share of the central bank total assets of real GDP. I normalized the scale of the shock so that the mean (as well as the sum) of the shock and the standard deviation of the shock are zero and one, respectively.

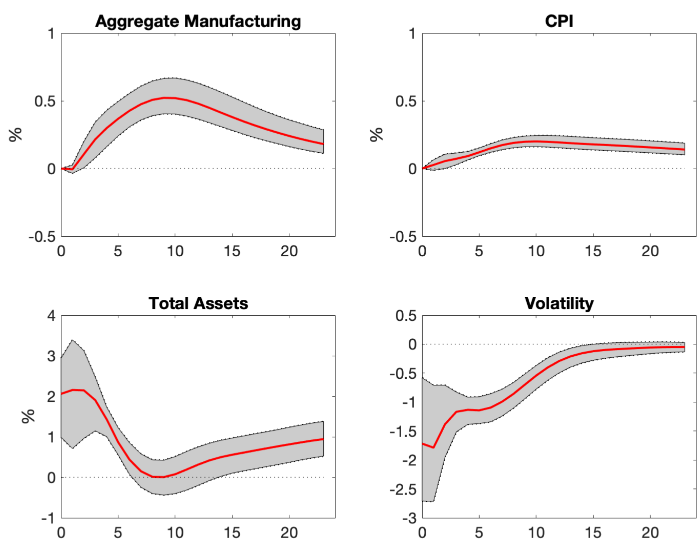
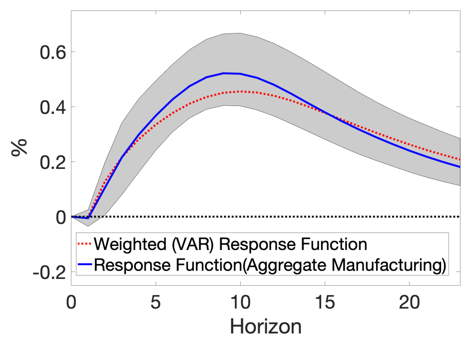
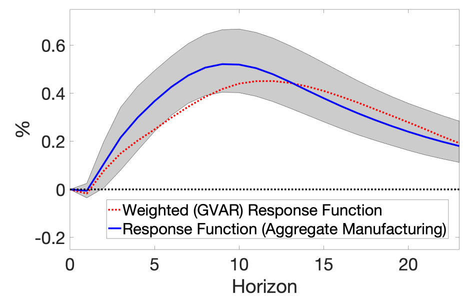



Figure 4. : National Impulse Response Functions

*Note:* The Median, $16^{\text{th}}$, and $84^{\text{th}}$ Bayesian percentiles. Monthly horizon.




(a) VAR




(b) GVAR

Figure 5. : Industry Impulse Response Functions

*Note:* The Median, 16th, and 84th Bayesian percentiles. Monthly horizon. The response function of aggregate manufacturing from the VAR model is attached for comparison.

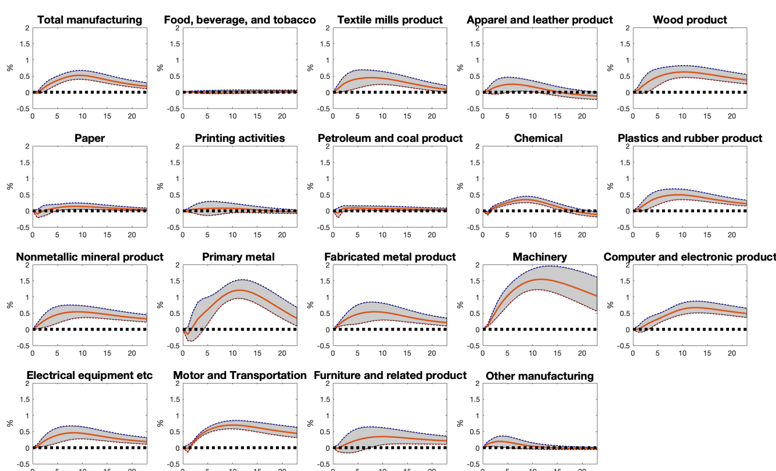



Figure 6. : Industry Response Functions from VAR Model

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

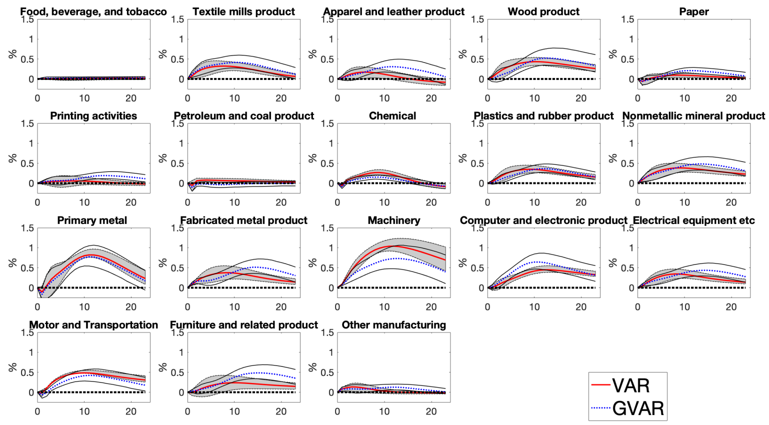


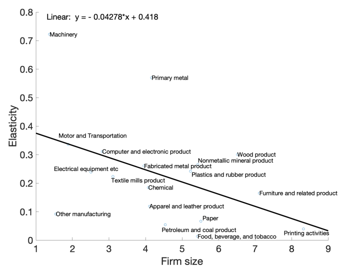

Figure 7. : Industry Response Functions from GVAR Model

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

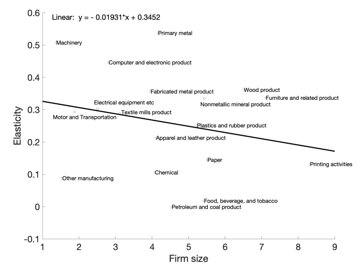
Table 3—: Monetary Policy Elasticity of Output

| Industry | Elasticity | | Industry | Elasticity | |
|---|---|---|---|---|---|
| | VAR | GVAR | | VAR | GVAR |
| Total manufacturing | 0.25 | | | | |
| | (0.20, 0.32) | | | | |
| Food, beverage, and tobacco | 0.01 | 0.02 | Nonmetallic mineral product | 0.27 | 0.33 |
| | (0.00, 0.03) | (-0.01, 0.04) | | (0.17, 0.36) | (0.23, 0.46) |
| Textile mills product | 0.22 | 0.29 | Primary metal | 0.57 | 0.54 |
| | (0.11, 0.33) | (0.19, 0.41) | | (0.45, 0.71) | (0.38, 0.73) |
| Apparel and leather product | 0.12 | 0.21 | Fabricated metal product | 0.26 | 0.36 |
| | (0.01, 0.22) | (0.11, 0.34) | | (0.13, 0.40) | (0.25, 0.49) |
| Wood product | 0.30 | 0.36 | Machinery | 0.72 | 0.51 |
| | (0.22, 0.39) | (0.24, 0.53) | | (0.57, 0.90) | (0.33, 0.74) |
| Paper | 0.07 | 0.14 | Computer and electronic product | 0.31 | 0.45 |
| | (0.03, 0.12) | (0.10, 0.20) | | (0.24, 0.40) | (0.32, 0.60) |
| Printing activities | 0.04 | 0.13 | Electrical equipment etc | 0.24 | 0.30 |
| | (-0.04, 0.13) | (0.08, 0.19) | | (0.14, 0.35) | (0.20, 0.43) |
| Petroleum and coal product | 0.05 | 0.00 | Motor and transportation | 0.34 | 0.29 |
| | (0.02, 0.09) | (-0.05, 0.03) | | (0.28, 0.40) | (0.19, 0.40) |
| Chemical | 0.18 | 0.11 | Furniture and related product | 0.17 | 0.34 |
| | (0.14, 0.24) | (0.07, 0.14) | | (0.05, 0.30) | (0.24, 0.47) |
| Plastic and rubber product | 0.24 | 0.25 | Other manufacturing | 0.09 | 0.09 |
| | (0.17, 0.33) | (0.19, 0.33) | | (0.02, 0.16) | (0.04, 0.14) |
| | | | Industry average | 0.23 | 0.26 |
| | | | Industry median | 0.23 | 0.29 |

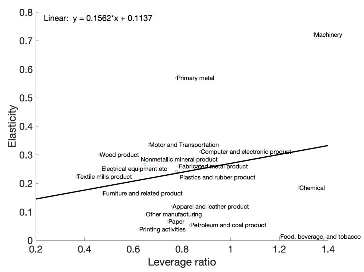
*Note:* Lower and upper values of credible band in parenthesis. Credible band is an interval within which the estimate falls with the probablity given. Elasticity is the maximum median impulse response function consistent with a 1% increase in central bank total asset. For example, for the aggregate manufacturing, a 1% increase in central bank total assets increase the aggregate output by 0.25%. Credible bands are also transformed by the same amount as the elasticity is scaled.



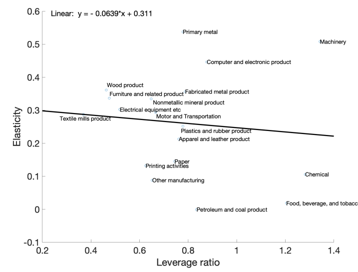

Firm size, VAR



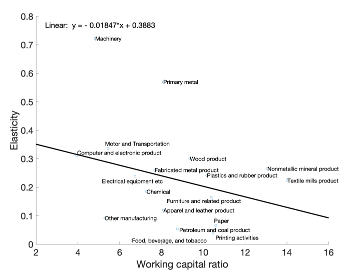

Firm size, GVAR



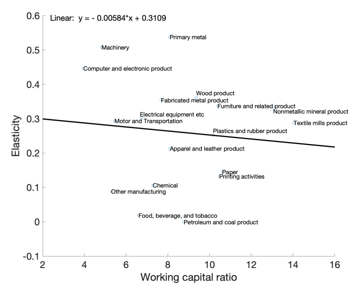

Leverage ratio, VAR



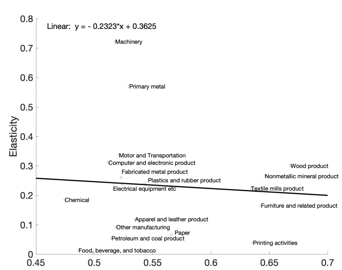

Leverage ratio, GVAR



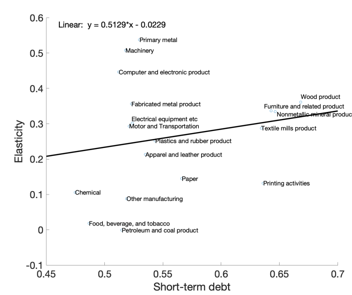

Working capital ratio, VAR




Working capital ratio, GVAR




Short-term debt, VAR




Short-term debt, GVAR

Figure 8. : Linear Plot of Industry Characteristics and Monetary Policy Elasticity of Output

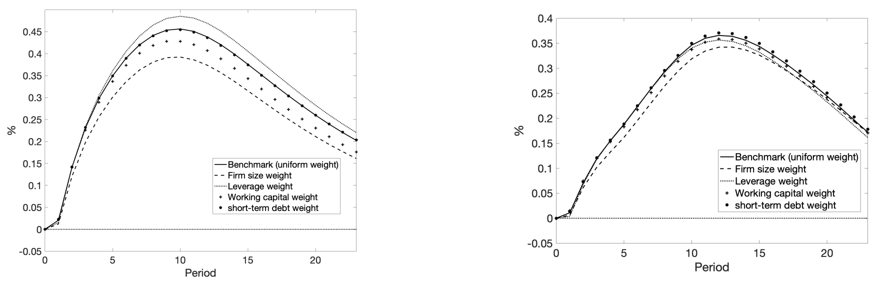



Figure 9. : Industry Characteristics Weighted Impulse Response Functions

*Note:* Monthly horizon. Weight is constructed based on $\frac{max(\text{industry characteristics}_i,0)}{\sum_i max(\text{industry characteristics}_i,0)}$ for each industry $i$.

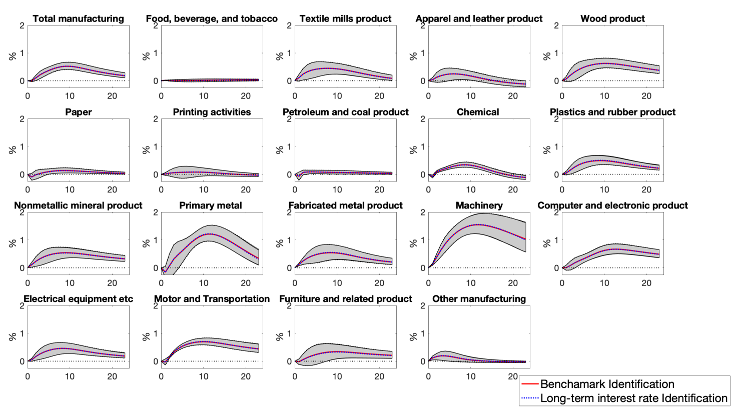



Figure 10. : Industry Impulse Response Functions with Longer Sign Restrictions

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

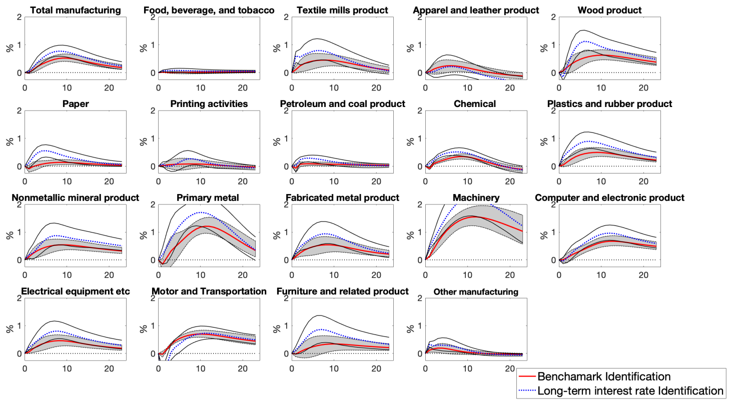



Figure 11. : Industry Impulse Response Functions with Long-term Interest Rate

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

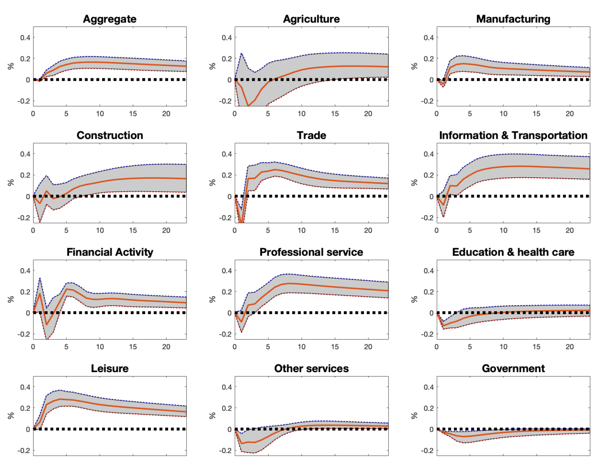



Figure 12. : Industry Response Functions from VAR Model (Robustness)

*Note:* The Median, 16$^{\text{th}}$, and 84$^{\text{th}}$ Bayesian percentiles. Quarterly horizon.

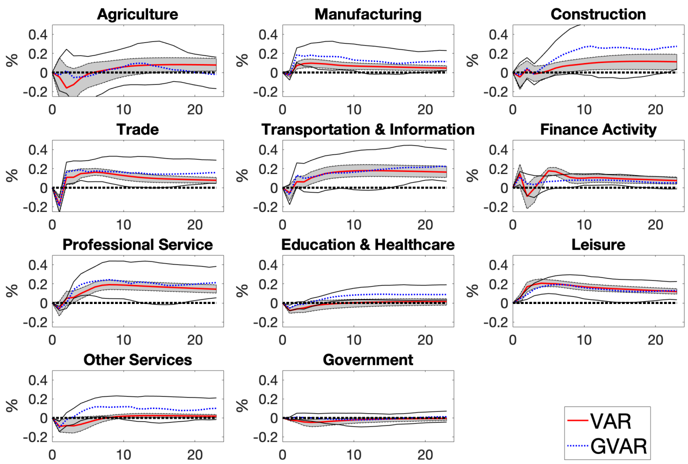


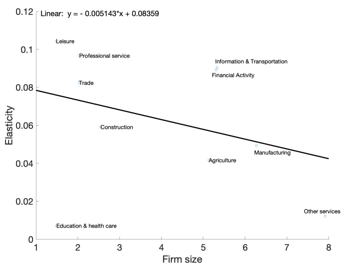

Figure 13. : Industry Response Functions from GVAR Model (Robustness)

*Note:* The Median, 16$^{\text{th}}$, and 84$^{\text{th}}$ Bayesian percentiles. Quarterly horizon.

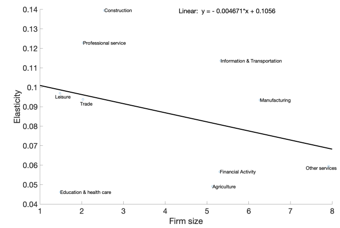
Table 4—: Regression Results

| | Dependent variable | | | |
|---|---|---|---|---|
| Explanatory variable | (1) Maximum Output Response from VAR | (2) Maximum Output Response from GVAR | (3) 24th period Output Response from VAR | (4) 24th period Output Response from GVAR |
| Firm size | -7.01** | -4.33* | -4.42** | -1.63 |
| (credit channel) | (1.93) | (1.76) | (1.37) | (1.26) |
| Leverage | 0.41* | 0.14 | 0.32* | 0.08 |
| (credit channel) | (0.16) | (0.13) | (0.13) | (0.11) |
| Working capital ratio | -1.72 | -2.29 | -2.65* | -2.33* |
| (interest rate channel) | (1.24) | (1.38) | (1.06) | (0.94) |
| Short-term debt | 2.97** | 2.55** | 2.80** | 2.01** |
| (interest rate channel) | (0.94) | (0.84) | (0.63) | (0.51) |
| Constant | -1.28* | -0.88 | -1.29** | -0.79* |
| | (0.55) | (0.49) | (0.36) | (0.33) |
| N | 18 | 18 | 18 | 18 |
| adj. R-sq | 0.32 | 0.13 | 0.23 | 0.21 |

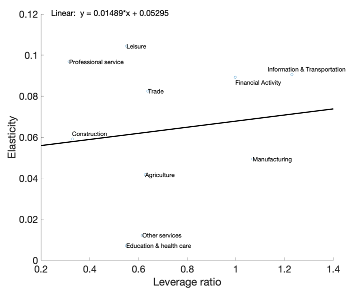
*Note:* columns (1) and (2) show the results when the maximum median output response are used as a dependent variable while the columns (3) and (4) show the results when the 24th (the last) period output response are used as a dependent variable. Robust standard errors in parentheses. For displaying purpose, firm size and working capital ratio are divided by 100. *$p < 0.5$; **$p < 0.01$.



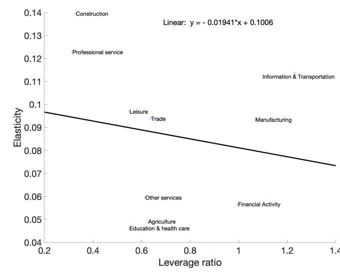

Firm size, VAR



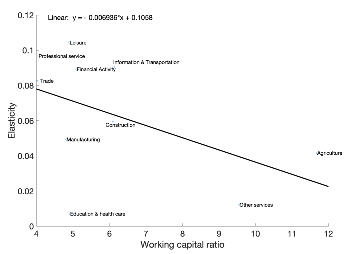

Firm size, GVAR



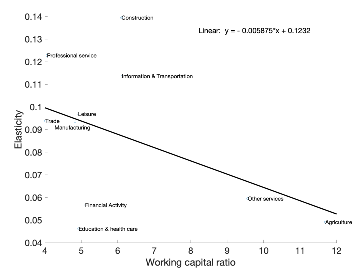

Leverage ratio, VAR



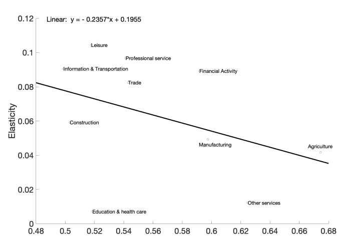

Leverage ratio, GVAR



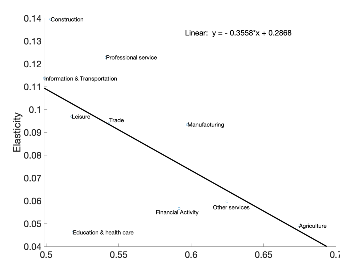

Working capital ratio, VAR




Working capital ratio,GVAR




Short-term debt, VAR




Short-term debt, GVAR

Figure 14. : Linear Plot of Industry Characteristics and Monetary Policy Elasticity of Output (Robustness)

Table 5—: 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 |

## REFERENCES

**Alam, Tasneem, and Muhammad Waheed.** 2006. "Sectoral effects of monetary policy: Evidence from Pakistan." *The Pakistan Development Review*, 1103–1115.

**Ampudia, Miguel, Dimitris Georgarakos, Jiri Slacalek, Oreste Tristani, Philip Vermeulen, and Giovanni Violante.** 2018. "Monetary policy and household inequality."

**Arnold, Ivo JM, and Evert B Vrugt.** 2002. "Regional effects of monetary policy in the Netherlands." *International Journal of Business and Economics*, 1(2): 123.

**Bauer, Michael D, and Glenn D Rudebusch.** 2013. "The signaling channel for Federal Reserve bond purchases." *International Journal of Central Banking, forthcoming.*

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

**Bhattarai, Saroj, Arpita Chatterjee, and Woong Yong Park.** 2015. "Effects of US quantitative easing on emerging market economies."

**Bhattarai, Saroj, Gauti B Eggertsson, and Bulat Gafarov.** 2015. "Time consistency and the duration of government debt: A signalling theory of quantitative easing (No. w21336)." National Bureau of Economic Research.

**Boeckx, Jef, Maarten Dossche, and Gert Peersman.** 2017. "Effectiveness and transmission of the ECB's balance sheet policies." *International Journal of Central Banking*, 13(1): 297–333.

**Burriel, Pablo, and Alessandro Galesi.** 2018. "Uncovering the heterogeneous effects of ECB unconventional monetary policies across euro area countries." *European Economic Review*, 101: 210–229.

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

**Chow, Gregory C, and An-loh Lin.** 1971. "Best linear unbiased interpolation, distribution, and extrapolation of time series by related series." *The Review of Economics and Statistics*, 372–375.

**Christiano, Lawrence J, Martin Eichenbaum, and Charles L Evans.** 1999. "Monetary policy shocks: What have we learned and to what end?" *Handbook of Macroeconomics*, 1: 65–148.

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

**Debortoli, Davide, Jordi Galí, and Luca Gambetti.** 2020. "On the empirical (ir) relevance of the zero lower bound constraint." *NBER Macroeconomics Annual*, 34(1): 141–170.

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

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

**Fisher, Jonas DM.** 1999. "Credit market imperfections and the heterogeneous response of firms to monetary shocks." *Journal of Money, Credit, and Banking*, 187–211.

**Gagnon, Joseph, Matthew Raskin, Julie Remache, Brian 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.

**Galesi, Alessandro, and Marco J Lombardi.** 2009. "External shocks and international inflation linkages: a global VAR analysis."

**Gambacorta, Leonardo, Boris Hofmann, and Gert 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, Joe, and Chris Salmon.** 1997. "The industrial impact of monetary policy shocks: some stylised facts."

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

**Geweke, John, et al.** 1991. *Evaluating the accuracy of sampling-based approaches to the calculation of posterior moments.* Vol. 196, Federal Reserve Bank of Minneapolis, Research Department Minneapolis, MN.

**Gospodinov, Nikolay, Ana María Herrera, and Elena Pesavento.** 2013. "Unit roots, cointegration and pre-testing in VAR models." *Advances in Econometrics*, 32: 81–115.

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

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

**Holston, Kathryn, Thomas Laubach, and John C Williams.** 2017*a*. "Measuring the natural rate of interest: International trends and determinants." *Journal of International Economics*, 108: S59–S75.

**Holston, Kathryn, Thomas Laubach, and John C Williams.** 2017*b*. "Measuring the natural rate of interest: International trends and determinants." *Journal of International Economics*, 108: S59–S75.

**Ibrahim, Mansor H.** 2005. "Sectoral effects of monetary policy: evidence from Malaysia." *Asian Economic Journal*, 19(1): 83–102.

**Kaplan, Greg, Benjamin Moll, and Giovanni L Violante.** 2018. "Monetary policy according to HANK." *American Economic Review*, 108(3): 697–743.

**Kilian, Lutz, and Helmut Lütkepohl.** 2017. *Structural vector autoregressive analysis.* Cambridge University Press.

**Koop, Gary, Dimitris Korobilis, et al.** 2010. "Bayesian multivariate time series methods for empirical macroeconomics." *Foundations and Trends® in Econometrics*, 3(4): 267–358.

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

**Mallick, Sushanta, Madhusudan S Mohanty, and Fabrizio Zampolli.** 2017. "Market volatility, monetary policy and the term premium."

**Neely, Christopher J.** 2015. "Unconventional monetary policy had large international effects." *Journal of Banking & Finance*, 52: 101–111.

**Peersman, Gert.** 2011. "Macroeconomic effects of unconventional monetary policy in the euro area."

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

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

**Schenkelberg, Heike, and Sebastian Watzka.** 2013. "Real effects of quantitative easing at the zero lower bound: Structural VAR-based evidence from Japan." *Journal of International Money and Finance*, 33: 327–357.

**Vansteenkiste, Isabel.** 2007. "Regional housing market spillovers in the US: lessons from regional divergences in a common monetary policy setting."

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

## Mathematical Appendix

### *A1. Appendix: Complete Description of Identification*

The reduced form variance-covariance matrix, $\Sigma_u$, can be expressed as:

$$\Sigma_u = BB' = BI_4B' = BQQ'B' \tag{A1}$$

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

$$Q = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & cos(\theta) & -sin(\theta) \\ 0 & 0 & sin(\theta) & cos(\theta) \end{bmatrix} \tag{A2}$$

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

$$\underbrace{\begin{bmatrix} u_{\text{Industry output}} \\ u_{\text{CPI}} \\ u_{\text{Total Assets}} \\ u_{\text{Volatility}} \end{bmatrix}}_{\substack{\text{Reduced form error} \\ u_t}} = \underbrace{\begin{bmatrix} * & * & 0 & 0 \\ * & * & 0 & 0 \\ * & * & + & + \\ * & * & -,0 & + \end{bmatrix}}_{BQ} \underbrace{\begin{bmatrix} \epsilon_{\text{Industry output}} \\ \epsilon_{\text{CPI}} \\ \epsilon_{\text{Total Assets}} \\ \epsilon_{\text{Volatility}} \end{bmatrix}}_{\substack{\text{Structural error} \\ \epsilon_t}} \tag{3 revisited}$$

When I estimate the GVAR model, the identity matrix is $I_{21}$ and $Q$ becomes a 21 by 21 matrix, where the first 19 by 19 matrix is an identity matrix.

### *A2. Complete Description of GVAR Specification*

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

$$y_{i,t} = c_i + \sum_{j=1}^{p_i} A_{i,j} y_{i,t-j} + \sum_{j=0}^{q_i} B_{i,j} y^*_{i,t-j} + \sum_{j=0}^{q_i} C_{i,j} x_{t-j} + u_{i,t} \tag{A3}$$

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 foreign 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 $\forall j \neq i$:

$$y^*_{i,t} = \sum_{j \neq i} w_{i,j} y_{j,t} \qquad \sum_{j \neq i} w_{i,j} = 1 \tag{A4}$$

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.[11]

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

$$x_t = c_x + \sum_{j=1}^{p_x} D_j x_{t-j} + \sum_{j=0}^{q_x} F_j \tilde{y}_{t-j} + u_{xt} \tag{A5}$$

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 GDP share of industry $i$.

Given the specifications of equation (A3) 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 (A3) can be transformed to:

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

$$G_{i,0}y_{i,t} = c_i + \sum_{j=1}^{p_i} G_{i,j}y_{i,t-j} + \sum_{j=0}^{q_i} C_{i,j}x_{t-j} + u_{i,t} \tag{A6}$$

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:

$$G_0 y_t = c + \sum_{j=1}^{p} G_j y_{t-j} + \sum_{j=0}^{q} C_j x_{t-j} + u_t \tag{A7}$$

Likewise, using the fact that $\tilde{y}_t = W^* y_t$, where $W^*$ is a link matrix based on the industry GDP share, equation (A5) becomes:

$$x_t = c_x + \sum_{j=1}^{p_x} D_j x_{t-j} + \sum_{j=0}^{q_x} F_j W^* y_{t-j} + u_{xt} \tag{A8}$$

By combining equations (A7) and (A8), we can construct a structural global VAR model:

$$H_0 Z_t = h_0 + \sum_{j=1}^{p} H_j Z_{t-j} + e_t \tag{A9}$$

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:

$$Z_t = k_0 + \sum_{j=1}^{p} K_j Z_{t-j} + \nu_t \tag{A10}$$

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

## A3. Appendix: Complete Description of Bayesian Estimation

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

$$g(vec(A), \Sigma_u) = g_{vec(A)}(vec(A)) * g_{\Sigma_u}(\Sigma_u)$$

The distributions for $vec(A)$ and $\Sigma_u$ are:

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

and

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

where $A^*$ is the OLS estimates, $S_* = I_4$, and $n = 5$. When I estimate the GVAR model, $S_* = I_{21}$ and $n = 22$. For the prior variance of the coefficients parameter, $V_{vec(A)}$, I impose the Minnesota prior. This enables the prior distribution to be tight and that is necessary to overcome the curse of dimensionarity, especially when estimating the global VAR model. First, I set the prior variance of the intercept to be infinity and the prior variance of the $j, k^{th}$ elements of $A_i$ to be:

$$v_{jk,i} = \begin{cases} (\lambda/i)^2 & \text{if j=k} \\ (\lambda\alpha\sigma_j/i\sigma_k)^2 & \text{if j} \neq \text{k} \end{cases} \tag{A11}$$

where $\lambda = 0.3$ and $\alpha = 0.05$. $\sigma_j$ and $\sigma_k$ are obtained from equation by equation OLS estimates of the VAR model. Then $V_{vec(A)}$ is:[12]

[12]When I estimate the GVAR model, the last element of $V_{vec(A)}$ is $v_{21,21,2}$.

$$V_{vec(A)} = \begin{bmatrix} \infty & & & & & & & & & & & \\ & \ddots & & & & & & & & & & \\ & & \infty & & & & & & & & & \\ & & & v_{11,1} & & & & & \mathbf{0} & & & \\ & & & & \ddots & & & & & & & \\ & & & & & v_{41,1} & & & & & & \\ & & & & & & v_{12,1} & & & & & \\ & & & & & & & \ddots & & & & \\ & & & & & & & & v_{42,1} & & & \\ & & & & & & & & & \ddots & & \\ & & & \mathbf{0} & & & & & & & v_{11,2} & \\ & & & & & & & & & & & \ddots \\ & & & & & & & & & & & & v_{44,2} \end{bmatrix}$$

Now, the posterior distributions are:

$$vec(A)|\Sigma_u, \mathbf{y} \sim \mathcal{N}(vec(\bar{A}), \bar{\Sigma}_{vec(A)})$$

and

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

where

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

$$vec(\bar{A}) = [V^{-1}_{vec(A)} + (ZZ' \otimes \Sigma_u^{-1})]^{-1}[V^{-1}_{vec(A)} vec(A^*) + (Z \otimes \Sigma_u^{-1})\mathbf{y}],$$

$$\bar{\Sigma}_{vec(A)} = [V^{-1}_{vec(A)} + (ZZ' \otimes \Sigma_u^{-1})]^{-1},$$

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

and

$$\tau = T + n.$$

Moreover, $\Sigma_u$ is the OLS estimate, $\mathbf{Z}_t = Z_t \otimes I_4$ and $Z = [Z_0, \cdots, Z_{T-1}]$ with $Z_{t-1} = (1, y'_{t-1}, y'_{t-2})'$. When I estimate the GVAR model, $\mathbf{Z}_t = Z_t \otimes I_{21}$.

Here the posterior distribution of $vec(A)$ is conditional on $\Sigma_u$ and the posterior distribution of $\Sigma_u$ is conditional on $vec(A)$. 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[13] and then the

[13] I also calculate the Geweke convergence criteria (Geweke et al., 1991) and almost all of the parameters

following steps are taken to generate response functions.
**Step 1:** Draw reduced form parameters $\nu^{*r}$, $A_i^{*r}s$, and $\Sigma_u^{*r}$ and compute the Cholesky decomposition of $\Sigma_u^{*r}$.
**Step 2:** For each $\nu^{*r}$, $A_i^{*r}s$, and $\Sigma_u^{*r}$, draw N random Given's rotation matrix, $Q^{i \in N}$. For each combination of $\nu^{*r}$, $A_i^{*r}s$, $\Sigma_u^{*r}$, and $Q^i$, calculate the response function.
**Step 3:** If the response function satisfies the sign restriction on Table 1 in Section III.B, 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.

### *A4. Appendix: Complete Description of GVAR Estimation*

To estimate the model, I impose $p_i = p_x = q_x = 2$ and $q_i = 0$ so that the estimation is consistent with Burriel and Galesi (2018) and the benchmark specification.[14] I define $y_{it} = ln(\text{Industry output}_{it})$ and $x_t = [ln(\text{CPI}_t) \quad ln(\text{Total Assets}_t) \quad \text{Volatility}_t]'$. Hypothetically, directly estimating equation (A10) 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 (A3) and the common equation (A5) individually using OLS. Finally, the identification and the Bayesian inference is the same as in Section III except that this estimate is the mean of the parameters of the prior distribution.

converged before 4,000 draws.
[14]This specification is a VAR model where the endogenous vector contains all of the industry output as well as CPI, central bank total asset, and stock market implied volatility with two lags.

## Appendix Figures

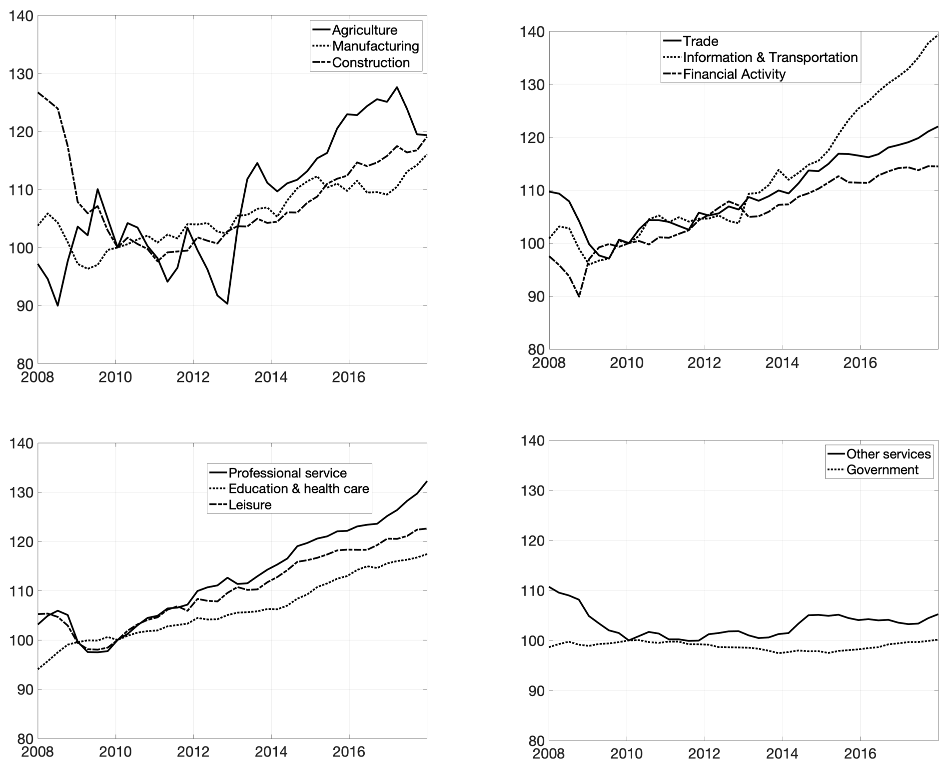



Figure B1. : Industry Output (Robustness)

*Note:* All of the variables are normalized so that 2010Q1=100.

*Source:* The Bureau of Economic Analysis.

## Appendix: Tables

Table C1—: 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 C2—: Industry definition (Robustness)

| Industry | NAICS |
| --- | --- |
| Agriculture | 11 |
| Manufacturing | 21-22, 31-33 |
| Construction | 23 |
| Trade | 42, 44-45 |
| Information & Transportation | 48-49, 51 |
| Financial activities | 52-53 |
| Professional service | 54-56 |
| Education & Healthcare | 61-62 |
| Leisure | 71-72 |
| Other Services | 81 |
| Government | 92 |

Table C3—: Monetary Policy Elasticity of Output (Robustness)

| Industry | Elasticity | |
|---|---|---|
| | VAR | GVAR |
| Aggregate | 0.06 | |
| | (0.04,0.07) | |
| Agriculture | 0.04 | 0.05 |
| | (0.00,0.08) | (-0.06,0.15) |
| Manufacturing | 0.05 | 0.09 |
| | (0.03,0.07) | (0.05,0.13) |
| Construction | 0.06 | 0.14 |
| | (0.02,0.10) | (-0.02,0.28) |
| Trade | 0.08 | 0.09 |
| | (0.06,0.11) | (0.04,0.14) |
| Information & Transportation | 0.09 | 0.11 |
| | (0.06,0.13) | (0.04,0.21) |
| Financial Activity | 0.09 | 0.06 |
| | (0.06,0.11) | (0.02,0.09) |
| Professional service | 0.10 | 0.12 |
| | (0.07,0.13) | (0.02,0.22) |
| Education & Healthcare | 0.01 | 0.05 |
| | (-0.01,0.02) | (0.02,0.09) |
| Leisure | 0.10 | 0.10 |
| | (0.08,0.14) | (0.05,0.14) |
| Other services | 0.01 | 0.06 |
| | (0.00,0.02) | (-0.01,0.12) |
| Government | 0.00 | 0.01 |
| | (-0.01,0.00) | (-0.02,0.04) |
| Industry average | 0.06 | 0.08 |
| Industry median | 0.06 | 0.09 |

*Note:* Lower and upper values of credible band in parenthesis. Credible band is an interval within which the estimate falls with the probablity given. Elasticity is the maximum median impulse response function consistent with a 1% increase in central bank total asset. For example, in the US for the aggregate, a 1% increase in central bank total assets increase the aggregate output by 0.06%. Credible bands are also transformed by the same amount as the elasticity is scaled.