Industry Impacts of Unconventional Monetary Policy*

Eiji Goto†

Job Market Paper

October 7, 2019

(click here for the most recent version)

Abstract

This paper studies the effects of unconventional monetary policy on industry output in the United States, the United Kingdom, and Japan. I use a strucutral Bayesian vector autoregressive model with zero and sign restrictions to identify an unconventional monetary policy shock. The effects on output across industries within a country have a substantial heterogeneity. For example, industry output responses in the United States varies from -0.01% to +0.28%, in response to a 1% increase in the shock. Industries across the three countries have some variation in output response to unconventional monetary policy, however, on average the effects are similar to conventional monetary policy. Furthermore, regression analysis shows that higher working capital is associated with a large industry output response to unconventional monetary policy. The finding indicates the relevance of the interest rate channel of unconventional monetary policy while the policy rates adhere to the zero lower bound.

JEL: E32; E52; G32

Keywords: Unconventional monetary policy; Industry ouput; Monetary transmission mechanism

* I am very thankful to my advisor Tara Sinclair for her valuable guidance and support. I also thank Saroj Bhattarai, Michael Bradley, Constantin Bürgi, Frederick Joutz, Xiaohan Ma, Claudia Sahm, Roberto Samaniego, and Toyoichiro Shirota for their comments and feedback. I am grateful to the Department of Economics at the George Washington University for awarding this paper for the 2019 Kendrick Prize for the Best Paper in Macroeconomics. Lastly, I thank participants at 13th Economics Graduate Student Conference at Washington University in St. Louis, 45th Eastern Economic Association Conference, 3rd GW Student Research Conference in Economics 2019, Georgetown Center for Economic Research Biennial Conference 2019, and 2019 Pennsylvania Economic Association Conference.

† *eijigoto@gwmail.gwu.edu. The George Washington University, 2115 G Street, NW, # 340, Washington, DC 20052*

1 Introduction

After the financial crisis, the policy rates of the highly advanced economies reached the zero lower bound 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, without controlling the policy rate. While the central banks try to stimulate aggregate variables, investigating the effects across industries provide new insights of the policy. First, possessing differential impacts across industries directly influences the relative performance of industries where people hold jobs, which, therefore, influences the wages and employment statuses. Second, by associating industry effects of unconventional policy with financial structure of the industry, the central banks are able to grasp monetary transmission mechanisms. While implementing unconventional policy is often regarded as an extreme circumstance, due to the steadily decline of the natural rate of interest (Holston et al., 2017a), re-occurrence of the zero lower bound is likely and therefore this analysis is relevant.

In my paper I estimate the impacts of unconventional policy on industry output in the US, the UK, and Japan. My paper also investigates whether the pattern of industry output responses from these countries are similar to the literature of conventional monetary policy (henceforth conventional policy).

My paper provides several contributions to the literature. First, it provides 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 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., 2015a; and many others), however, the differential impacts of unconventional policy in the literature is scarce. My paper fills this gap in the literature and examines the effects of unconventional policy on industry output.

Second, my paper compares the industry-level output responses from the three countries. Previous studies focus on a single country to assess the industry output effects of conventional policy (Dale and Haldane, 1995; Carlino and DeFina, 1998; Ganley and Salmon, 1997; and many others). This observation is also true for other macroeconomic topics such as fiscal policy (Bénétrix and Lane, 2010 and Monacelli and Perotti, 2008) and news shock (Vukotić, 2019). My paper adds a cross-country dimension to those studies to examine the relevance of country characteristics.

Third, I provide the implications of monetary transmission mechanisms of unconventional policy. One of the advantages of estimating the effects of monetary policy on industry output is to provide monetary transmission mechanisms because it is then 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, specifically to observe to what extent the monetary transmission mechanims between unconventional and conventional policies are similar.

I use a structural Bayesian vector autoregressive model with zero and sign restrictions as in Gambacorta et al. (2014) to identify an unconventional policy shock. Given the shock, I generate impulse response functions (henceforth response functions). I use monthly industry output data for the UK and Japan and quarterly output data for the US to individually estimate the model for each country and each industry.

I find that the industry-level output responses are different within a country. For example, in the US the magnitude varies from -0.01% in healthcare to 0.35% in mining, in response to a one standard deviation shock to the central bank total assets[1]. Notably, the effect of the finance industry (0.28% in the US[2]) is significantly positive and higher than the industry median (except in the UK). This observation is in line with the event study literature which stresses the importance of the finance industry (Baumeister and Benati, 2012; Mallick et al., 2017; Gagnon et al., 2011; and Krishnamurthy and Vissing-Jorgensen, 2011). To justify the industry level estimates, I construct a weighted response function from the industry response functions as a weight being GDP share of the industry. The weighted response functions are approximately the same as the national-level response functions.

Next, the observed industry-level output responses moderately vary across those three countries. However, I find that, on average, manufacturing, construction, and trade are the most responsive. Those three industries are also the most responsive to conventional policy (Dale and Haldane, 1995; Ganley and Salmon, 1997; and Ibrahim, 2005) which suggests that industrial impacts of unconventional policy are qualitatively similar to conventional policy. Furthermore, I find that higher industry working capital is associated with a larger output response to unconventional policy. This observation implies the existence of traditional interest rate channel, which contributes to the similarity of unconventional and conventional policies.

In robustness analysis, I estimate a structural Bayesian global vector autoregressive model (Burriel and Galesi, 2018) for the UK and Japan[3] to take into account the fact that industries are interrelated. The results from the joint estimation and single industry estimation are generally compa-

[1] In the UK the magnitude varies from -0.04% in finance to 0.24% in construction and in Japan the magnitude varies from -0.02% in arts, entertainment, and recreation to 0.39% in manufacturing

[2] -0.04% in the UK and 0.16% in the US

[3] The US was not included in this analysis because the sample size is small with quarterly series.

rable to each other, though there are some industries whose responses are very different. Notably, mining responds positively in global vector autoregressive model but negatively in single industry vector autoregressive model which suggests that the industry is stimulated by the interaction with manufacturing. I also found that the UK experiences more spillover effects than Japan, however, this does not radically change the results obtained from the benchmark model.

The rest of my paper is organized as follows: section 2 describes the datasets that are used, Section 3 outlines the methodology (including the model, identification, and estimation), section 4 presents the main results, section 5 conducts regression analyses, section 6 checks robustness, and finally section 7 concludes.

2 Data

I analyze the following countries: the US, the UK, and Japan. These three countries are suitable for this analysis. They all experience the ZLBs, they all implemented UMPs, and they are relatively closed economies and so they are less likely to have spillover effects from other countries[4]. In addition to this, the US has been the center of the intensive research of UMP since the onset of financial crisis, the UK provides a large variety of datasets available ideal for the industrial analysis, and Japan has a feature of prolonged ZLB and the pioneer of the large scale assets purchasing.

Based on data availability, the US is of quarterly frequency while the Japanese and UK data are of monthly frequency. The datasets cover 2008Q1-2017Q4 for the US, 2008M1-2018M6 for the UK, and 2003M1-2018M2 for Japan. I chose these ranges based on when these central banks operate UMP and when the policy rates are generally below 1 and near zero, representing the ZLB.

My VAR framework consists of the following four endogenous variables: industrial output (IO), consumer price index (CPI), central bank total assets (AT)[5], and stock market implied volatility (VOL). These variables, excluding VOL, are seasonally adjusted.

The industrial output data for the US is real value added and is obtained from the Bureau of Economic Analysis. The UK data is monthly GDP and Japanese output data is quantity indices and are retrieved from the Office of National Statistics and the Ministry of Economy, Trade and Industry, respectively. Since the Japanese dataset is not commonly used[6], I provide a brief description. The series is quantity index and is made to systematically understand the production activities of the various industries in Japan. The series is of monthly frequency and is available

[4]For that reason, countries in the EU area are excluded.

[5]AT for the UK does not contain other foreign currency assets from 2014M10 onward. Thus it may underestimate the effects. Despite this limitation, it is better to have a larger sample size than to exclude these periods to have a more accurate measure of AT.

[6]Though it was used in Du et al. (2010) and Shintani (2005)

with relatively short time lags[7]. The base year is 2010 which takes the value of 100. For each industry, main products that represent the industry are chosen and the index represents the transitions of quantitative fluctuations of those selected products within the industry. The selected products cover a relatively large share in the industry. For example, for Indices of Industrial Production, the selected products are chosen so that they account for 90% of the aggregate values of the industry.

Figures **??**, **??**, and **??** represent the industrial output for each country. Only for the figures, the US and UK data are normalized so that the first period of 2010 is 100. For the US, the over all movement is an upward trend. However, the movements of some industries, such as mining, agriculture, and utilities are quite different and idiosyncratic compared to this trend. For the UK, most industries also exhibit slight upward movement, and there are also some industries that behave differently such as mining and utilities. On the contrary, industries in Japan behave differently compared to these two countries. Their behaviors do not show a consistent trend. For example, healthcare increases its activity, food and accommodation stays at about the same level, and utilities decreases its activity. Also for a motivational purpose, I plotted the composition of industries in GDP for the respective sample years for each country in Appendix B (Figures B.31, B.32, and B.33). I also plot the aggregate output, CPI, AT, and VOL series in Figure 3[8].

To combat the financial crisis, these countries implement UMPs and increase their total assets in an unprecedented degree: all of the central banks more than quadruple their size of assets. These substantial increases in central bank total assets are correlated with the increase in aggregate output and consumer price index, though Japan does not show as much of a rise in these variables. In this paper I investigate whether UMP contributes to these rises in aggregate output, whether there exists any heterogeneity in industrial output, and, if so, whether the pattern is similar to CMP.

There are several limitations of the datasets. First, unlike the US and UK datasets that provide comprehensive coverage of 17 industries, the industries in the Japanese datasets are not perfectly comprehensive since agriculture and government are excluded. Additionally, the education industry in Japan does not include public components. Second, unlike the UK and Japanese data, the frequency of the US data is quarterly which is not as suitable for the analysis of monetary policy as the monthly frequency as used in Gambacorta et al. (2014) and Bhattarai et al. (2015a)[9]. The quarterly data and limited ZLB period provide a small sample period of 40 in the US, while the Japanese data covers a large sample period of 182, thanks to the prolonged ZLB periods. Third, even though the UK and Japanese data have a bigger sample size, the coverage of the industries

[7]Datasets are available within a one and half month lag. A revision is only done approximately a month after the first release.

[8]I use CBOE volatility index for the US, FTSE 100 volatility index for the UK, and Nikkei volatility index for Japan.

[9]They use the interpolation method (Chow and Lin, 1971) to generate a monthly GDP. However, in order to implement this method, I would need relevant monthly frequency data for each industry's output.

is limited due to the nature of monthly data. That is, the series does not capture the entire, but rather, a highlighted movement of the individual industries. Finally, the industry definitions do not match perfectly across countries, since each country provides output data based on their own definitions of industries. Even though I attempt to match industry definitions across countries as much as possible, caution still needs to be taken.

Lastly, the following is the complete set of industries examined in this paper: agriculture (excluding Japan); mining; utilities; construction; manufacturing (also durable goods and non-durable goods); trade (sum of the wholesale and retail trade); transportation; information; finance; real estate; professional service; education; healthcare; arts, entertainment, and recreation; accommodation and food; other services ; and government (excluding Japan). Further details of the industry definitions are available in Appendix A.1.

3 Methodology

Structural VAR models have been widely used for studying impacts of monetary policy since Christiano et al. (1999). In this paper, I also use the structural VAR model but follow the identification methodology in Gambacorta et al. (2014) to identify an UMP shock, generate IRFs, and assess the industrial effects. Section 3.1 describes the model, Section 3.2 states the identification, and Section 3.3 depicts the estimation.

3.1 The Empirical Model

I estimate the following VAR (p) model for each industry and for each country:

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

where p is the number of lags, y_t is a column vector of endogenous variables, ν is a column vector of intercept terms, A_is are coefficient matrices, and u_t is white noise with nonsingular covariance matrix Σ_u. In this paper, y_t consists of the following variables: log of industrial output (IO_t), log of consumer price index (CPI_t), log of central bank total assets (AT_t), and level of stock market implied volatility (VOL_t).

Output variables are not first differenced by following the standard monetary policy literature (for example, Gambacorta et al., 2014; Boeckx et al., 2017; Christiano et al., 1999; Ibrahim, 2005; and many others). However, there are some studies in which the authors take the first-difference of the output (for example Arnold and Vrugt, 2002; Carlino and DeFina, 1998). To understand the behavior of the variables that I use, I operate unit root and stationarity tests. Detailed descriptions and results are available in Appendix A.2. I find that for each industrial output, test results generally contradict each other. When test results are consistent, the implication is usually I(1) or non-stationary. It is known that the ADF test suffers power and the KPSS test, when the sample is large, has a large size problem. This may be the reason that it is easier to get I(1) rather than I(0). Since many variables have mixed results, there is a possibility that some of the series are actually I(0). Thus, taking the difference of these series may lead to a misspecification, even though there is an economic meaning (growth rates). When I compared the effects of monetary policy across industries, if some series are first differenced and others are level, then it is difficult to precisely compare cross industrial effects. If I include the variables in levels for all of the series, I can avoid the problem. However, a caveat is that under the level specification, a monetary policy shock may lead to a permanent effect. Given these diverse test results, it is safe to use level in my specification and I implicitly keep the long run relationship of these variables in my VAR.

These 4 variables are intended to capture the minimal dynamics of macroeconomics and to identify an UMP shock. As is standard in the monetary policy literature, industrial output and CPI are in the system to ensure the macroeconomic and industrial dynamics. While industrial output itself may not necessarily summarize the entire aggregate dynamics and the reaction function may be different for each industry, I add aggregate output excluding the industry in the system in the robustness check to examine whether or not the results change radically.

Central bank total assets are included as a monetary policy instrument, due to the fact that short-term nominal interest rate is no longer an instrument under the ZLB. Central bank total asset is a general measure of UMP and can compare the effects of monetary policy across countries of different states and situations. 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 the long-term securities and sell the short term securities by the same amount. 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. While my identification is coming from the literature of event study showing that UMP has a effect to mitigate the financial market distress, the frequency of VAR framework is significantly lower than those event studies. So while it is possible that this instrument may be able to capture the forward guidance component, the forward guidance component is at most implicit.

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.

3.2 Identification

I follow the identification of 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 VAR model (I omit the time subscript):

$$\underbrace{\begin{bmatrix} u_{IO} \\ u_{CPI} \\ u_{AT} \\ u_{VOL} \end{bmatrix}}_{\substack{\text{Reduced form error} \\ u_t}} = \begin{bmatrix} * & * & 0 & 0 \\ * & * & 0 & 0 \\ * & * & + & + \\ * & * & -/0 & + \end{bmatrix} \underbrace{\begin{bmatrix} \epsilon_{SO} \\ \epsilon_{CPI} \\ \epsilon_{AT} \\ \epsilon_{VOL} \end{bmatrix}}_{\substack{\text{Structural error} \\ \epsilon_t}} \tag{2}$$

where the components of ϵ_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 industrial output and price. In other words, UMP 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 UMP shock from other contemporaneous shocks, such as demand or supply shocks.

To identify an UMP shock, I apply a short run sign restriction. An UMP shock is essentially an increase in central bank total asset. However, a mere increase in it contains some endogenous components. To separate them from an increase in central bank total assets, stock market implied volatility plays a role as a financial market distress measure. The endogenous component is a shock to stock market volatility that increases the central bank total assets. The central banks endogenously respond to financial turmoil and economic uncertainty by UMP. This component is a reverse causality of UMP: a higher financial market distress increases the central bank total assets. On the contrary, an exogenous component is a shock to the central bank total assets that decreases (or keep) the stock market volatility. This notion is consistent with the literature that UMP reduces the financial uncertainty (for example, Baumeister and Benati, 2012; Mallick et al., 2017) and improves the financial market condition (for example, Gagnon et al., 2011; Krishnamurthy and Vissing-Jorgensen, 2011). I then only take the latter component of an increase in central bank total asset and call it as an UMP 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 et al. (2014). The complete description of the identification is in Appendix A.3. The mixture of the zero and sign restriction is imposed on the impact period for all of the countries. As in Gambacorta et al. (2014), I also impose the same sign restriction the next period after the shock except for the US, since my US data is quarterly unlike the monthly frequency used in Gambacorta et al. (2014). If I were to impose the same sign restriction, it would imply that the sign restriction is effective for three months (a quarter). This assumption may not be realistic. Thus I impose the restriction only in the impact period for the US. However, I relax this assumption in the robustness check to examine how the results are affected.

The following table summarizes the restrictions that I imposed[10].

Table 1: Sign Restriction

	all countries at period = 0	The US at period = 1	The UK & Japan at period = 1
IO	0	*	*
CPI	0	*	*
AT	>0	*	>0
VOL	≤0	*	≤0

3.3 Estimation

I estimate Bayesian VAR and generate IRFs 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 the parameter distributions to be tight. 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 et al. (2014). I follow the Bayesian method of Kilian and Lütkepohl (2017) and Koop et al. (2010). A detailed explanation of the Bayesian estimation and how I generated IRFs are in Ap-

[10] 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)

pendix A.4.

4 Results

In this section, I first provide the national results and compare them to the existing literature in Section 4.1. Then I show the results of industrial output in Section 4.2 and briefly compare the observed industrial patterns across these countries and the literature of CMP in Section 4.3.

4.1 National Results

Figure 4 shows the IRFs from a one standard deviation shock to the central bank total assets on aggregate output, CPI, AT, and VOL for each country from the corresponding sample periods. The 68% Bayesian credible bands are reported as is standard in the literature. The results show that for all of these countries, UMP has a statistically positive impact on both aggregate output and CPI. Central bank total asset (the identified shock) is positive and stock market volatility is negative at the first period and slowly revert back to zero, these observations are in line with the literature of empirical UMP (such as Gambacorta et al., 2014; Bhattarai et al., 2015a; Boeckx et al., 2017, and many others) Figure 4 shows that the effects on aggregate output and price are long lasting for all of the countries and stay significantly positive until the last period.

Now, I investigate whether my results are in line with the studies in the empirical literature of UMP. The following table summarizes my results as well as the results from the other studies.

Table 2: Comparison of national effects across UMP studies

Authors	Country	Estimate			Sample periods	Estimation	Output variable
		GDP in %	CPI in %	1 STD UMP shock in %			
This paper	the US	0.16	0.11	2.86	2008Q1-2017Q4	Bayesian	Quarterly GVA
	the UK	0.12	0.09	2.23	2008M1-2018M6	Bayesian	Monthly GDP
	Japan	0.23	0.07	1.80	2003M1-2018M2	Bayesian	Monthly quantity index
Gambacorta et al. (2014)	the US	0.10	0.06	2.70	2008M1-2011M6	Frequentist	interpolated GDP
	the UK	0.12	0.01	4.50	2008M1-2011M6	Frequentist	interpolated GDP
	Japan	0.10	0.02	1.20	2008M1-2011M7	Frequentist	interpolated GDP
	EU	0.10	0.08	2.40	2008M1-2011M8	Frequentist	interpolated GDP
Bhattarai et al. (2015a)	the US	0.40	0.10	2.00	2008M1-2014M11	Bayesian	interpolated GDP
Boeckx et al. (2017)	EU	0.10	0.10	1.50	2007M1-2014M12	Bayesian	interpolated GDP
Burriel and Galesi (2018)	EU	0.08	0.03	1.00	2007M1-2015M9	Frequentist	interpolated GDP
Schenkelberg and Watzka (2013)	Japan	0.40	0.05	7.00	1995M1-2010M9	Bayesian	Industrial production
Peersman (2011)	EU	0.40	0.07	1.75	1999M9-2009M12	Bayesian	industrial production
Average		0.20	0.06	2.67			
Median		0.10	0.06	2.00			

The table shows the maximum value of the median IRF functions of output and price from a one standard deviation shock to the central bank assets. The one standard deviation shock is a

2.86% increase in central bank total assets in the US. This is equivalent to an increase in \$100 billion on average. 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 maximum median IRFs of output for the US, the UK, and Japan of this paper are 0.16%, 0.12%, and 0.23% and price are 0.11%, 0.09%, and 0.07%, respectively. The range of effect from the other studies lies between 0.08% to 0.4% for output and between 0.01% to 0.1% for price. The averages (medians) are 0.2% (0.1%) for output and 0.06% (0.06%) for price. My results of output are comparable to those numbers, however, my results of price are a bit higher, though statistically insignificant.

While there are several similarities of my methodologies to these studies, such as identification (Gambacorta et al., 2014) and estimation (Boeckx et al., 2017), generally my responses to the shock are slightly larger than those studies. The main difference is that these studies did not generally include the periods after 2012. There were a few large increases in central bank total assets after 2012. It could be the case that these large increases in total assets provide the slightly larger magnitude of my results. I also compare the national results of this paper to several CMP studies in Appendix A.5.

While the estimation method, identification, countries, and sample periods are different, my results are overall comparable to the results of those studies, especially with regard to output, which is the focus of my paper.

4.2 Industrial Results

First, I plot the weighted IRFs and national IRFs on Figure 5 to ensure that the industrial results approximately sum up to the national results. One of the purposes of this paper is to uncover the heterogeneous responses to the UMP shock. If the industrial IRFs sum up to the national IRF, it is credible to argue the validity of the industrial IRFs, since the output comovements across industries are sufficiently small. The weighted IRFs are calculated by following:

$$WIRF_t = \sum_{i=1}^{I} weight_i * MIRF_{it} \tag{3}$$

where $WIRF_t$ represents weighted IRF at period t, and $MIRF_{it}$ represents the median IRFs for industry i at period t, and I is the total number of industries. I calculate the weight for the US and the UK the following way. First, I calculate the average gross value added (GVA) of the sample periods 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 individual industries over total GVA. Japanese data provides the weight from the GDP share and so I used the weight for the calculation of the weighted IRFs. In Figure 5, for each country, the bold line represents the national IRF and the dotted line represents the weighted IRF. I also reported the credible bands of the national IRFs.

For each country, the weighted IRF is similar to the national IRF but not identical. For example, weighted IRF of the US is lower than the national IRF for the second half of the entire period. The weighted IRF in the UK is systematically lower than the respective national IRFs. The Japanese weighted IRF is slightly higher than the national IRF. The potential explanations of those deviations are estimation uncertainty, statistical measurement error between aggregate output and sum of the industrial output, and missing industry comovement due to my separate industry level estimation. While there are some deviations, for each country the deviation is not large and is generally within the credible band. Therefore, the weighted IRFs overall match the national results.

Now Figures 6, **??**, and **??** show the industrial IRFs for each country. I report the 16% and 84% credible bands. I find that 15 out of 17 (88%) industries in the US, 13 out of 17 (76%) industries in the UK, and 8 out of 15 (53%) industries in Japan are statistically significant and positive. The number of industries which are significantly positive is similar between the US and the UK, however Japan is different from these two countries.

To compare the impacts of UMP across industries, table 3 shows the UMP elasticity of output. It shows the percentage change in median peak IRF to a 1 percent increase in central bank total asset for these three countries. Under each elasticity, I listed 32% credible band in parenthesis analogous to standard errors.

Table 3: Monetary Policy Elasticity of Output

Country	the US	the UK	Japan	Country	the US	the UK	Japan
Industry		Elasticity		Industry		Elasticity	
Aggregate	0.06	0.05	0.13	Information	0.10	0.09	0.04
	(0.02)	(0.02)	(0.07)		(0.03)	(0.06)	(0.04)
Agriculture	0.04	0.06		Finance	0.28	-0.04	0.16
	(0.01)	(0.07)			(0.11)	(0.04)	(0.05)
Mining	0.35	-0.11	0.00	Real estate	0.07	0.02	0.01
	(0.19)	(0.05)	(0.10)		(0.01)	(0.01)	(0.01)
Utilities	0.18	0.10	0.02	Professional service	0.09	0.12	0.02
	(0.03)	(0.04)	(0.04)		(0.03)	(0.04)	(0.04)
Construction	0.05	0.24	0.08	Education	0.03	0.01	0.09
	(0.04)	(0.08)	(0.06)		(0.01)	(0.00)	(0.06)
Manufacturing	0.06	0.07	0.39	Healthcare	-0.01	0.03	0.01
	(0.03)	(0.04)	(0.25)		(0.06)	(0.03)	(0.01)
Durable goods	0.16	0.17	0.52	Arts, entertainment, and recreation	0.10	-0.01	-0.02
	(0.04)	(0.06)	(0.33)		(0.04)	(0.03)	(0.03)
Non-durable goods	0.00	-0.01	0.17	Accommodation	0.12	0.02	0.04
	(0.04)	(0.02)	(0.12)		(0.03)	(0.03)	(0.03)
Trade	0.09	0.08	0.19	Other services	0.02	0.08	0.24
	(0.02)	(0.03)	(0.09)		(0.02)	(0.01)	(0.08)
Transportation	0.08	0.07	0.10	Government	0.00	0.03	
	(0.02)	(0.01)	(0.03)		(0.03)	(0.03)	
				Industry average	0.10	0.06	0.12
				Industry median	0.09	0.07	0.06

Note: credible bands (32%) in parenthesis. Elasticity is the maximum median impulse response function consistent with a 1% increase in central bank total asset. Credible bands are also transformed by the same amount as the elasticity is scaled.

The elasticity of UMP on aggregate are 0.06 in the US, 0.05 in the UK, and 0.13 in Japan. The elasticity in Japan is twice as large as in the US or the UK, while Japan has a broader credible band. When it comes to the industries, the results uncover the differential responses to the UMP shock. The elasticity varies from -0.01 to 0.28 in the US, -0.11 to 0.24 in the UK, and -0.02 to 0.39 in Japan, indicating that the same policy creates industries that are expanding and industries that are contracting. This implies that there are winners and losers. The industries that show the strongest elasticity are mining in the US, construction in the UK, and manufacturing in Japan. It is interesting that the most affected industry is different for each country.

In order to know which industry is more responsive to the shock than the national average, I look for industries whose credible band is above the industry median elasticity[11]. Mining, utilities, finance, and accommodation and food respond stronger than the industry median in the US, construction, professional, and other service respond stronger than the industry median in the UK, and manufacturing, trade, transportation, finance, education, and other service respond stronger than the industry median in Japan. The industries mentioned above include construction, manufacturing, and trade. Those industries are very responsive to CMP shock which is in line with the literature (for example, Ganley and Salmon, 1997), while it turns out generally responsive industries vary by country.

As mentioned in Section **??**, the financial market has been given a large amount of attention in the literature of UMP. In the UK, the effect on the finance industry are indeed negative, which is surprising (I observed this result using both GVA and monthly GDP in the UK). However, the IRFs of the US and Japan indicate that UMP has significantly positive effects on the finance industry. Additionally, the credible band of finance industry is greater than the industry median in the US and Japan as well. This observation is consistent with the literature (such as Krishnamurthy and Vissing-Jorgensen, 2011 and Neely, 2015). The effect to the financial market is one of the main goals of UMP.

Also mentioned in Section **??**, interest rate sensitive industries are usually responsive to CMP and durable goods manufacturing industry is known to be the most interest rate sensitive industry. Despite that under ZLB the interest rate channel is blocked, I find that elasticity of durable goods manufacturing is greater than the industry median for all of the countries. One possibility is that signaling theory, (such as Bauer and Rudebusch, 2013 and Bhattarai et al., 2015b) a central bank's promise to keep the interest rate lower towards the future, lower the expected short term real interest rates. This creates incentive for capital intensive firms to invest in projects which involve money borrowing. Thus this signaling channel may make the effect of UMP similar to that of CMP.

Finally, some industries respond weaker than the industry median. Those industries include education (excluding Japan), healthcare, and government. These industries have a tight link to the public sector and seem to be isolated from the policy shock.

4.3 Cross-Country Analysis

The literature of industrial studies in CMP uncovers heterogeneous industrial effects. However, these analyses typically limit their attention to a single country and have not compared the indus-

[11]It is important to compare with the median elasticity not the national elasticity. The Japanese national elasticity is higher than the US and the UK, however, this is coming from the manufacturing industry whose elasticity is exceptionally large and composition in GDP is around 20%. If one industry has a very large or small elasticity with non-negligible GDP share, the national elasticity tend to be skewed and may not be suitable for a central tendency measure.

trial effects across countries[12]. In this section, I briefly compare the pattern obtained in Section 4.2 across the US, the UK, and Japan and observe to what extent the pattern is similar to CMP.

The observed pattern of industrial responses show some similarities across countries. There are 6 industries which have significantly positive impacts for all of the countries. These 6 industries are construction, manufacturing[13], trade, transportation, education[14] and other services. Thus, this implies that there are some similar patterns of heterogeneity in each country. Some of these industries belong to the production sector, such as construction and manufacturing which tend to be interest rate sensitive. Despite that the interest rate channel is blocked due to the ZLB, the effect to the industries still exist. Industries that are not responsive to the policy are industries that have a strong link to the public sector. Those industries includes education, healthcare, and government.

However, when it comes to relative responsiveness to the national median, cross country effects are not so similar. For example, accommodation and food is significantly stronger than the industry median only in the US, construction and professional service is significantly stronger than the industry median only in the UK, and manufacturing and trade are significantly stronger than the industry median only in Japan, even though industries that respond relatively weak are similar such as real estate, healthcare, and government.

To compare to the literature of CMP, I generated industry mean IRFs, a simple average of IRFs for each period within an industry across countries. Frequencies of IRFs in the US and IRFs in the UK and Japan are different, however, they can show a tendency of which industries, on average, strongly respond to the policy. Figure **??** shows the results. The red line represents the average of the median IRFs and the average of credible bands are attached. Figure **??** shows that construction, manufacturing, and trade are stronger than the overall average[15] and they are the top 3 most responsive industries. This suggests that, on average, responsive sectors between UMP and CMP are similar. Additionally, industries that have a link to public sector did not respond well on average (except for utilities). These industries generally do not comove with business cycle (Berman and Pfleeger, 1997). While monetary policy is typically not a large source of business cycles (Gambacorta et al., 2014), UMP affects these industries in a similar manner.

Based on the cross-country analysis, I find that the pattern of heterogeneity is not so similar. However, based on the industry average from the investigated countries, the observed differential impacts are similar to the literature of CMP, suggesting UMP creates not only idiosyncratic responses across countries but also common responses across countries.

[12]However, Dedola and Lippi (2005) and Peersman and Smets (2005) did explore the industrial impact of monetary policy across countries.

[13]Durable goods manufacturing is significant as well

[14]This industry responds positively but most of the IRFs are in the insignificant or negative range

[15]Contrary to the national IRFs, this average is not a weighted average. Thus it is less likely to be biased by a specific industry that responds very strongly with a large GDP share.

5 Implication of Transmission Channels

In the previous chapter, I find that industrial impacts are heterogeneous. In this chapter I seek to understand the transmission mechanisms of UMP by running simple regressions. In specific, I regress the industrial elasticity on several industrial characteristics. The elasticity comes from the median IRFs from the previous chapter. Explanatory variables are constructed from the Mergent Online by FTSE Russell which is a firm-level database that covers annual balance sheets and income statements information for public and private companies for both domestic and international companies. The database contains the information of 743,242 companies in the US, 106,678 companies in the UK, and 152,686 companies in Japan. Explanatory variables are constructed from the periods used in my VAR analysis.

However, there are the following limitations of this dataset. First, since the dataset only contains NAIC and SIC for the industry definition, I need to use the US industry definition to classify the UK and Japanese companies to the respective industries. Second, many of the UK and Japanese companies do not contain the information of NAIC, which loses many observations. Third, the balance sheet information and income statement information are generally only available to public firms. Therefore, explanatory variables constructed from these financial statements are less accurate than explanatory variables such as firm size. After all, the numbers of firms that contain the financial statements and NAIC are 125,033 in the US, 3,020 in the UK, and 5989 in Japan, which produces less accurate constructions of the variables in the UK and Japan.

Following Dedola and Lippi (2005), the explanatory variables are: firm size (= number of employees / number of firms), leverage (= total liabilities / shareholders' equity), interest burden (= interest payment / operating profit), working capital (= [current assets – current liabilities] / total assets), and short-term debt (= current liabilities / total liabilities). These explanatory variables are meant to be proxies for traditional transmission mechanisms.

The 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 the variables over the sample period, and for each industry I take median of the variable[16].

Firm size and leverage are proxies of borrowing capacity of an industry and represent credit channel. An industry with larger firms or higher leverage firms on average tend to possess more borrowing capacities than other industries with smaller firms or lower leverage 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,

[16] I chose median over mean because of the following reasons: first, there are some outliers and they distort the overall averages of some variables in some industries. Second, the variables do not necessarily have to be normally distributed.

1999). Also, large firms access direct finance in addition to indirect finance, while small firms do not always have that option. Since credit supply helps small or low leverage firms increase their production, these firms tend to respond to the policy strongly.

Interest Burden is a proxy for the cost channel of monetary policy. This theory originates to explain the "price puzzle" of monetary policy: when interest rate is higher due to tightening, it raises the firms' marginal cost of production, which raises the price of output as well. The literature also supports this view of monetary policy (Barth III and Ramey, 2001 and Gaiotti and Secchi, 2006). Along with this view, I use interest burden. An industry with a higher interest burden responds to the shock strongly.

Lastly, working capital and short-term debt are proxies of channels on the supply side, mainly traditional interest rate channel: change in the nominal interest rate alters the real interest rate and user cost of capital, which alters the 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 and higher short-term debt are expected to respond strongly. Since the policy rates are attached to the ZLB during UMP periods, it is of interest to know to what extent interest rate channel plays a role.

These channels are introduced as if they work independently. However, as in Bernanke and Gertler (1995), those channels are interrelated and hard to disentangle. For example, interest burden is a proxy of the cost channel, a change in interest rate affects the user cost of capital which also contains the element of the interest rate channel.

If I assume that UMP transmission mechanisms are the same as CMP transmission mechanisms, industries that have smaller firm size, lower leverage, higher interest burden, lower working capital, and higher short-term debt are expected to respond to the policy strongly. The following table summarizes the expected signs if UMP transmission mechanisms are the same as CMP transmission mechanisms:

Table 4: Expected Sign if it were CMP

Firm size	Leverage	Interest Burden	Working capital	Short-term debt
-	-	+	-	+

I estimate pooled OLS (cross-section and cross-country) with robust standard errors by following Dedola and Lippi (2005). They estimate the industry impacts of CMP for the US, the UK, Germany, Italy, and France using a VAR model. The industries they investigated are within manufacturing. Also, they estimate the effects of monetary tightening instead of easing unlike this paper[17]. Therefore the results obtained in this paper are not the direct comparison to theirs. Among these five variables they find that firm size, leverage, and working capital are significant.

I have the following four different dependent variables: (1) maximum and (2) 24 th period median elasticity from the benchmark VAR, (3) maximum, and (4) 24th period median elasticity from 5-variable VAR (the details of this can be found in section 6.1.1). I include country fixed effect and industry fixed effects for all of the regressions.

Table 5: Regression Results

	Dependent variable			
	(1)	(2)	(3)	(4)
Explanatory variable	Maximum elasticity	24th period elasticity	Maximum elasticity from GDP excluding the industry	24th period elasticity from GDP excluding the industry
Firm size (credit channel)	0.217	0.128	0.402	0.181
	(0.376)	(0.190)	(0.339)	(0.181)
Leverage (credit channel)	0.725	1.000***	0.510	0.686***
	(0.588)	(0.210)	(0.467)	(0.163)
Interest burden (cost channel)	0.472	-0.0520	0.307	-0.204
	(0.290)	(0.225)	(0.312)	(0.191)
Working capital (interest rate channel)	-0.690***	-0.346***	-0.556***	-0.299***
	(0.242)	(0.102)	(0.192)	(0.0897)
Short-term debt (interest rate channel)	0.0161	-0.00566	0.0280	0.0211
	(0.172)	(0.0783)	(0.139)	(0.0628)
Country fixed effects				
US	0.102	0.0346	0.0825	0.0118
	(0.0705)	(0.0331)	(0.0787)	(0.0288)
UK	-0.0316	0.00133	-0.0427	-0.0192
	(0.103)	(0.0524)	(0.106)	(0.0445)
JP	0.0324	0.0112	0.0127	-0.0198
	(0.125)	(0.0646)	(0.128)	(0.0545)
Industry fixed effects	Yes	Yes	Yes	Yes
N	49	49	49	49
adj. R-sq	0.439	0.453	0.580	0.591

Note: pooled OLS (cross-industry and cross-country). Robust standard errors in parentheses. $*p < 0.10 * *p < 0.05 * * * p < 0.01$.

The second column shows the effects of transmission measures on maximum elasticity. The results show that only working capital is significant with the expected sign. Interest burden and short-term debt have the expected sign, however, they are not significant. Interestingly enough, credit channel measures of firm size and leverage have the opposite sign. The third through fifth columns show the results when the dependent variables are different. For each specification, working capital is significant with the expected sign, interest burden and short-term debt are insignificant, and credit channel measures are again the opposite sign. Also, leverage is significant with the opposite sign when the 24 th period elasticity is used.

Based on the results, it seems that the interest rate channel plays a role, even though policy rate is attached to the ZLB. It implies that real or expected interest rate still affects the production decisions of firms. Again this can be possibly explained by signaling theory (Bauer and Rudebusch, 2013 and Bhattarai et al., 2015b). Cost channel is generally insignificant, which is also observed in

[17]However, the specification of the VAR model is not nonlinear and does not differentiate the impacts differences between easing and tightening. Thus, the impacts are symmetric.

Dedola and Lippi (2005). The surprising result is that both credit channel measures have positive signs and leverage is sometimes significant, which disagrees with the traditional view of credit channel.

There are two potential explanations of this. First, the credit channel may have an asymmetric reaction depending on tightening and easing (Gertler and Gilchrist (1994)). Contractionary policy makes small firms face borrowing constraints and their production falls dramatically. However, monetary easing might have the homogeneous impact on small and large firms. Therefore, firm size does not matter for easing, however this observation is not seen in Dedola and Lippi (2005). Second, traditional credit channel exists but UMP also provides an additional monetary transmission mechanism which is the portfolio balance channel: the central banks purchase long-term securities, which forces investors to change their portfolio. Those investors shift their holdings towards some assets that have similar characteristics to long-term securities, such as corporate bonds. This approach helps large firms or highly leverage firms to acquire additional funding easier through direct finance. Even though the traditional credit view might still exist, large or high leverage firms also responded strongly to the policy due to the portfolio balance channel. Therefore, the regression results cannot show the insignificant results of credit view.

Through this regression analysis, the impacts of UMP seem to be related to the traditional interest rate channel. However, this analysis does not reject the possibility that UMP has an additional channel through which large firms benefit. This might be the reason that construction industry, whose firm size is smaller in general, is not relatively more responsive than other industries in the US and Japan.

6 Robustness Analysis

In this section I conduct two types robustness analyses. In section 6.1, I investigate the industrial impacts of UMP by estimating multiple industries jointly, in section 6.2, I estimate the model with different identifications, and in section 6.3, I estimate the effects of UMP during non-ZLB periods.

6.1 Joint Consideration

The first set of robustness analyses carries out joint estimations. In section 6.1.1, I consider a minimal scale joint estimation and in section 6.1.2, I seek an explicit joint estimation with a global VAR model.

6.1.1 Including Aggregate Output Excluding the industry

The structural VAR model for monetary policy analysis is based upon the three equations New Keynesian model. The model is a system of aggregate variables, not disaggregated variables. In spite of the underline assumption, there are many papers investigating the industry effect of monetary policy without controlling aggregate output. Omitting the aggregate dynamics may lead to a biased estimation. I estimate the model including aggregate output (or GDP) excluding the industry, defined as $GDPex_t$ in the endogenous vector, y_t, so that the system is able to capture not only the dynamics of the industry but also the dynamics of the aggregate output and the output of the other industries. By including aggregate output excluding the industry into the system, the endogenous vector, y_t, consists of five variables. I add log of $GDPex_t$ after industrial output, so that the endogenous vector, y_t, is now:

$$y_t = \begin{bmatrix} ln(IO_t) \\ ln(GDPex_t) \\ ln(CPI_t) \\ ln(AT_t) \\ VOL_t \end{bmatrix} \tag{4}$$

The inclusion of the variable generates the additional zero restriction for the identification: a shock to the central bank total assets has at most a lagged impact on aggregate output excluding the industry. This additional zero restriction is reasonable since I impose the same identification on the industrial output. The inclusion of the variable and the identification are used in Ibrahim (2005) in the same manner. Aside from the additional identification, I estimate the model the same way as in Section 3.3. The number of lag, p, is the same as before (p=2).

Figures 7, 8, and 9 show the industrial IRFs where aggregate dynamics are controlled. For each industry, the solid line represents median IRF from the benchmark (Section 3.3) VAR model while the dotted line represents the median IRF from the new specification (Benchmark VAR with $GDPex_t$).

Even though I controlled the overall dynamics of the economy, there is not many qualitative differences of the industrial IRFs between the benchmark VAR and Benchmark VAR with aggregate output excluding the industry. The results imply that the single industry VAR is generally sufficient enough to generate its own IRF. Exceptions to this are the agriculture and mining industries for these countries. Their results dramatically changed by the inclusion of the variable. These industries account for very small shares in GDP. Thus it is likely that not including the aggregate information causes the system to be misspecified.

Although there are some disparities, industry impacts of UMP were not largely affected by the inclusion of aggregate output excluding the industry.

6.1.2 Global VAR Model

In the previous section, I estimated the VAR model with GDP excluding the industry to deal with the potential problem of treating each industry independently and found that the inclusion of GDP excluding the industry does not change the results overall. However, there is still a potential misspecification when some industries crucially depend on another industry. For example, if the trade industry is crucially dependent on manufacturing, estimating the model for trade industry with GDP excluding the industry may lose the relationship between these two industries by the aggregation of manufacturing with the other industries. In this case, the obtained results above may still be misspecified.

In this section, I estimate a global VAR (GVAR) model to take into account the industry interactions to circumvent this problem. I estimate the model only for the UK and Japan[18]. A GVAR model is a panel expression of VARs (Pesaran et al., 2004). A general form of a GVAR model is:

$$y_{i,t} = v_i + A_i Y_{i,t-1} + W(L) y^*_{i,t} + u_{i,t}$$

where $W(L)$ represents a matrix polynomial in the lag operator, $Y_{i,t-1}$ includes all of the $y_{i,t-1}$s, lags of all of the industries that have influences on $y_{i,t}$, and $y^*_{i,t}$ is a foreign variable capturing the 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 j in the model for i. A typical weight used in the literature is bilateral trade flow.

I setup a GVAR model following Burriel and Galesi (2018) whose framework is an extension of Pesaran et al. (2004). A detailed explanation of the GVAR estimation is in Appendix A.4.

I use an IO table for constructing the weight of the foreign variable. For the IO table I use the newest data available: 2016 data for the UK retrieved from the Office for National Statistics and 2015 data for Japan retrieved from the Ministry of Economy, Trade and Industry. The use of a specific IO table for the weight may bias the results or the weight can be altered by the advent of UMP. To circumvent the potential problem, I use the different year (2007 for the UK and 2005 for

[18]Due to the limited sample size, I am not able to estimate the model in the US.

Japan[19]) for robustness.

Figures 10 and 11 show the industrial IRFs from a one standard deviation shock to the central bank total assets using the GVAR model. For each industry, the solid line represents the median IRF from the benchmark VAR model (section 3.3) while the dotted line represents the median IRF from the new specification (GVAR model). 64 % credible bands from both specifications are attached.

For the UK, IRFs from the GVAR is overall qualitatively similar to the benchmark IRFs. When the benchmark IRF responses positively, so does the IRF from the GVAR. Generally, IRFs from the GVAR model follows the benchmark IRFs for the first few periods and then they start deviating. It seems that industry interactions are in place. A notable industry is mining. For the first few periods it follows the benchmark IRF then it jumps to the opposite direction. Since mining industry is behaving in a similar manner as in the previous section as well, estimating this industry itself seems misspecified. In addition, trade, education & health and leisure (sum of accommodation, food, arts, recreation, and entertainment) industries also deviate from the credible bands of the benchmark estimation.

For Japan, similar to the observations in the UK, the IRFs from GVAR follow the benchmark IRFs and both IRFs are very similar for the first few periods and then deviate. Generally Japanese results are more close to the benchmark IRFs. As is seen in the UK, the mining industry also responds very differently after the first few periods. This observation is consistent with the previous section and the GVAR results in the UK. It also shows that mining industry requires a joint estimation. Trade, finance, education, and other service also deviate from the respective IRFs credible bands.

To assess why mining industry deviates dramatically from the benchmark IRF, I include the weighting matrices on Appendix Figures B.34 and B.35. According the weighting matrices, mining industry is largely dependent on manufacturing (and utilities in the UK). As manufacturing expands due to the UMP shock, it spills over to mining industry.

Figures 12 and 13 show the results from the GVAR model but the weighting matrix is constructed from the IO table in 2007 for the UK and 2005 in Japan. The results are qualitatively and quantitatively no difference and show that the use of IO table before financial crisis does not change the results as much.

Exercises from this section suggest that joint consideration is useful for the industry estimation for both the UK and Japan, while most of the stylized facts of IRFs are preserved by the single industry estimation.

[19]Since Japan started QE before 2005, the use of 2005 data is not quite reasonable. However, at least the unprecedented degree of UMP started after the financial crisis in 2008.

6.2 Different Identifications

6.2.1 Changing the Sign Restriction Effective Periods

In this section I change the periods that the sign restriction is effective. To study the effect of UMP, identification is a key point and the results should not be radically altered by the choice of the effective periods of sign restriction. Previously the sign restriction was imposed for the shock period (period = 0) for all of the countries and the first period in the UK and in Japan. To see how sensitive my 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 in the shock period as well as the 1st period after the shock in the US and through the 3rd period after the shock in the UK and Japan. The following table summarizes the new identification.

Table 6: Sign Restriction (Robustness)

	all countries at period = 0	all countries at period = 1	The US at periods = 2 & 3	The UK and Japan at periods = 2 & 3
IO	0	*	*	*
CPI	0	*	*	*
AT	>0	>0	*	>0
VOL	≤0	≤0	*	≤0

The Figures 14, 15, and 16 show the results. The results are not largely affected by the new specification. Rather two results are almost identical. Therefore, imposing the sign restriction on Table 1 in Section 3.2 is sufficient to generate an ideal UMP shock.

6.2.2 Endogeneous Identification

This paper's identification is the following:

$$\underbrace{\begin{bmatrix} u_{IO} \\ u_{CPI} \\ u_{AT} \\ u_{VOL} \end{bmatrix}}_{\substack{\text{Reduced form error} \\ u_t}} = \begin{bmatrix} * & * & 0 & 0 \\ * & * & 0 & 0 \\ * & * & + & + \\ * & * & -/0 & + \end{bmatrix} \underbrace{\begin{bmatrix} \epsilon_{IO} \\ \epsilon_{CPI} \\ \epsilon_{AT} \\ \epsilon_{VOL} \end{bmatrix}}_{\substack{\text{Structural error} \\ \epsilon_t}} \tag{5}$$

An UMP shock needs to be exogenous. Gambacorta et al. (2014) use stock market implied volatility and assume that an UMP shock reduces VIX, since UMP is known to mitigate financial market distress and economic uncertainty in the literature. In section 3.2, I also state that endogenous part of an increase in central bank total assets is when VIX increases (mainly contemporal reverse causality from the stock market volatility). In this section I estimate this endogenous part and see if this identification struggles with generating clear results.

I estimate the VAR model using the following identification:

$$\underbrace{\begin{bmatrix} u_{IO} \\ u_{CPI} \\ u_{AT} \\ u_{VOL} \end{bmatrix}}_{\substack{\text{Reduced form error} \\ u_t}} = \begin{bmatrix} * & * & 0 & 0 \\ * & * & 0 & 0 \\ * & * & + & + \\ * & * & + & + \end{bmatrix} \underbrace{\begin{bmatrix} \epsilon_{IO} \\ \epsilon_{CPI} \\ \epsilon_{AT} \\ \epsilon_{VOL} \end{bmatrix}}_{\substack{\text{Structural error} \\ \epsilon_t}} \tag{6}$$

That is, the sign of the structural covariance of total asset and stock market volatility is positive. The identified shock captures the effect of an increase in central bank total assets when VIX is higher. I estimate the VAR model with the identification in equation (6). I call the identification as endogenous identification.

Figures 17, 18, and 19 show the results. The red line represents median IRFs from the identification in equation (5) as a benchmark, while the blue line represents median IRFs from identification in equation (6). Credible bands from both specifications are attached.

The US results on Figure 17 suggest this identification generates very similar IRFs compared to the benchmark identification, which suggests the model struggles differentiating exogenous and endogenous UMP shocks. This finding is not surprising as the frequency of the data is quarterly, and it is difficult to use financial market variable on a model with quarterly basis. However, results for the UK (Figure 18) and Japan (Figure 19) are contrary to the US results. The effect on aggregate output is negative for both countries, while this goes to the positive range in Japan. Also, durable goods manufacturing responds negatively. Sine this industry is the most responsive industry to conventional policy and business cycle sensitive, it is counterintuitive that expansionary UMP shock suppresses their activities. It seems that monthly data can extract the exogenous part of the policy shock better[20]. From this section, I obtain support for using the Gambacorta et al. (2014) identification and show that it is important to use monthly series for UMP analysis. Also generalizing the findings only from quarterly frequency data itself might be misleading.

[20]When I use the monthly GDP data in the US retrieved from the Macroeconomic Advisor, the effect from the exogenous shock is statistically significantly positive, while the effect from the endogenous identification was insignificant (results are not attached.)

6.2.3 UMP Shock with Long-term Interest Rate

In this section, I use long-term asset yields to identify an UMP shock which has a taste of the UMPs operated in the US and the UK by following Bhattarai et al. (2015a). The UMPs operated in the US and the UK focus on long term asset purchases. In section 3.2, I use the identification in Gambacorta et al. (2014), which is a general measure of UMP. For a cross-country analysis, it is important use a general measure of UMP rather than some identification that is specific to certain policies, since the Bank of Japan's main purpose of UMP is direct lending to banks. However, in this section, I relax the setting and see how a use of the long term asset yields changes the results from the benchmark identification.

The identification is to include the long-term interest rate in VAR. I retrieved 10-year government bond yield from the FRED database for each country. One of the purposes of UMP is to reduce long-term interest rates through assets purchase. This identification allows the UMP shock to be more specific to the policy. Now the endogenous vector y_t contains:

$$y_t = \begin{bmatrix} ln(IO_t) \\ ln(CPI_t) \\ LInt_t \\ ln(AT_t) \\ VOL_t \end{bmatrix} \tag{7}$$

where $LInt_t$ is the 10-year government bond yield. I impose an additional sign restriction so that a shock to central bank asset decreases long-term interest rate. One caveat of this identification is that not all of the central banks aim at reducing long term asset yields. For example, the main purposes of the Bank of Japan is direct lending to banks. Therefore, this identification may not work well for Japan. The following is my identification:

$$\underbrace{\begin{bmatrix} u_{IO} \\ u_{CPI} \\ u_{LInt} \\ u_{AT} \\ u_{VOL} \end{bmatrix}}_{\substack{\text{Reduced form error} \\ u_t}} = \begin{bmatrix} * & * & 0 & 0 & 0 \\ * & * & 0 & 0 & 0 \\ * & * & * & - & * \\ * & * & * & + & + \\ * & * & * & -/0 & + \end{bmatrix} \underbrace{\begin{bmatrix} \epsilon_{IO} \\ \epsilon_{CPI} \\ \epsilon_{LInt} \\ \epsilon_{AT} \\ \epsilon_{VOL} \end{bmatrix}}_{\substack{\text{Structural error} \\ \epsilon_t}} \tag{8}$$

Figures 20, 21, and 22 show the results. As is mentioned in the previous section, the red line represents median IRFs from the benchmark identification, while the blue line represents median IRFs from this identification. Credible bands from both specifications are attached. For the US in

Figure 20, the IRFs from the benchmark identification and new identification are qualitatively comparable but generally effects of this identification are a bit smaller than the benchmark results. That applies to the aggregate, manufacturing, trade, information, real estate, etc, while some industries' responses, such as in healthcare or education, are not affected by the choice of identification.

The UK results on Figure 21 also add additional support of this finding. The effects between the benchmark shock and new shock are quantitatively and qualitatively more similar than the results in the US. The aggregate effects are almost identical. While some industries such as agriculture and construction change their responses compared to the benchmark, the median IRFs from the new identification is within the credible bands on the benchmark. Since the difference between the benchmark identification and this identification are not so small, the benchmark identification seems sufficient for the US and the UK. However, as Figure 22 suggests, this shock does not work so well for Japan. The aggregate and durable goods manufacturing are both insignificant. This finding is consistent with the notion that the UMP in Japan does not purposely seek to reduce the long-term asset yields.

6.2.4 UMP Shock with Interest Rate Spread

The main purposes of the Bank of Japan and European Central Bank is direct lending to banks. The third identification is to capture this behavior following Boeckx et al. (2017). The identification is to include the spread between discount rate (ECB policy rate) and interbank rate. An exogenous shock, which involves direct lending to banks, stimulates the demand for bank reserves which then increases the interbank rate. Meanwhile, the discount rate is unchanged. Thus, an UMP shock decreases the spread between discount rate and interbank rate. They add this identification on top of the Gambacorta et al. (2014) identification. Similar to the previous section, this identification is more specific to the bank lending policy instead of a general measure of UMP.

I retrieved interbank rates from FRED for each country and discount rate from the respective central banks. The endogenous vector y_t is:

$$y_t = \begin{bmatrix} ln(IO_t) \\ ln(CPI_t) \\ Spread_t \\ ln(AT_t) \\ VOL_t \\ Policy_t \end{bmatrix} \tag{9}$$

The sign restriction is:

$$\underbrace{\begin{bmatrix} u_{IO} \\ u_{CPI} \\ u_{Spread} \\ u_{AT} \\ u_{VOL} \\ u_{Policy} \end{bmatrix}}_{\substack{\text{Reduced form error} \\ u_t}} = \begin{bmatrix} * & * & 0 & 0 & 0 & 0 \\ * & * & 0 & 0 & 0 & 0 \\ * & * & * & - & * & * \\ * & * & * & + & + & * \\ * & * & * & -/0 & + & * \\ * & * & * & 0 & * & * \end{bmatrix} \underbrace{\begin{bmatrix} \epsilon_{IO} \\ \epsilon_{CPI} \\ \epsilon_{Spread} \\ \epsilon_{AT} \\ \epsilon_{VOL} \\ \epsilon_{Policy} \end{bmatrix}}_{\substack{\text{Structural error} \\ \epsilon_t}} \tag{10}$$

The above identification works in the euro area, since the intention of ECB was to directly lend to banks and discount rate is the policy rate. However, this identification may not work for the countries in this paper. First a central bank's policy rate can be interbank rate, which is true in the US and Japan. Thus, bank lending behavior may not be captured. Second, some central banks do not seek to directly lend to banks. The UMP in the US and UK are to focus on purchasing long term assets. So, this identification is not likely to work in any of my sample countries.

Figures 23, 24, and 25 show the results. The red line represents median IRFs from the benchmark identification, while the blue line represents median IRFs from this identification. Credible bands from the both specifications are attached.

The results for the US on Figure 23 show that most of IRFs are insignificant with broad credible bands and are very different from the benchmark results. The identification struggles to generate a clear shock. The results in the UK on Figure 24 also suggest that this identification does not work for the country. In the UK, the discount rate is the policy rate and this identification is suitable. However, the aggregate and almost all of the industries, show insignificant effects. Since the direct lending to banks is not the feature of the UK UMP, the shock was not identified well. Lastly, the results for Japan on Figure 25 show that the shock are not identified well. The aggregate and almost all of the industries again show insignificant effects. Since the policy rate is the interbank rate in Japan, the identification suffered correctly articulating the policy implemented in Japan. Based on the literature of UMP, this shock seems to be work in the Euro area but does not work for the countries investigated in this paper.

6.3 Does UMP Shock Work During Non-ZLB Peirods

While UMP has only been used during ZLB periods, it also has the potential to be used during non-ZLB periods for a future policy action. During non-ZLB periods, CMP controls short-term nominal interest rates. However, in addition to this CMP, UMP tools such quantitative easing, credit easing, and forward guidance could potentially be used by itself or combined with CMP to stimulate an economy. An increase in the variety of policy options during non-ZLB future periods could be appealing to central banks if they are effective.

To study the effects of UMP during non-ZLB periods, I identify UMP shocks during non-ZLB periods. However, because I identify shocks using pre-2008 sample periods, there are some caveats. First, a change in the central bank total asset before ZLB periods almost exclusively comes from a change in short-term government security. Thus, effects of purchases of a different type of asset, such as long-term securities or corporate bonds, are not captured. Second, UMP measures do not necessarily decrease the policy rate. Third, the degree of asset purchases between ZLB and non-ZLB periods is significantly different[21].

The sample periods are 1992M1-2007M12 for the US (only aggregate), 2000M1-2007M12 for the UK, and 1993M1-1999M12 for Japan based on the data availability. The data are retrieved from the same sources as in section 2 except for the monthly GDP in the US which is from the Macroeconomic Advisers. The data are seasonally adjusted except for stock market volatility. The identification and estimation are the same as before.

Table 26 shows the national results. The red line represents median IRFs during the ZLB periods and the blue line represents median IRFs during non-ZLB periods. Since they are estimated using completely different regimes in terms of central bank total assets, I rescaled the IRFs of the non-ZLB so that the shock has the same percent increase in central bank total assets.

Regarding the impacts on output, the effects are insignificant for all of the countries except for Japan, but effects are smaller during non-ZLB than ZLB. Regarding the price, the effect is positive and stronger during non-ZLB in the US, insignificant in the UK, and negative but moves to the positive range in Japan. Generally, UMP measure does not work well during non-ZLB periods, even though the US price increases. Prior to 2008, the policy rate plays the main role for monetary policy and affects economic agents' expectations and behaviors. Here, the identified shock does not inform us whether the rate increases, decreases, or stays the same. It seems that UMP might not work well unless the policy rate decreases.

The industrial results for the UK and Japan are on Figures 28 and 29, respectively. For both countries, the responses are heterogeneous, which is in line with my industrial results of UMP during ZLB periods. Some of the UK results are also in line with the results during ZLB in terms of magnitudes and signs of industries, such as manufacturing and professional service. However, it is odd that some cyclical industries, such as construction and trade, do not respond positively. The results for Japan on Figure 29 show that the effects are different by industries. Similar to the UK, cyclical industries such as construction and trade do not necessarily respond positively.

[21] As mentioned before, in the US the identified UMP shock during ZLB period is equivalent to an increase in central bank assets of \$100 billion on average. However, the identified UMP shock during non-ZLB period is equivalent to \$5.6 billion on average. Both are one standard deviation shocks.

Based on the overall results, UMP during non-ZLB does not seem effective for the aggregate. The industrial results are heterogeneous across industries but questionable because the two different interest rate sensitive industries are affected in opposite ways: manufacturing is positively affected while construction is negatively affected.

Given the finding, it is now interesting to see how UMP works when the policy rate is guaranteed to decrease. To investigate this, I include the respective policy rates (retrieved from the FRED) in the VAR for each country. I impose an additional sign restriction so that an UMP shock decreases the policy rate at the shock period. Although the identified shock decreases policy rate, it is not an interest rate shock itself.

Figures B.36, B.37, and B.38 (in Appendix) show the results when the policy rate is included. Surprisingly enough, the inclusion of policy rate does not change the results much. The aggregate IRFs are still insignificant (except for Japan). The industrial effects are getting weaker but qualitatively very similar[22]. Thus, the inclusion of policy rate does not seem to change the effect of UMP during non-ZLB periods, at least not during the pre-financial crisis periods.

7 Conclusion

This paper estimates the industrial impacts of UMP for the US, the UK, and Japan using a Bayesian VAR model. The industrial IRFs reveal some interesting features. First, UMP stimulates industries heterogeneously. Among those responses, I find that UMP strongly stimulates finance industry, which is stressed in the literature on event studies. Second, industrial responses are not so similar across countries, however, heterogeneous impacts of UMP is similar to the heterogeneous impacts of CMP on average across countries. Third, the industrial responses are related to working capital, implying the relevance of the interest rate channel.

These differential effects of UMP is lost with aggregation and policy makers should take these effects into account in order to anticipate the impact and to prevent unintended negative outcomes. Given the potential decline of the natural rate of interest in highly advanced countries (Holston et al., 2017b), it is likely that the ZLB spreads to other countries and requires other central bankers to implement an UMP. The results obtained in this paper provides some bottom line predictions for countries that have not yet experienced ZLB and aid central bankers in creating an UMP. Lastly, this paper did not assess impacts across policies. This would be a great subject for future research.

[22]However, surprisingly, manufacturing industry in Japan responded negatively.

References

Alam, T. and Waheed, M. (2006). Sectoral effects of monetary policy: Evidence from Pakistan. *The Pakistan Development Review*, pages 1103–1115.

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

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

Bagliano, F. C. and Favero, C. A. (1998). Measuring monetary policy with VAR models: An evaluation. *European Economic Review*, 42(6):1069–1112.

Barth III, M. J. and Ramey, V. A. (2001). The cost channel of monetary transmission. *NBER macroeconomics annual*, 16:199–240.

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

Baumeister, C. and Benati, L. (2012). Unconventional monetary policy and the great recession: Estimating the macroeconomic effects of a spread compression at the zero lower bound (No. 2012-21). Technical report, Bank of Canada Working Paper.

Bénétrix, A. S. and Lane, P. R. (2010). Fiscal shocks and the sectoral composition of output. *Open Economies Review*, 21(3):335–350.

Berman, J. and Pfleeger, J. (1997). Which industries are sensitive to business cycles. *Monthly Lab. Rev.*, 120:19.

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

Bernanke, B. S. and Mihov, I. (1998). Measuring monetary policy. *The Quarterly Journal of Economics*, 113(3):869–902.

Bhattarai, S., Chatterjee, A., and Park, W. Y. (2015a). Effects of US quantitative easing on emerging market economies.

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

Boeckx, J., Dossche, M., and Peersman, G. (2017). Effectiveness and transmission of the ECB's balance sheet policies. *INTERNATIONAL JOURNAL OF CENTRAL BANKING*, 13(1):297–333.

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

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

Chodorow-Reich, G. (2014). Effects of unconventional monetary policy on financial institutions (No. w20230). Technical report, National Bureau of Economic Research.

Chow, G. C. and Lin, A.-l. (1971). Best linear unbiased interpolation, distribution, and extrapolation of time series by related series. *The review of Economics and Statistics*, pages 372–375.

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

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

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

Du, L., Yanan, H., and Wei, C. (2010). The relationship between oil price shocks and China's macro-economy: An empirical analysis. *Energy policy*, 38(8):4142–4151.

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

Fawley, B. W., Neely, C. J., et al. (2013). Four stories of quantitative easing. *Federal Reserve Bank of St. Louis Review*, 95(1):51–88.

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

Gagnon, J., Raskin, M., Remache, J., Sack, B., 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.

Gaiotti, E. and Secchi, A. (2006). Is there a cost channel of monetary policy transmission? an investigation into the pricing behavior of 2,000 firms. *Journal of Money, Credit and Banking*, pages 2013–2037.

Galesi, A. and Lombardi, M. J. (2009). External shocks and international inflation linkages: a global VAR analysis.

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

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

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

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

Ghosh, S. (2009). Industry effects of monetary policy: Evidence from India. *Indian Economic Review*, pages 89–105.

Greenlaw, D., Hamilton, J. D., Harris, E., and West, K. D. (2018). A Skeptical View of the Impact of the Fed's Balance Sheet (No. w24687). Technical report, National Bureau of Economic Research.

Hancock, D. and Passmore, W. (2011). Did the Federal Reserve's MBS purchase program lower mortgage rates? *Journal of Monetary Economics*, 58(5):498–514.

Hayo, B. and Uhlenbrock, B. (2000). Industry effects of monetary policy in Germany. In *Regional aspects of monetary policy in Europe*, pages 127–158. Springer.

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

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

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

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

Jordà, O. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, 95(1):161–182.

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

Kilian, L. and Lütkepohl, H. (2017). *Structural vector autoregressive analysis*. Cambridge University Press.

Kim, S. (1999). Do monetary policy shocks matter in the G-7 countries? using common identifying assumptions about monetary policy across countries. *Journal of International Economics*, 48(2):387–412.

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

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

Lucas, D. and Vissing-Jorgensen, A. (2014). Comments and Discussion. *Brookings Papers on Economic Activity*, pages 205–227.

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

Mojon, B. and Peersman, G. (2001). A VAR description of the effects of monetary policy in the individual countries of the euro area.

Monacelli, T. and Perotti, R. (2008). Openness and the sectoral effects of fiscal policy. *Journal of the European Economic Association*, 6(2-3):395–403.

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

Ng, S. and Perron, P. (2001). Lag length selection and the construction of unit root tests with good size and power. *Econometrica*, 69(6):1519–1554.

Peersman, G. (2011). Macroeconomic effects of unconventional monetary policy in the euro area.

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

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

Schenkelberg, H. and Watzka, S. (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.

Shintani, M. (2005). Nonlinear forecasting analysis using diffusion indexes: An application to Japan. *Journal of Money, Credit and Banking*, pages 517–538.

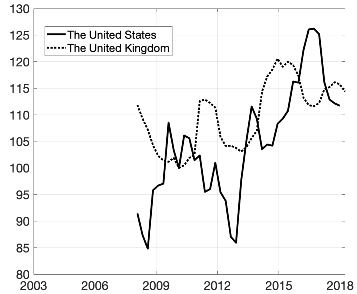
Vansteenkiste, I. (2007). Regional housing market spillovers in the US: lessons from regional divergences in a common monetary policy setting.

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

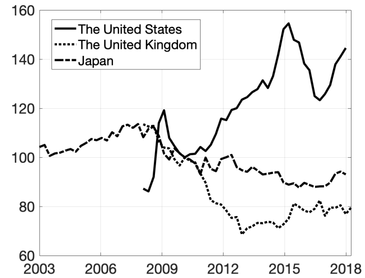
Vukotić, M. (2019). Sectoral effects of news shocks. *Oxford Bulletin of Economics and Statistics*, 81(2):215–249.

Figures

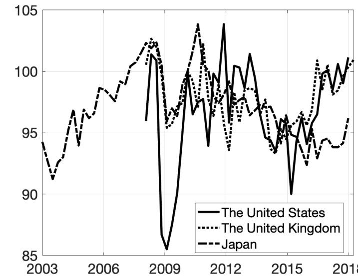
Figure 1: Industry Output I



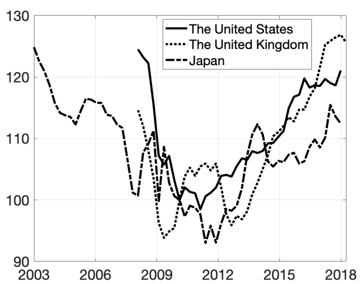
(a) Agriculture



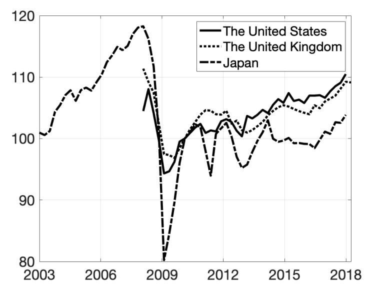
(b) Mining



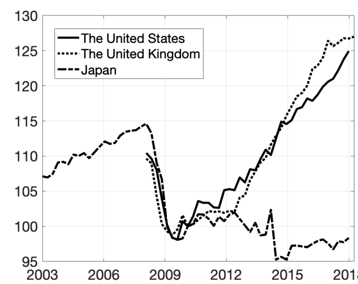
(c) Utilities



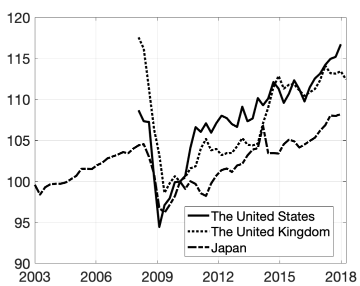
(d) Construction



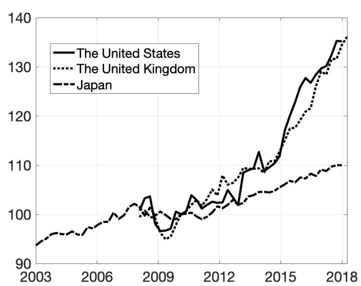
(e) Manufacturing



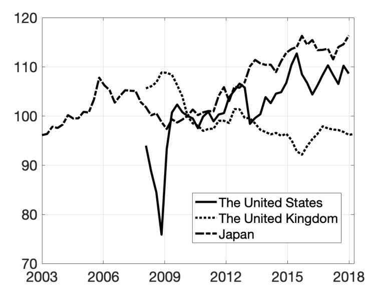
(f) Trade



(g) Transportation



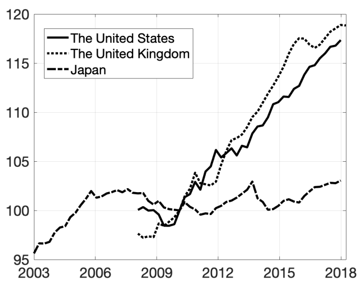
(h) Information



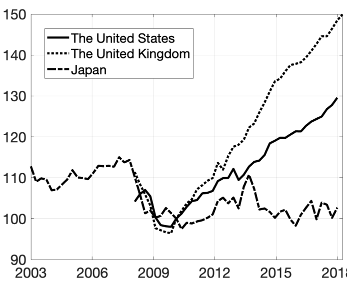
(i) Finance

Sources:
The Bureau of Economic Analysis (the US), The Office for National Statistics (the UK), and The Ministry of Economy, Trade, and Industry Analysis (Japan)
Note: All of the variables are normalized so that 2010Q1=100.

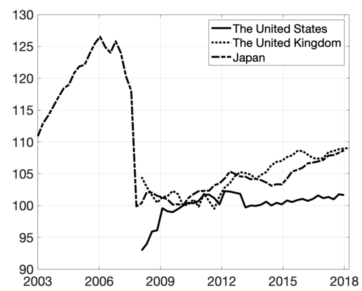
Figure 2: Industry Output II



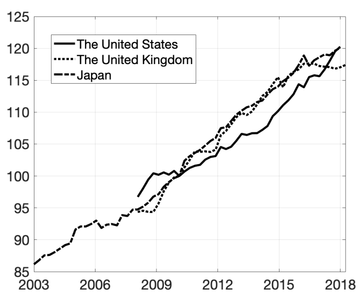
(a) Real Estate



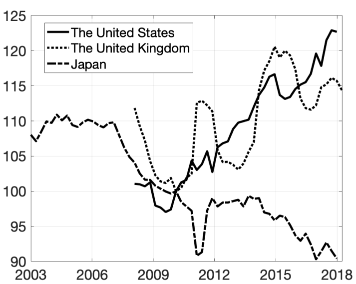
(b) Professional service



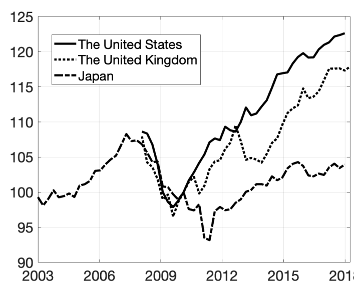
(c) Education



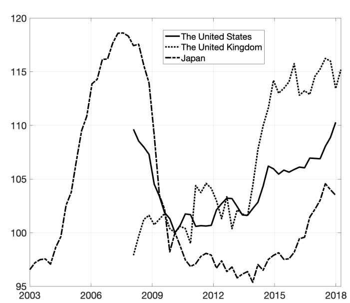
(d) Healthcare



(e) Arts, entertainment, and recreation



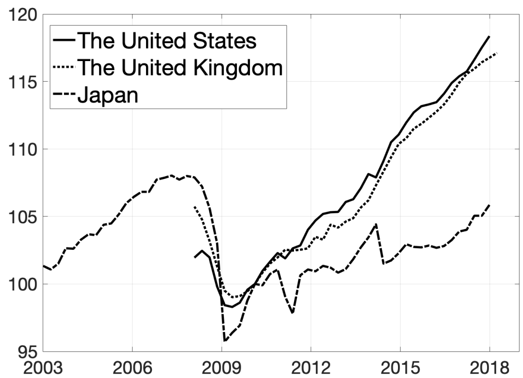
(f) Accommodation and food



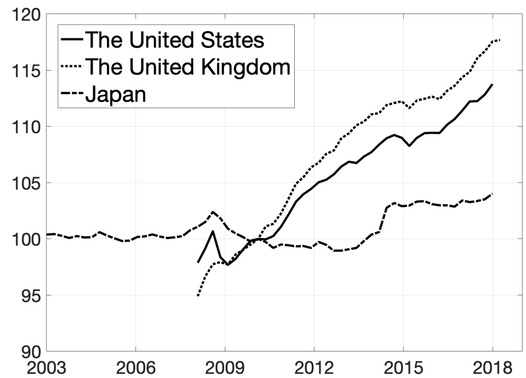
(g) Other services

Sources:
The Bureau of Economic Analysis (the US), The Office for National Statistics (the UK), and The Ministry of Economy, Trade, and Industry Analysis (Japan)
Note: All of the variables are normalized so that 2010Q1=100.

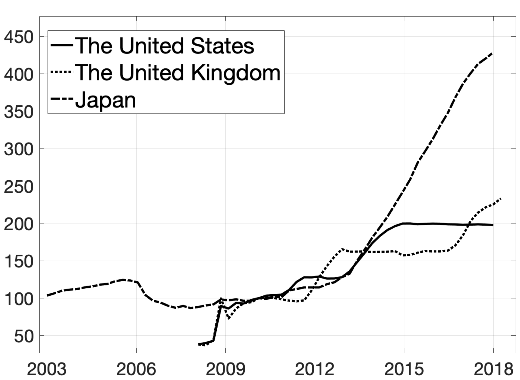
Figure 3: Aggregate Output, Consumer Price Index, Central Bank Total Assets, and Stock Market Implied Volatility



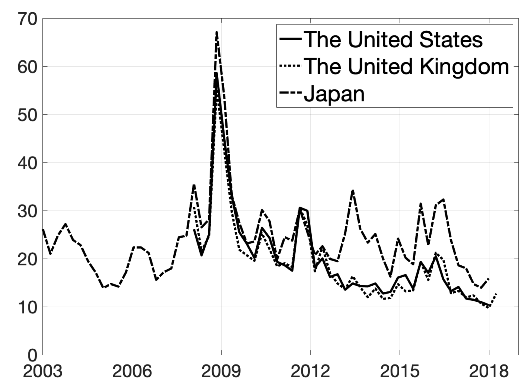
(a) Aggregate Output



(b) Consumer Price Index



(c) Central Bank Total Assets

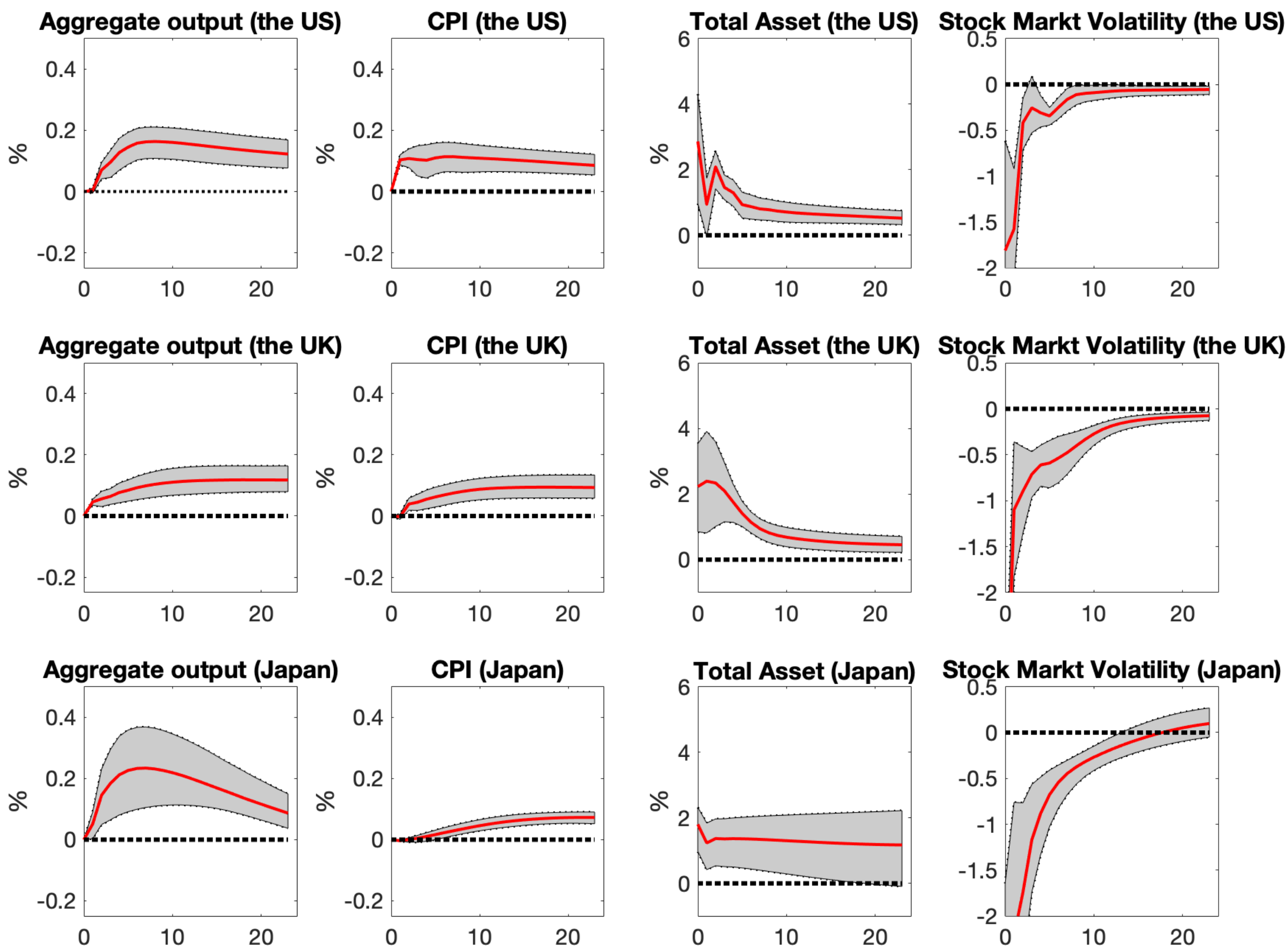


(d) Stock Market Implied Volatility

Sources:
Aggregate Output: the Bureau of Economic Analysis (the US), the Office for National Statistics (the UK), the Ministry of Economy, Trade, and Industry (Japan). CPI: the Bureau of Labor Statistics (the US) and Datastream (the UK and Japan). AT: the FRED database (the US), Bank of England (the UK) and Datastream (Japan). VOL: the FRED database (the US), Datastream (the UK and Japan).

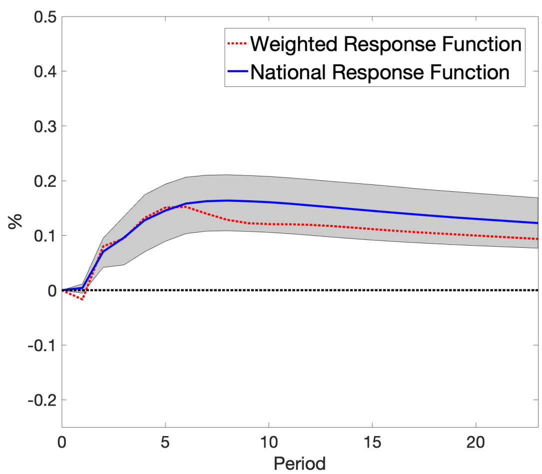
Note: All of the variables except for VOL are normalized so that 2010Q1=100.

Figure 4: National Impulse Response Functions

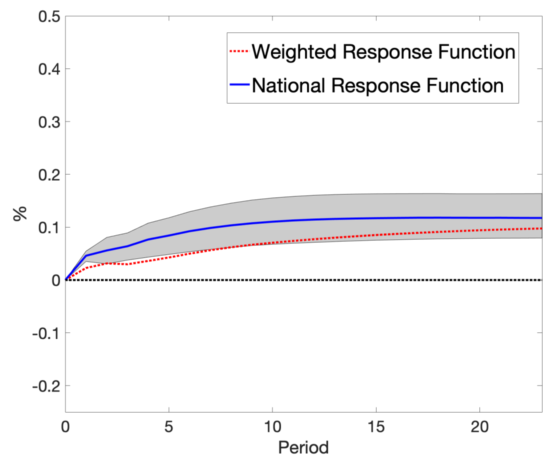


Note: The Median, 16th, and 84th Bayesian percentiles. Quarterly horizon (the US) and Monthly horizon (the UK and Japan).

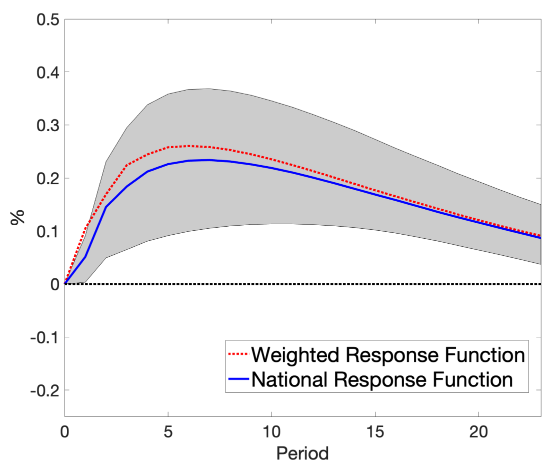
Figure 5: Weighted Average of Industry Impulse Response Functions



(a) The United States



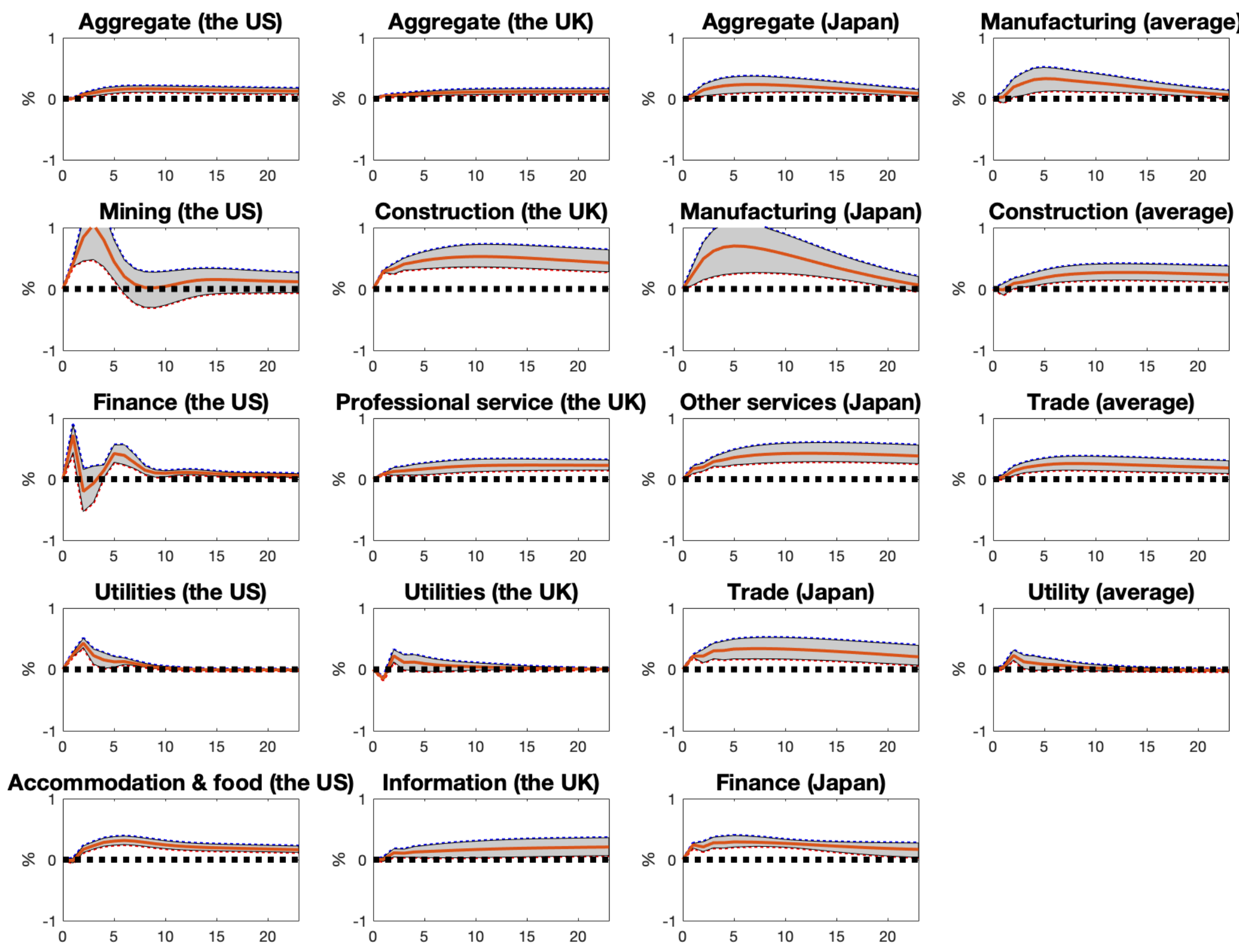
(b) The United Kingdom



(c) Japan

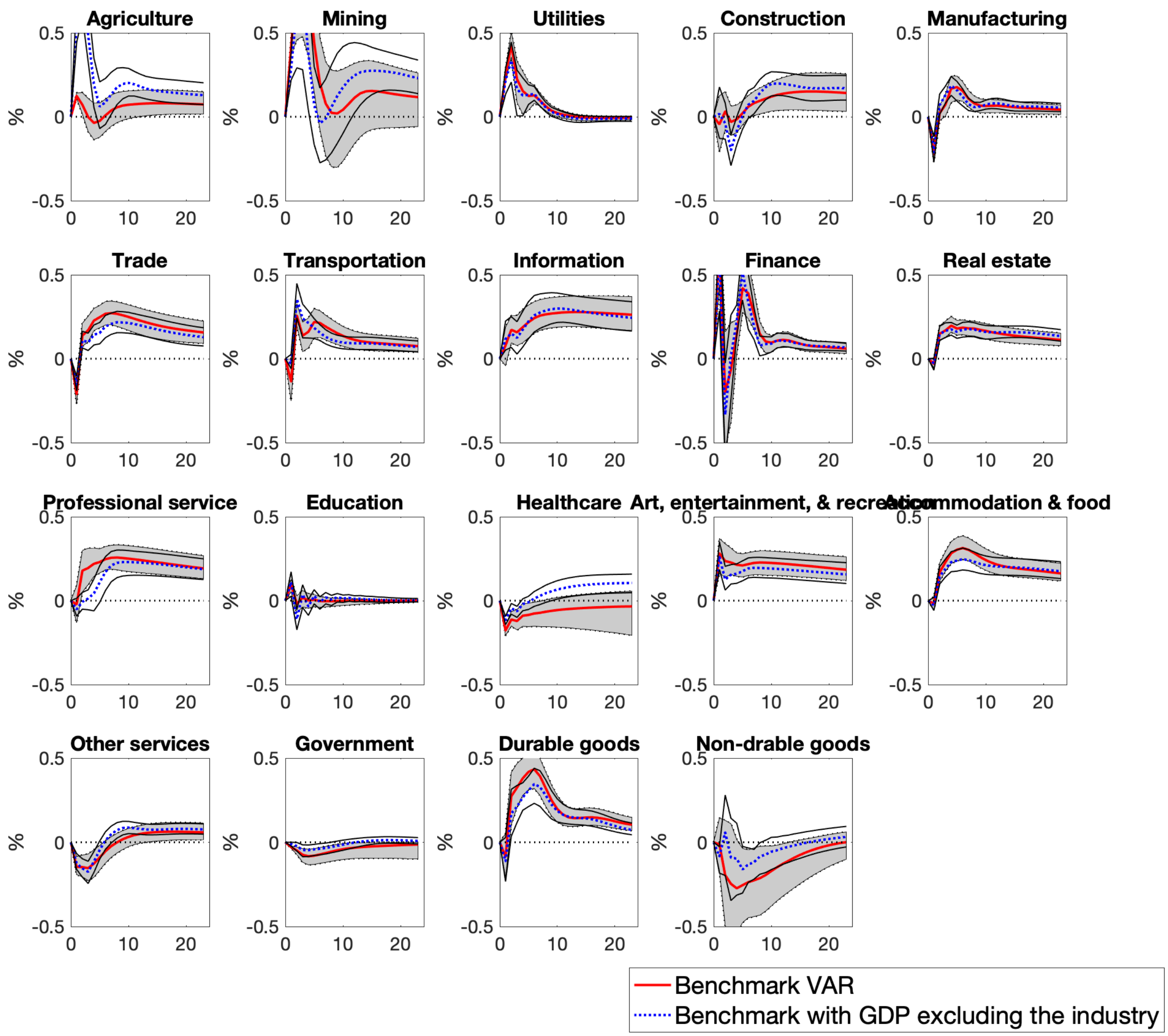
Note: (a) Quarterly horizon. (b), (c) Monthly horizon. The bold lines represent the national impulse response functions and the dotted lines represent the weighted impulse response functions. The credible bands are from the national impulse response functions.

Figure 6: Industry Impulse Response Functions



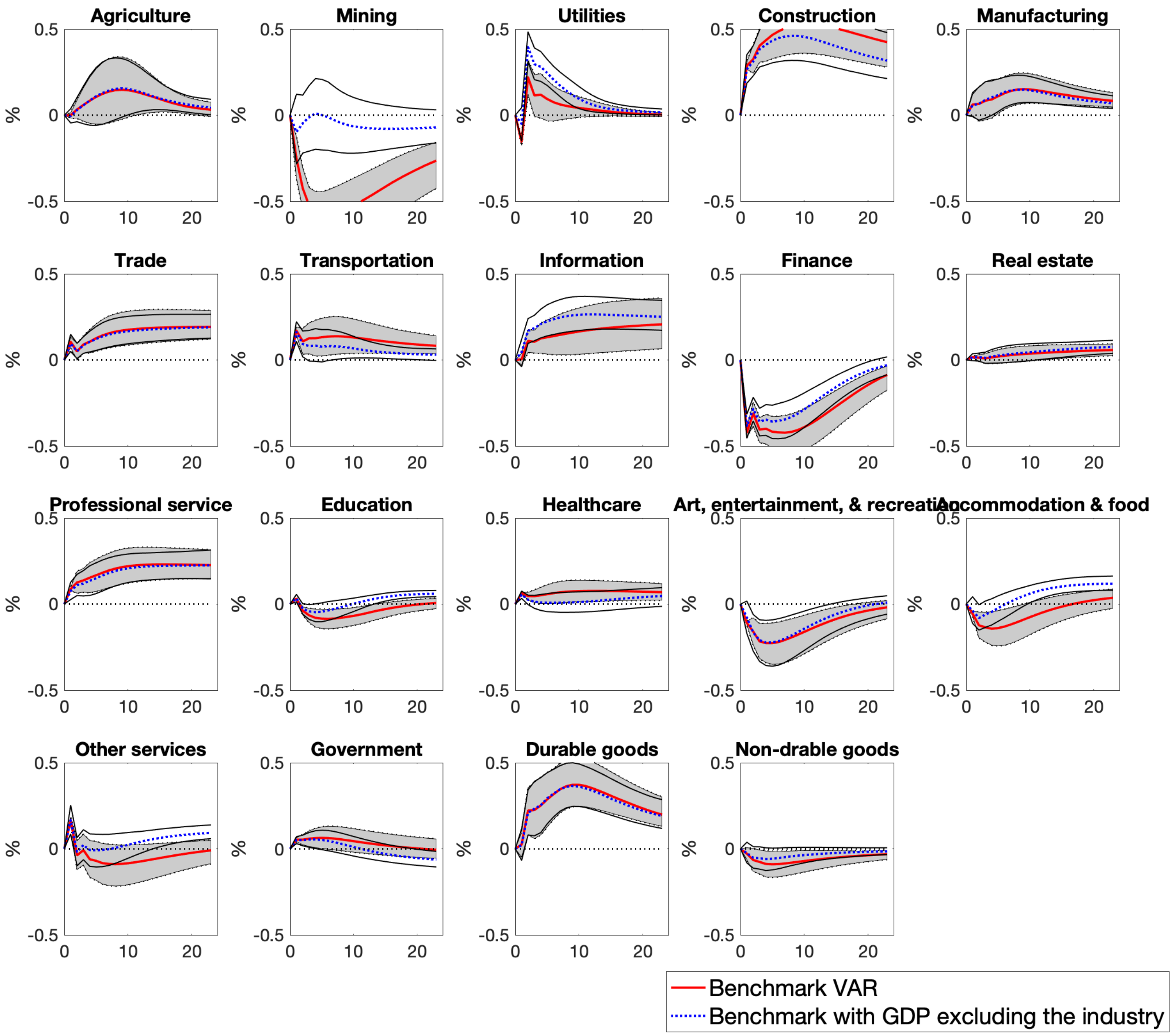
Note: The 1st column shows the results from the US (quarterly horizon), the 2nd column shows the results from the UK (monthly horizon), the 3rd column shows the results from Japan (monthly horizon), and the 4th column shows the average of the three countries (mixed horizon). Responsive industries are selected for the display. The Median, 16th, and 84th Bayesian percentiles.

Figure 7: The United States - Industrial Impulse Response Functions with Aggregate Output Excluding the Industry



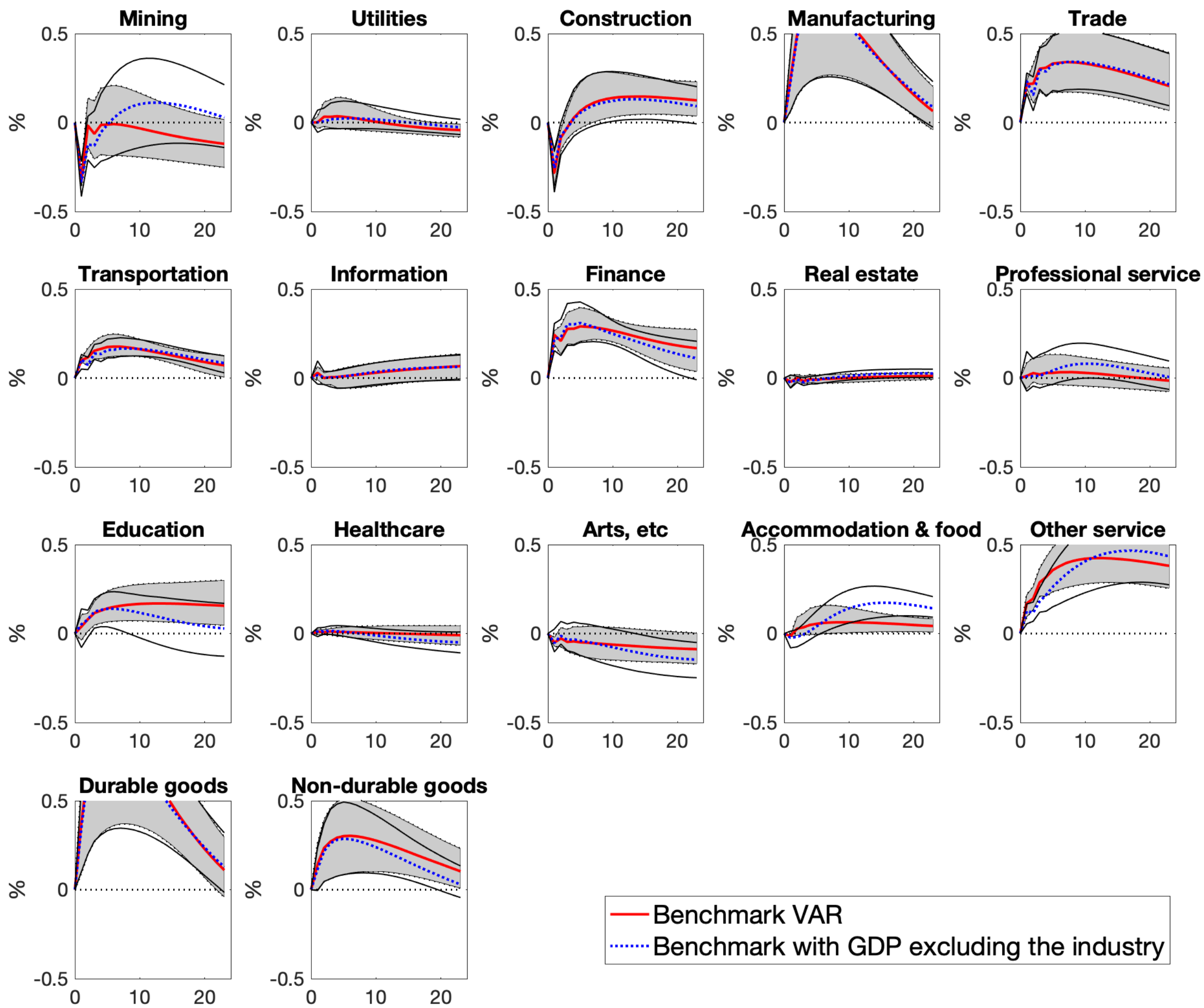
Note: The Median, 16th, and 84th Bayesian percentiles. Quarterly horizon.

Figure 8: The United Kingdom - Industrial Impulse Response Functions with Aggregate Output Excluding the Industry



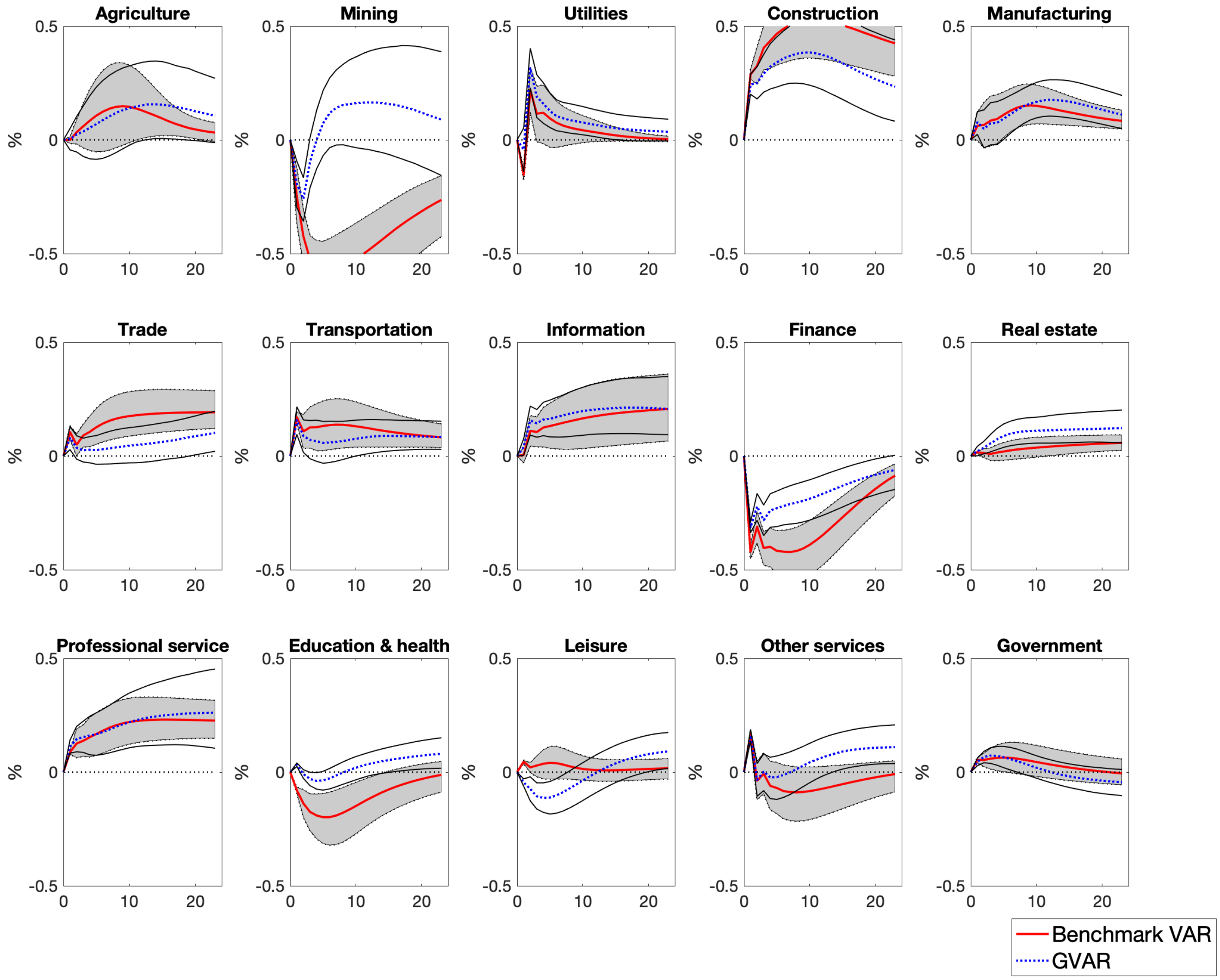
Note: The Median, 16th, and 84th Bayesian percentiles. Monthly horizon.

Figure 9: Japan - Industrial Impulse Response Functions with Aggregate Output Excluding the Industry



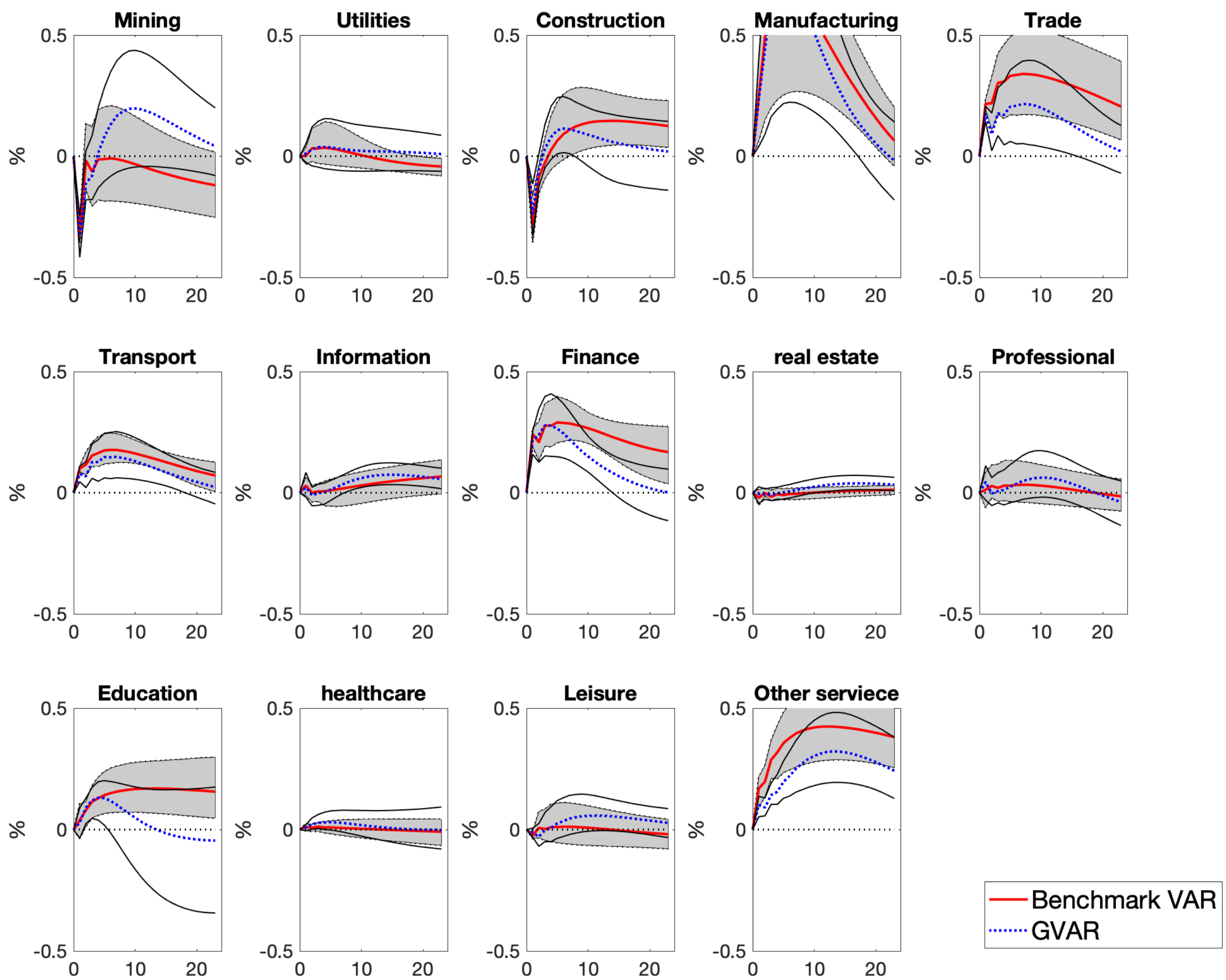
Note: The Median, 16th, and 84th Bayesian percentiles. Monthly horizon.

Figure 10: The United Kingdom - Industrial Impulse Response Functions with GVAR



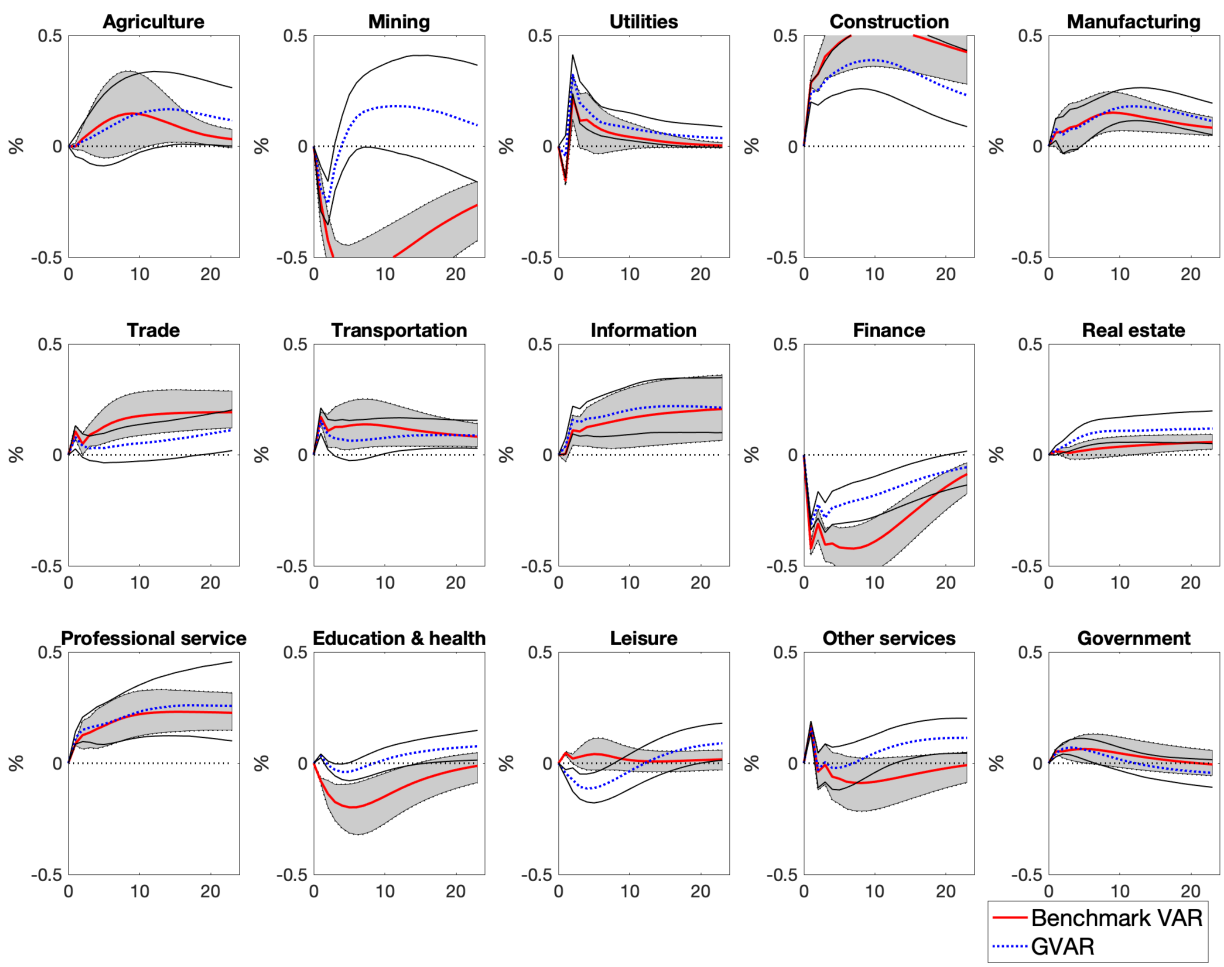
Note: The Median, 16th, and 84th Bayesian percentiles. Monthly horizon.

Figure 11: Japan - Industrial Impulse Response Functions with GVAR



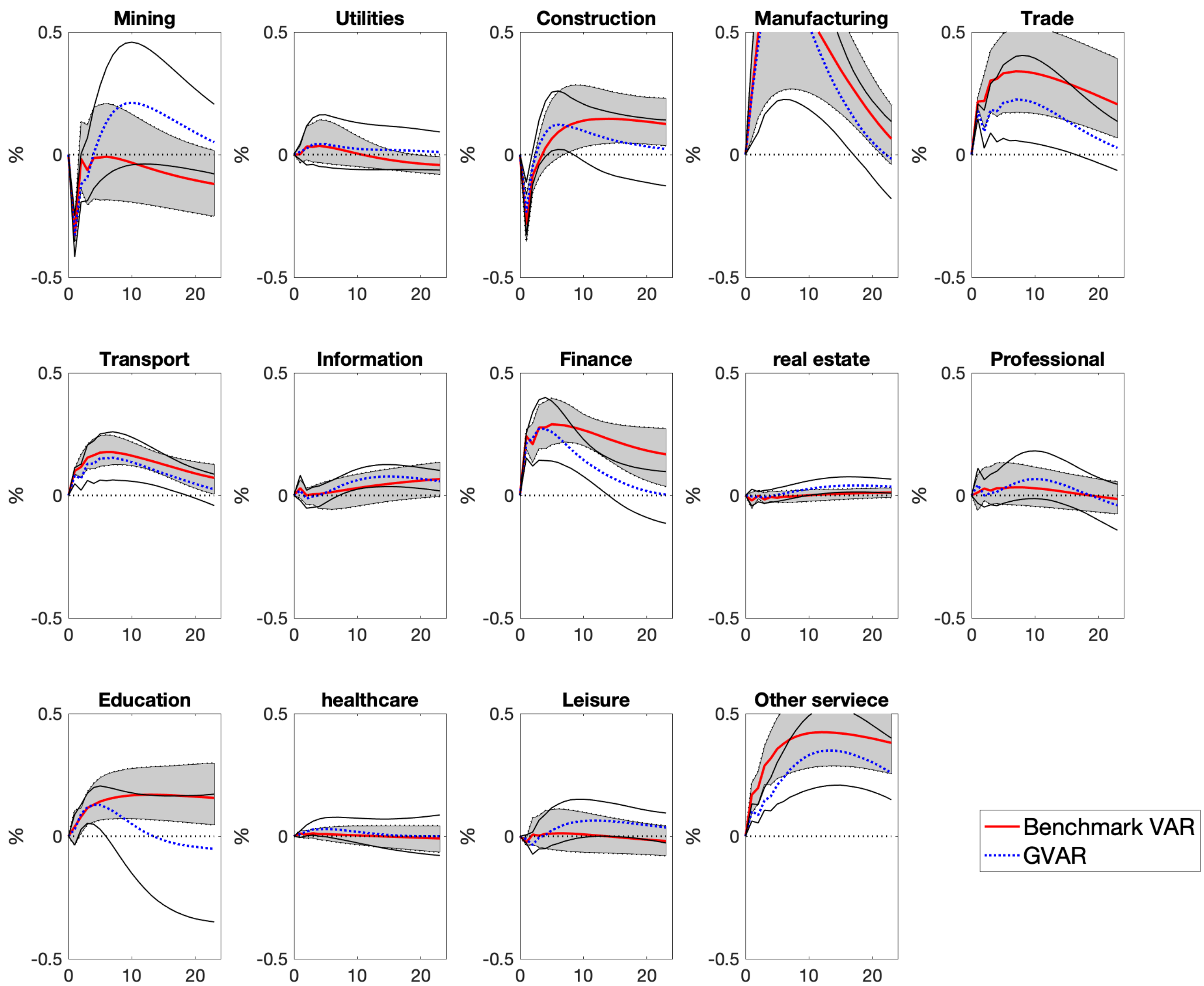
Note: The Median, 16th, and 84th Bayesian percentiles. Monthly horizon.

Figure 12: The United Kingdom - Industrial Impulse Response Functions with GVAR (weight 2007)



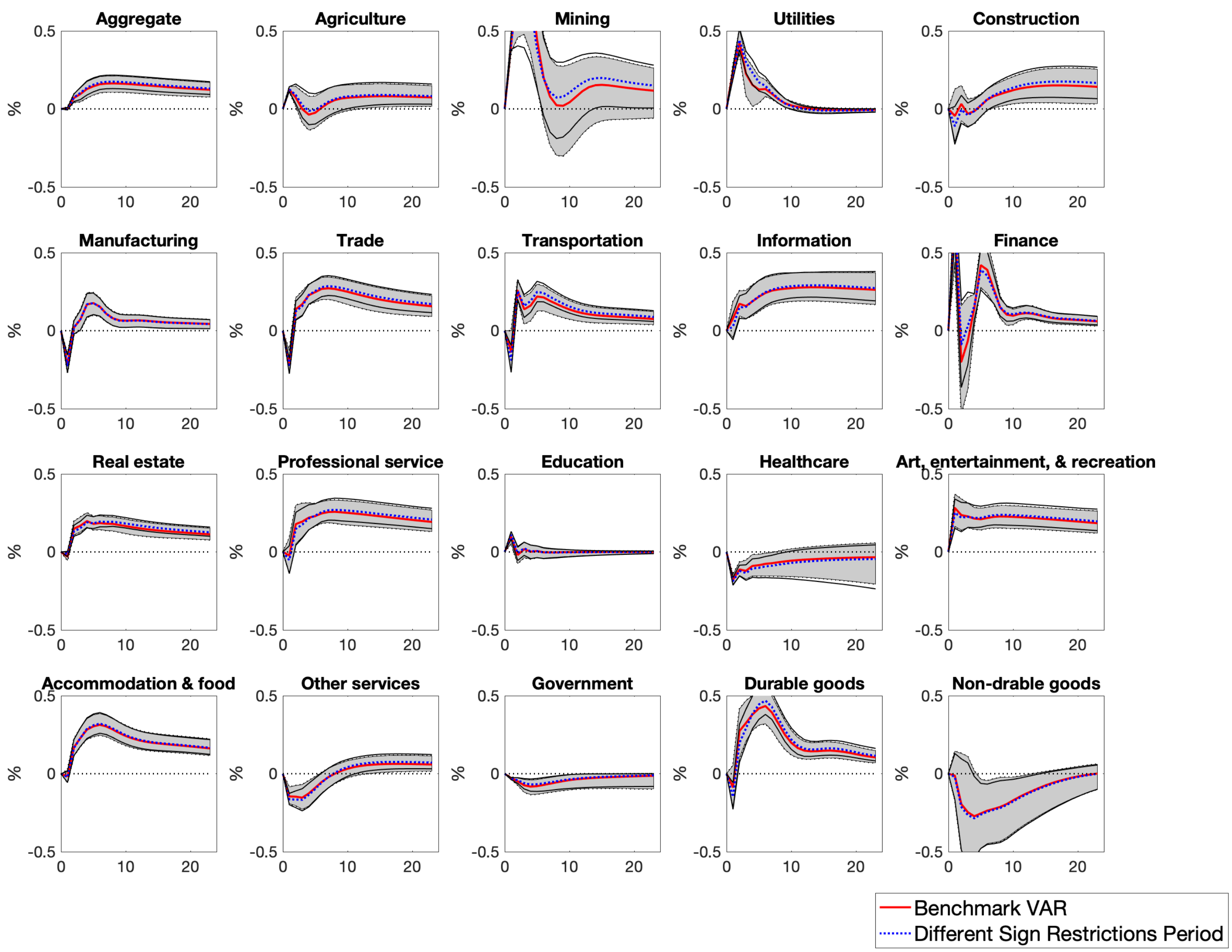
Note: The Median, 16th, and 84th Bayesian percentiles. Monthly horizon.

Figure 13: Japan - Industrial Impulse Response Functions with GVAR (weight 2005)



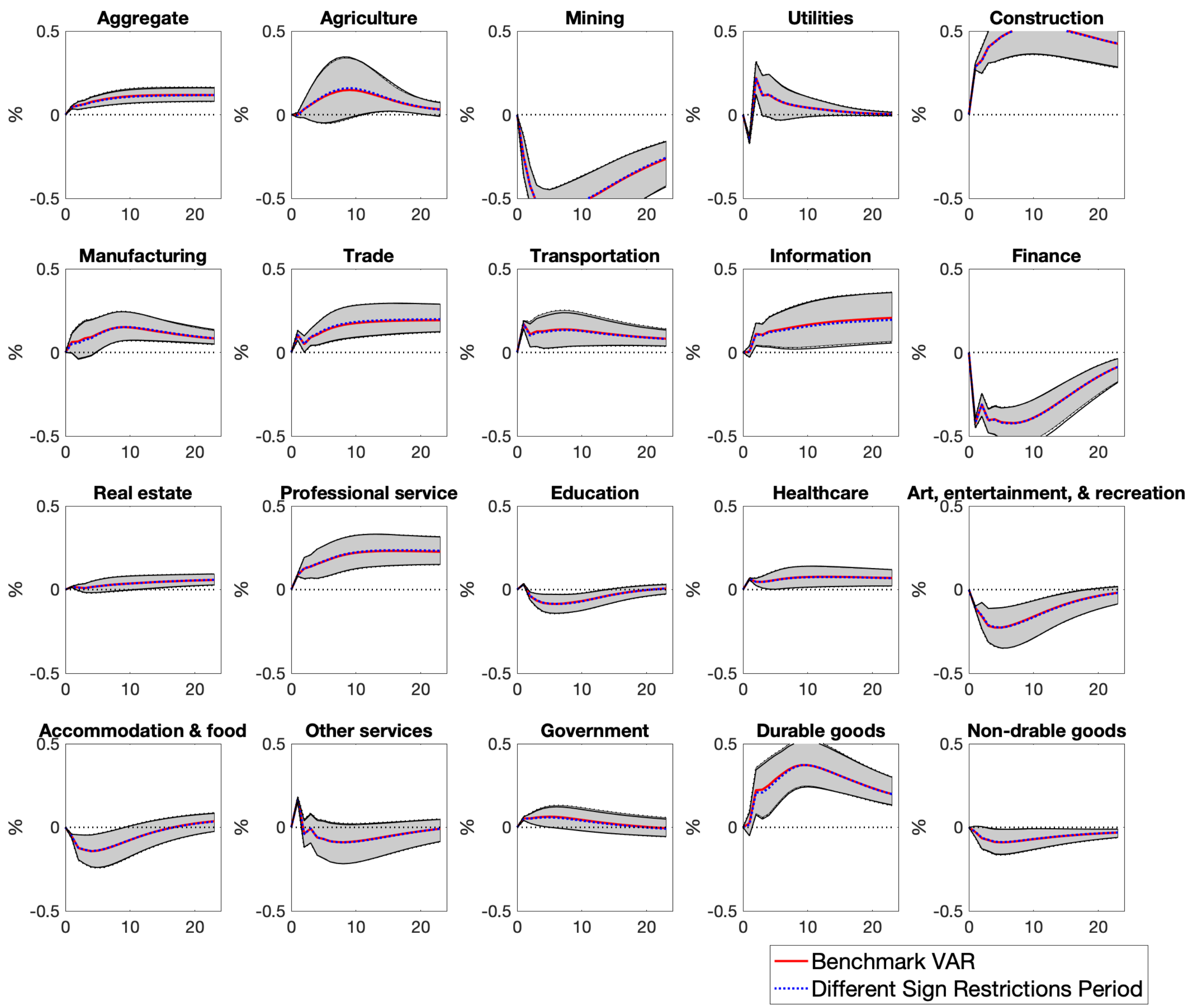
Note: The Median, 16th, and 84th Bayesian percentiles. Monthly horizon.

Figure 14: The United States - Industrial Impulse Response Functions with Different Identification Periods



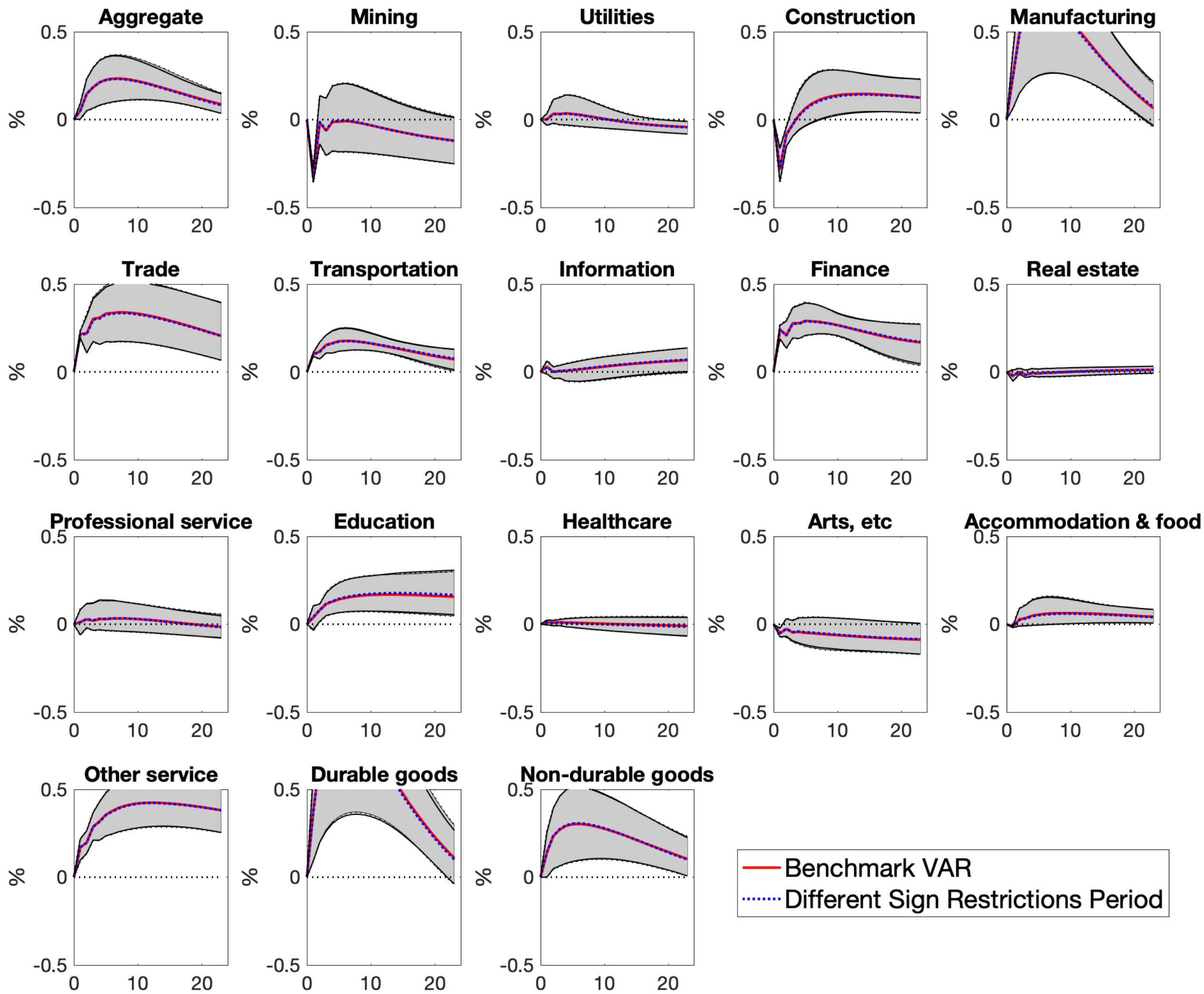
Note: The Median, 16th, and 84th Bayesian percentiles. Quarterly horizon.

Figure 15: The United Kigdom - Industrial Impulse Response Functions with Different Identification Periods



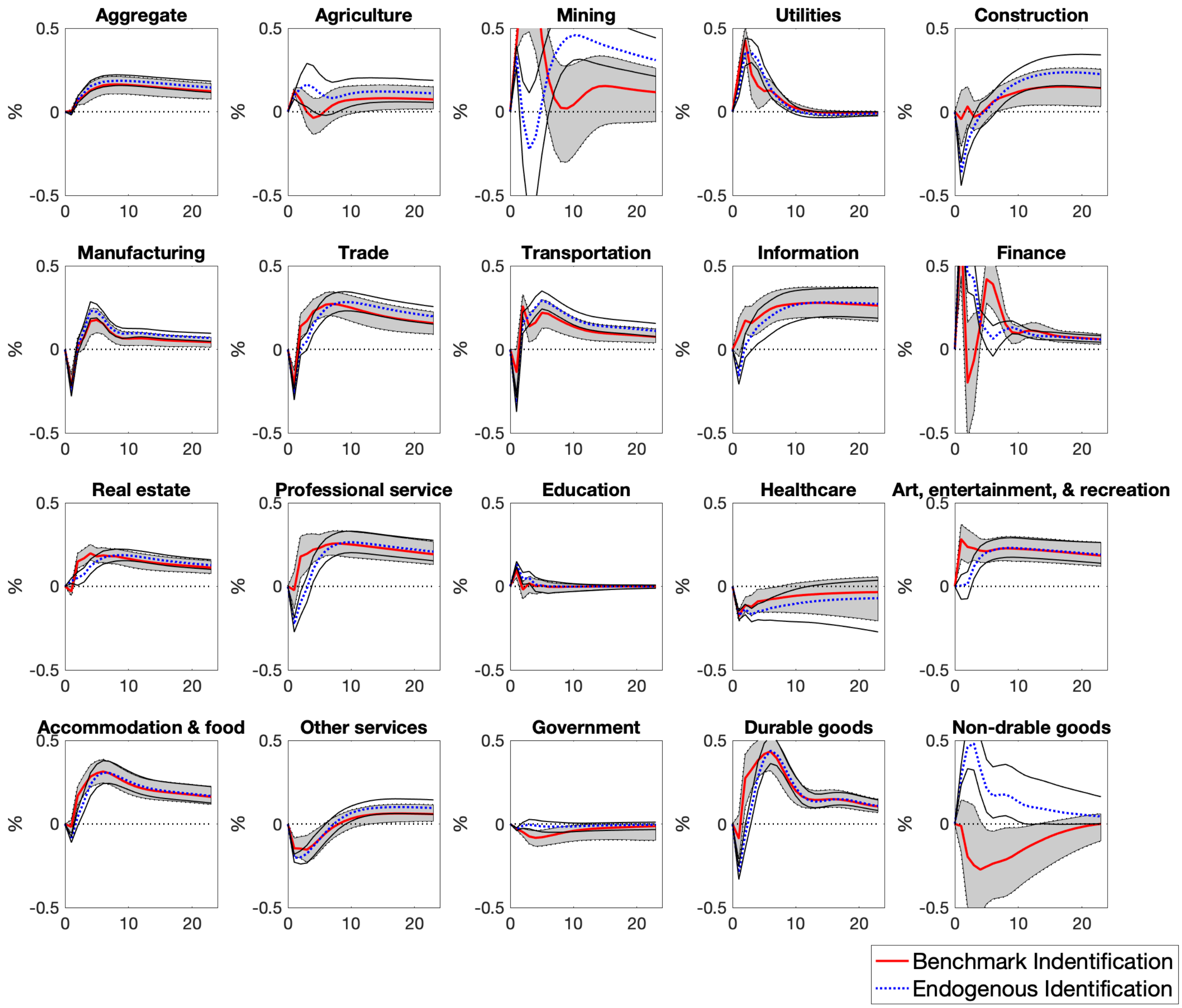
Note: The Median, 16th, and 84th Bayesian percentiles. Monthly horizon.

Figure 16: Japanese - Industrial Impulse Response Functions with Different Identification Periods



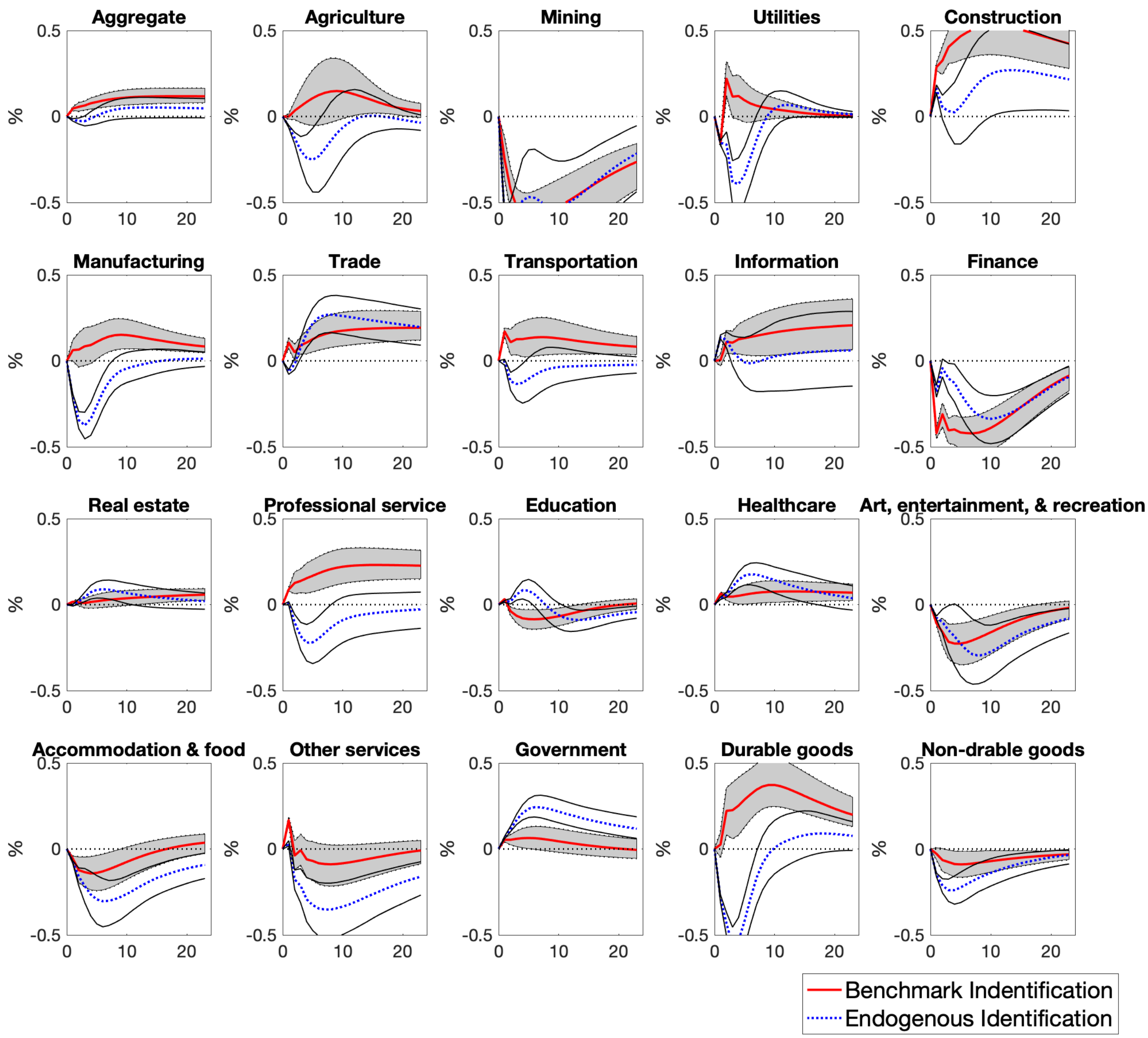
Note: The Median, 16th, and 84th Bayesian percentiles. Monthly horizon.

Figure 17: The United States - Industrial Impulse Response Functions with Endogenous Identification



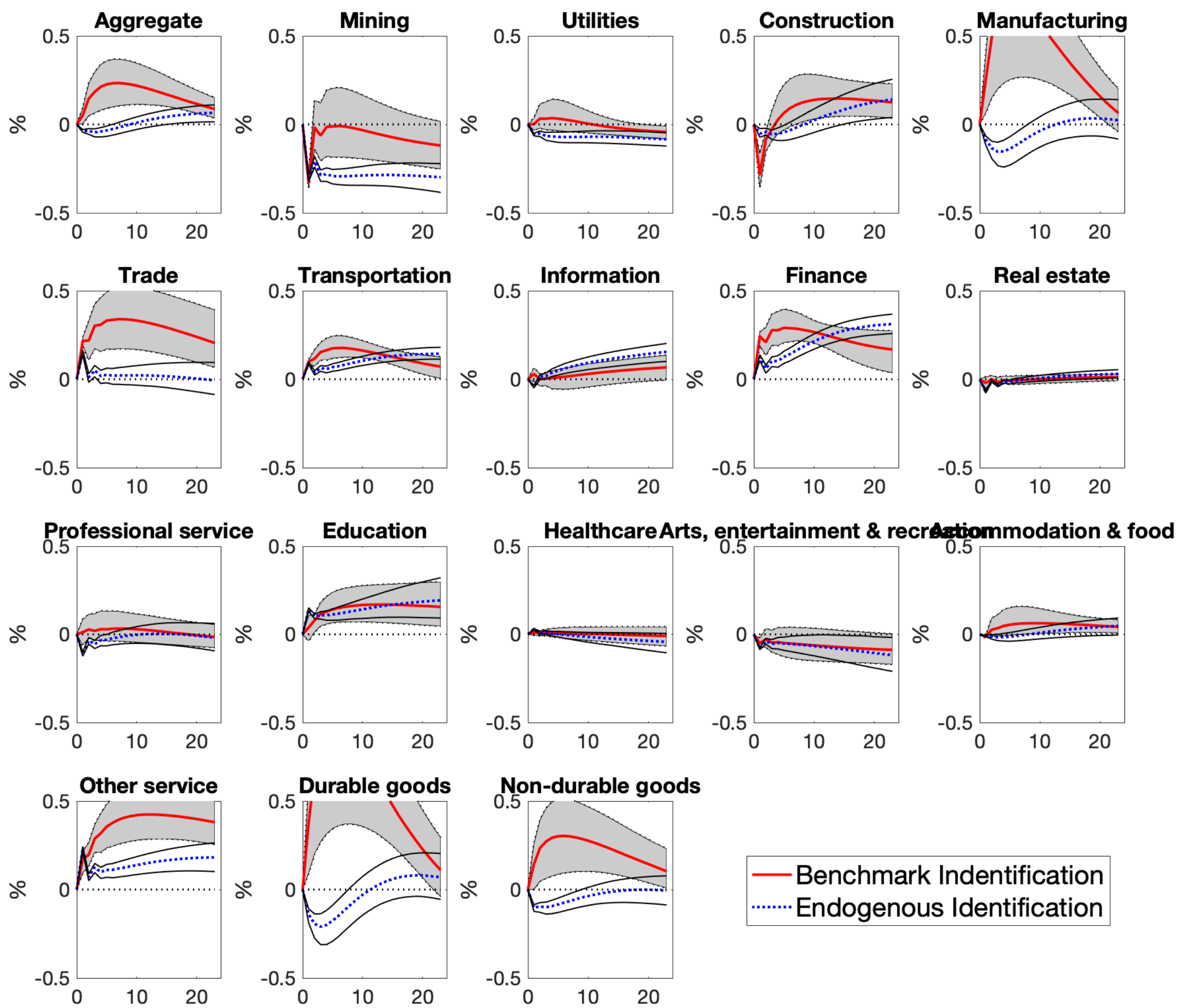
Note: The Median, 16th, and 84th Bayesian percentiles. Quarterly horizon.

Figure 18: The United Kingdom - Industrial Impulse Response Functions with Endogenous Identification



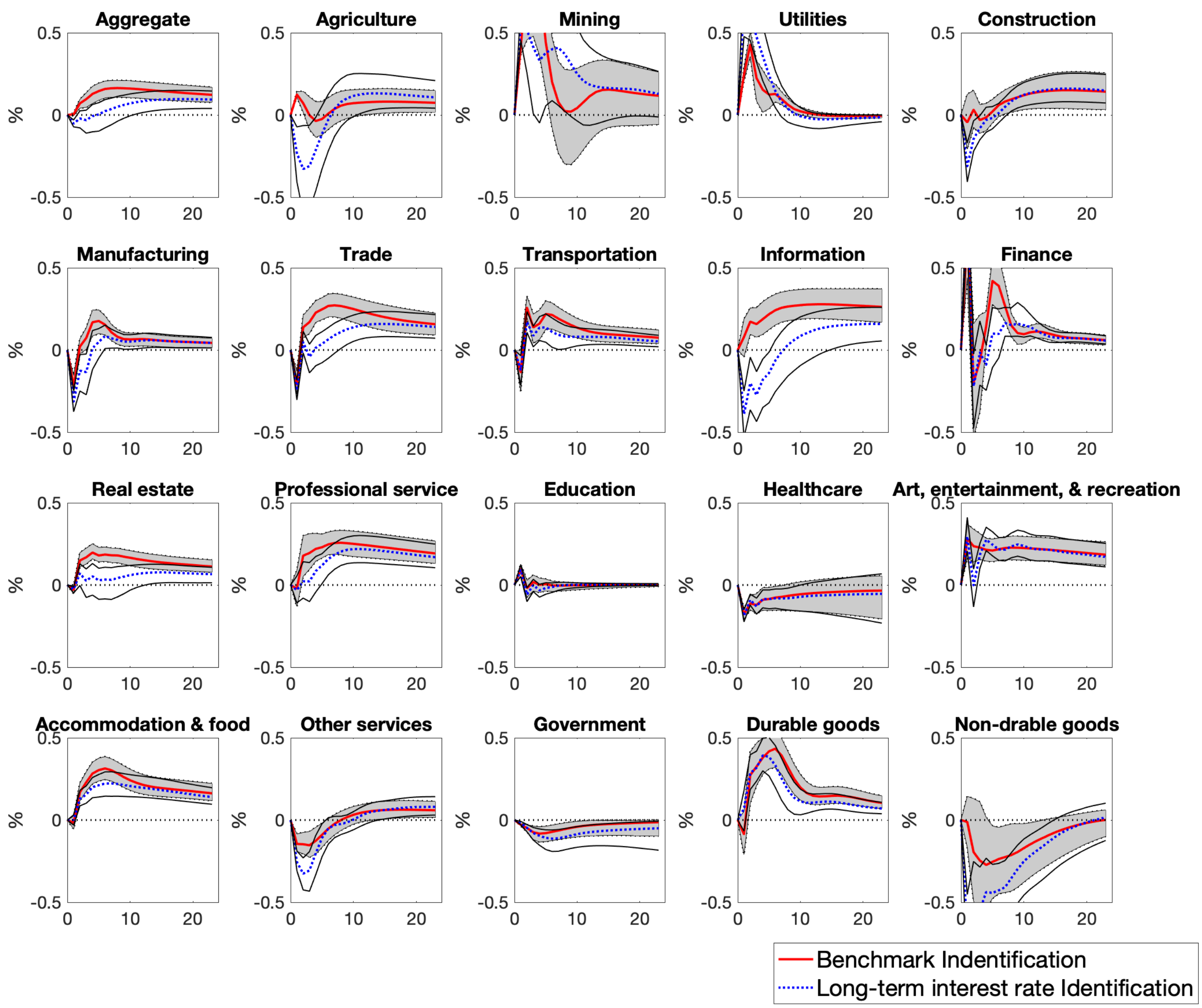
Note: The Median, 16th, and 84th Bayesian percentiles. Monthly horizon.

Figure 19: Japan - Industrial Impulse Response Functions with Endogenous Identification



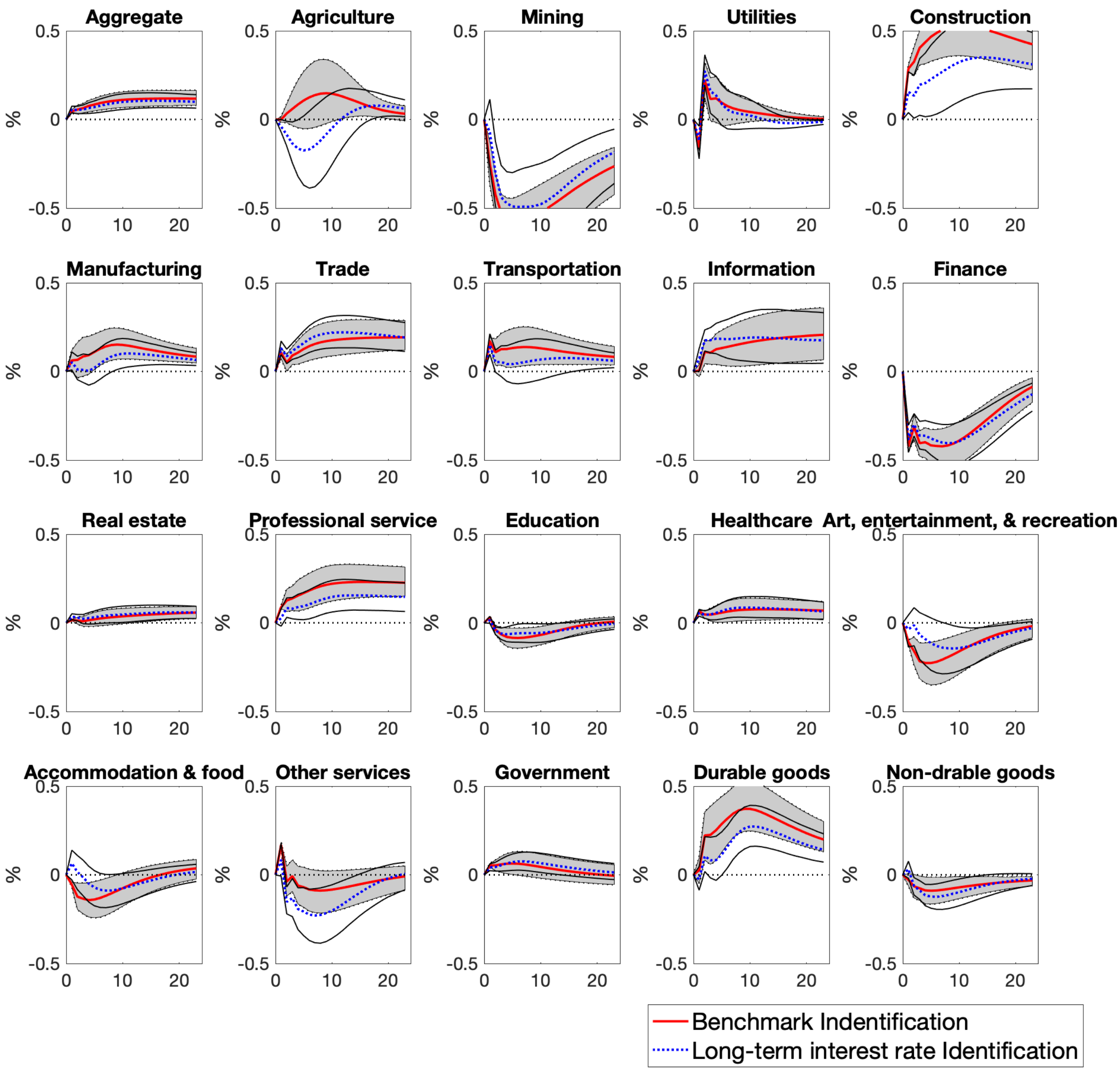
Note: The Median, 16th, and 84th Bayesian percentiles. Monthly horizon.

Figure 20: The United States - Industrial Impulse Response Functions with Long-term Interest Rate



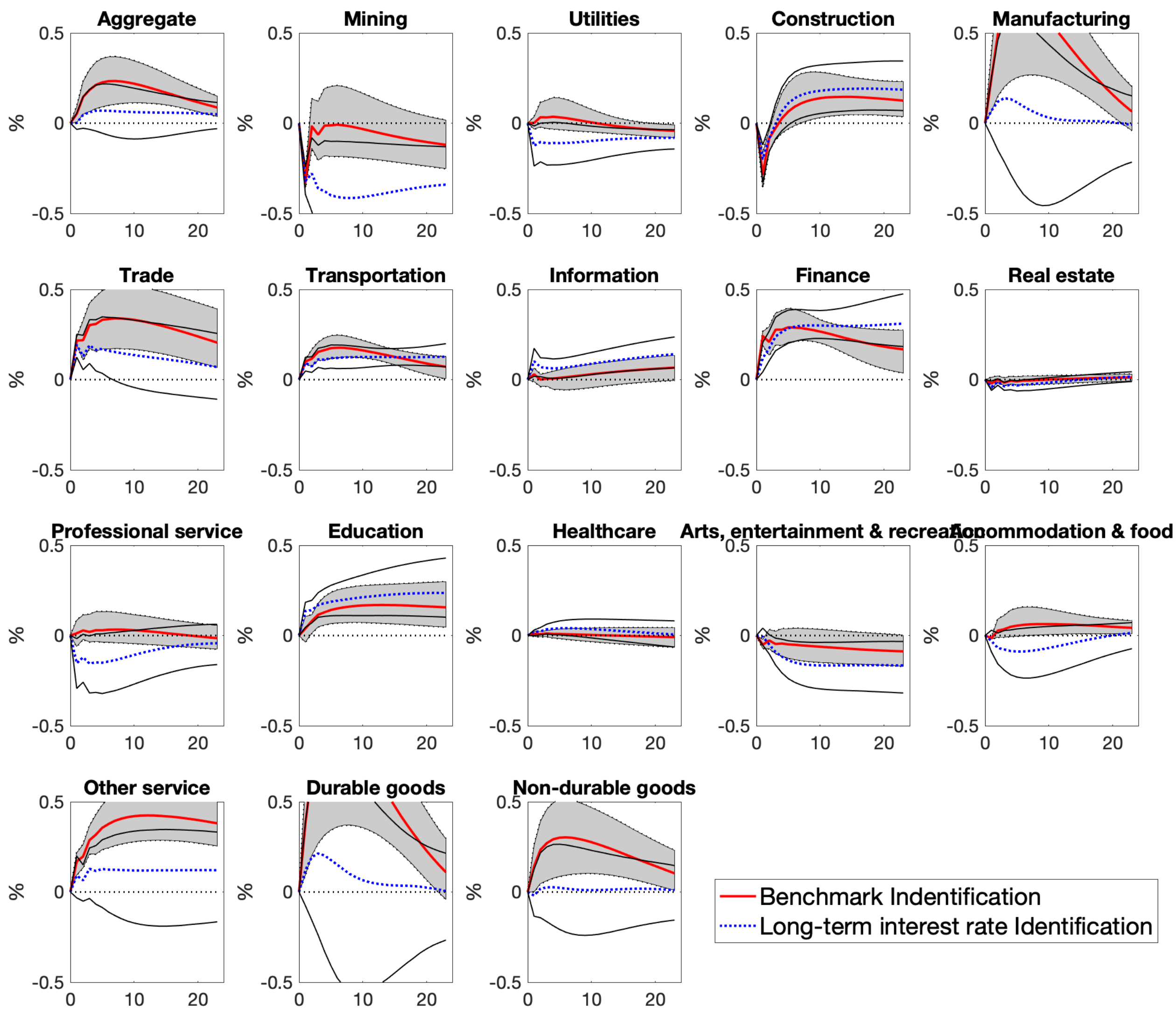
Note: The Median, 16th, and 84th Bayesian percentiles. Quarterly horizon.

Figure 21: The United Kingdom - Industrial Impulse Response Functions with Long-term Interest Rate



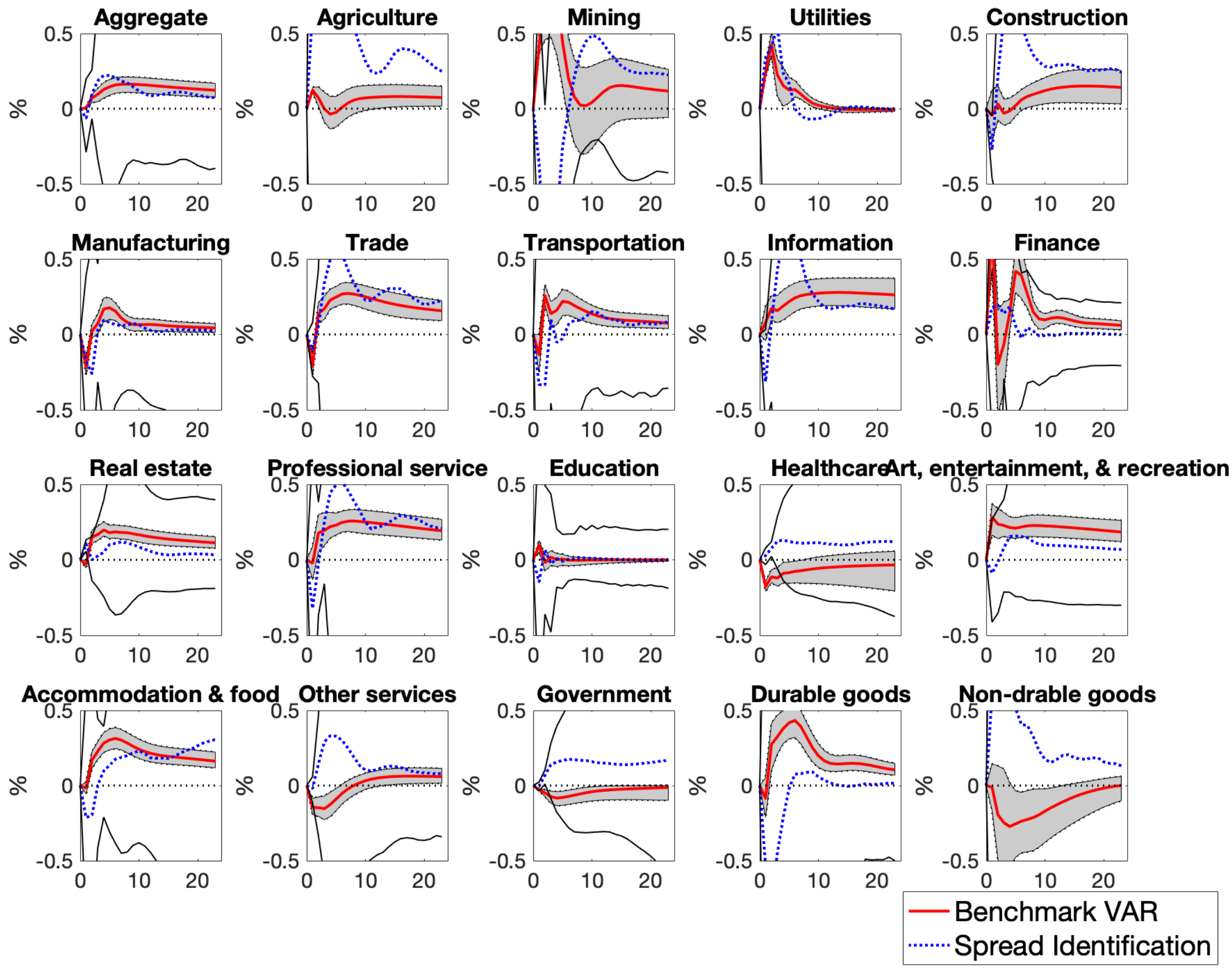
Note: The Median, 16th, and 84th Bayesian percentiles. Monthly horizon.

Figure 22: Japan - Industrial Impulse Response Functions with Long-term Interest Rate



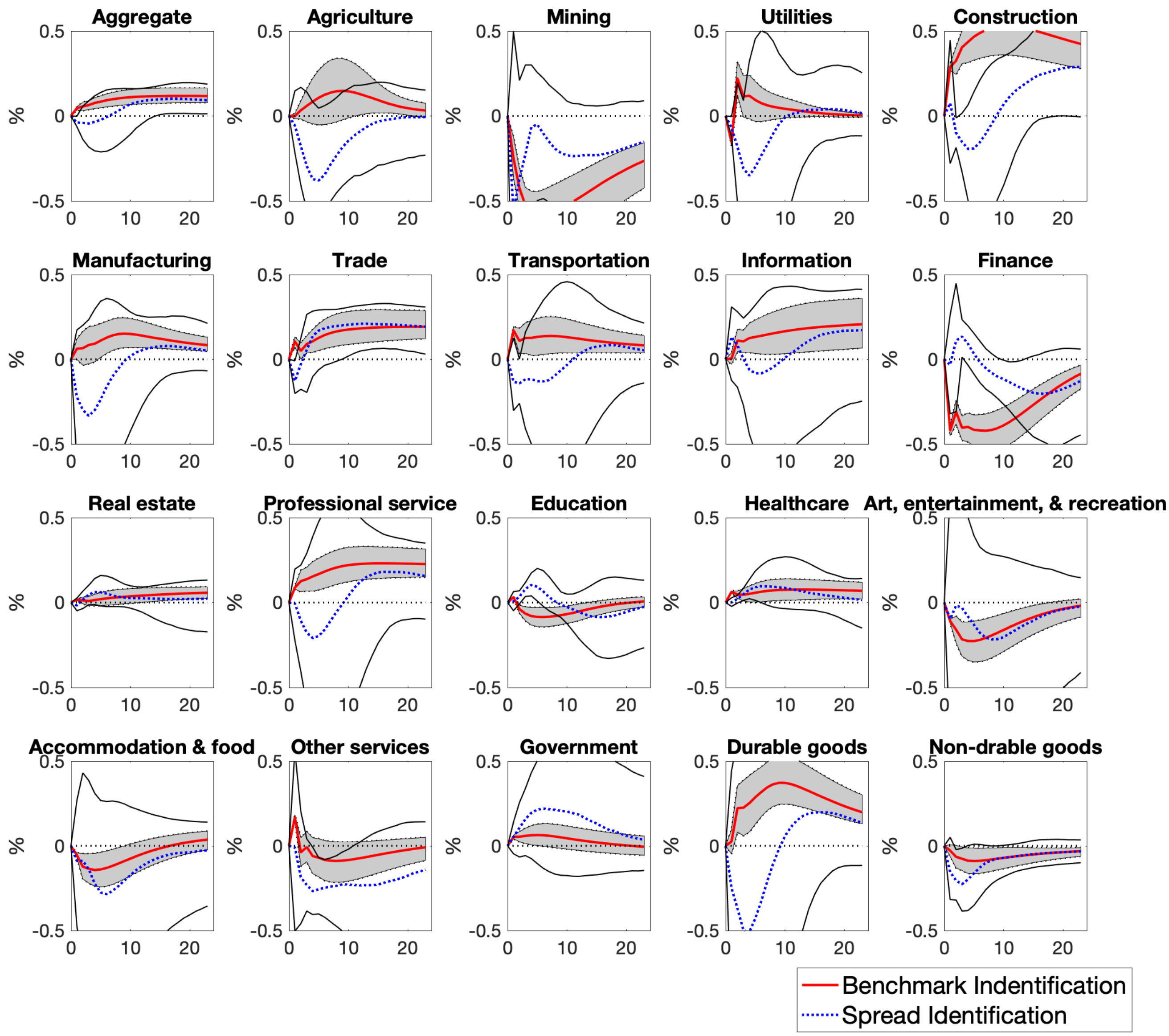
Note: The Median, 16th, and 84th Bayesian percentiles. Monthly horizon.

Figure 23: The United States - Industrial Impulse Response Functions with Interest Rate Spread



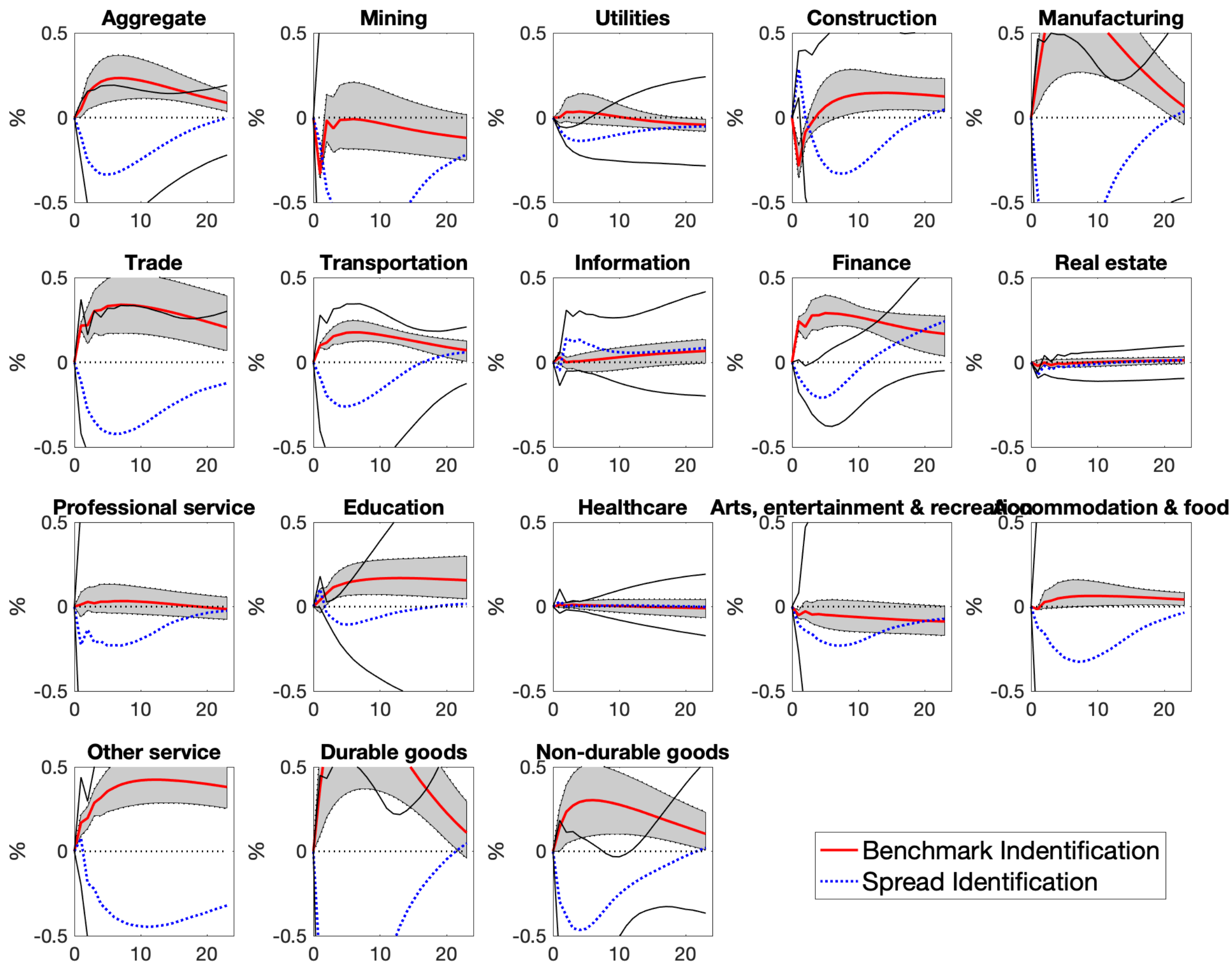
Note: The Median, 16th, and 84th Bayesian percentiles. Quarterly horizon.

Figure 24: The United Kingdom - Industrial Impulse Response Functions with Interest Rate Spread



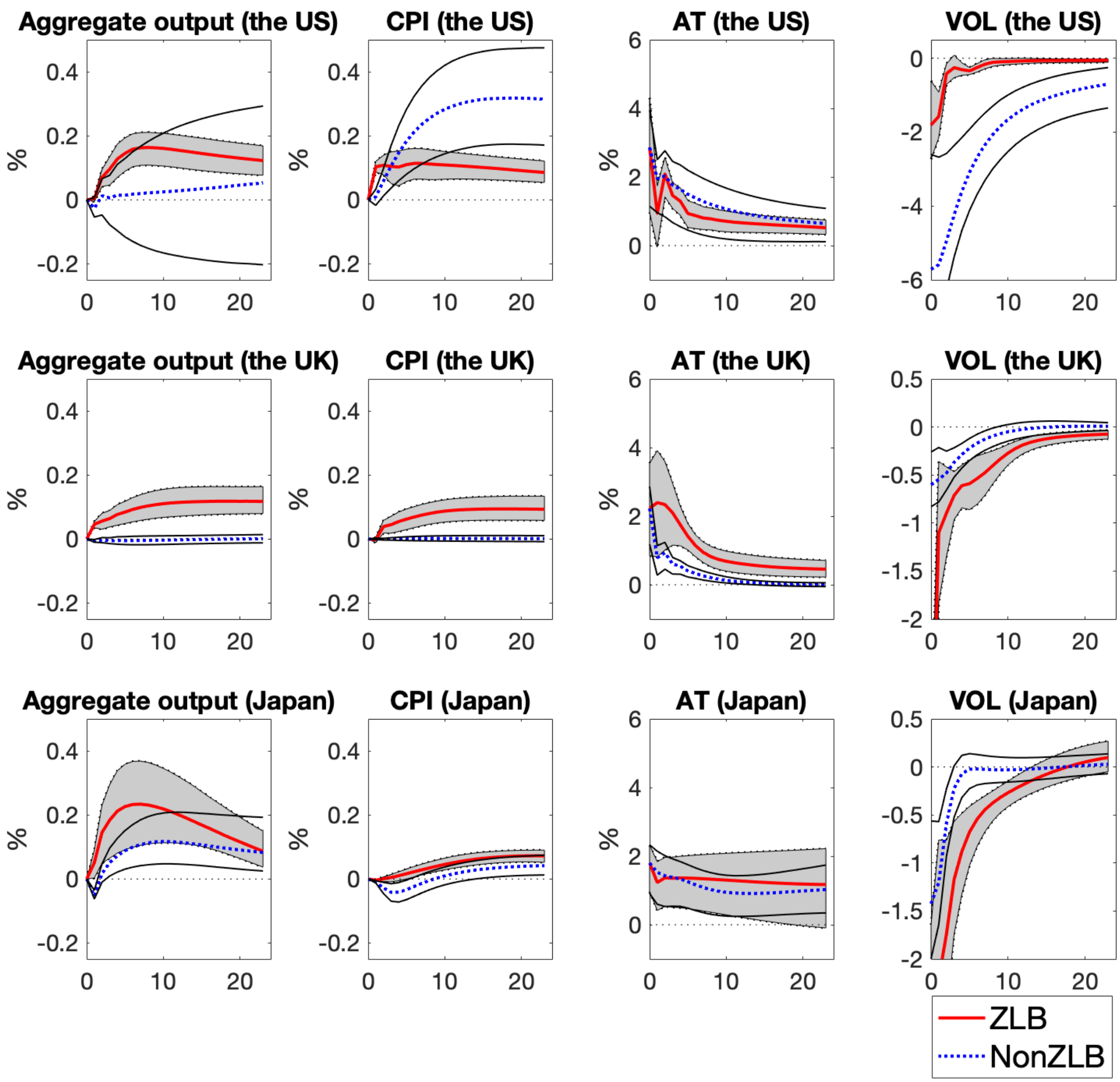
Note: The Median, 16th, and 84th Bayesian percentiles. Monthly horizon.

Figure 25: Japan - Industrial Impulse Response Functions with Interest Rate Spread



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

Figure 26: National Impulse Response Functions During Non-ZLB

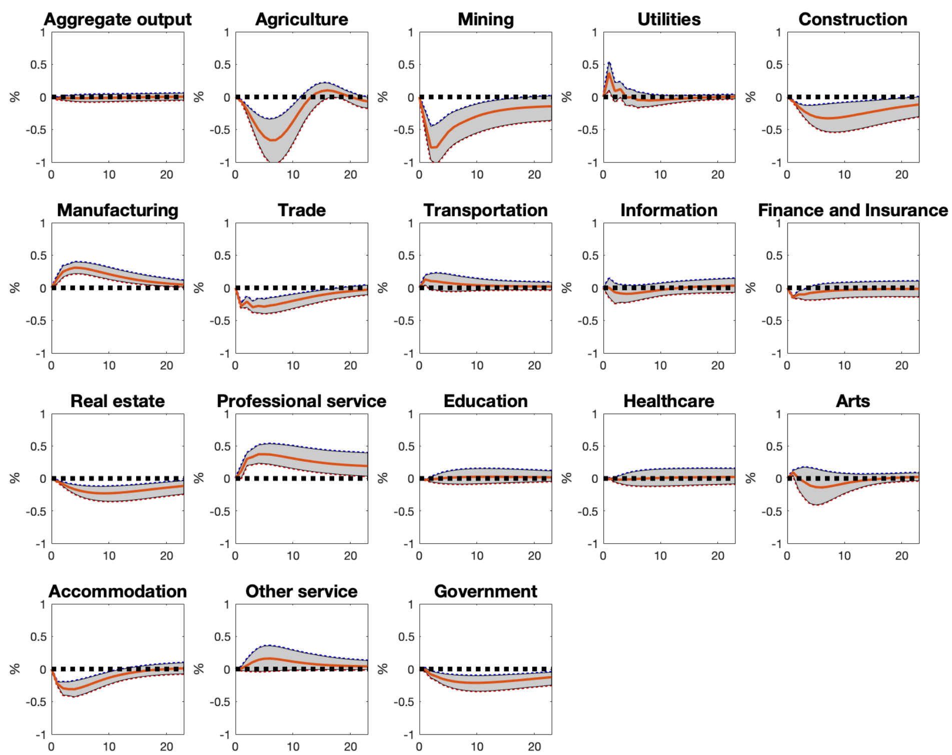


Note: The Median, 16th, and 84th Bayesian percentiles. Quarterly horizon (the US) and Monthly horizon (the UK and Japan).

Figure 27: The United States - National Impulse Response Functions During Non-ZLB

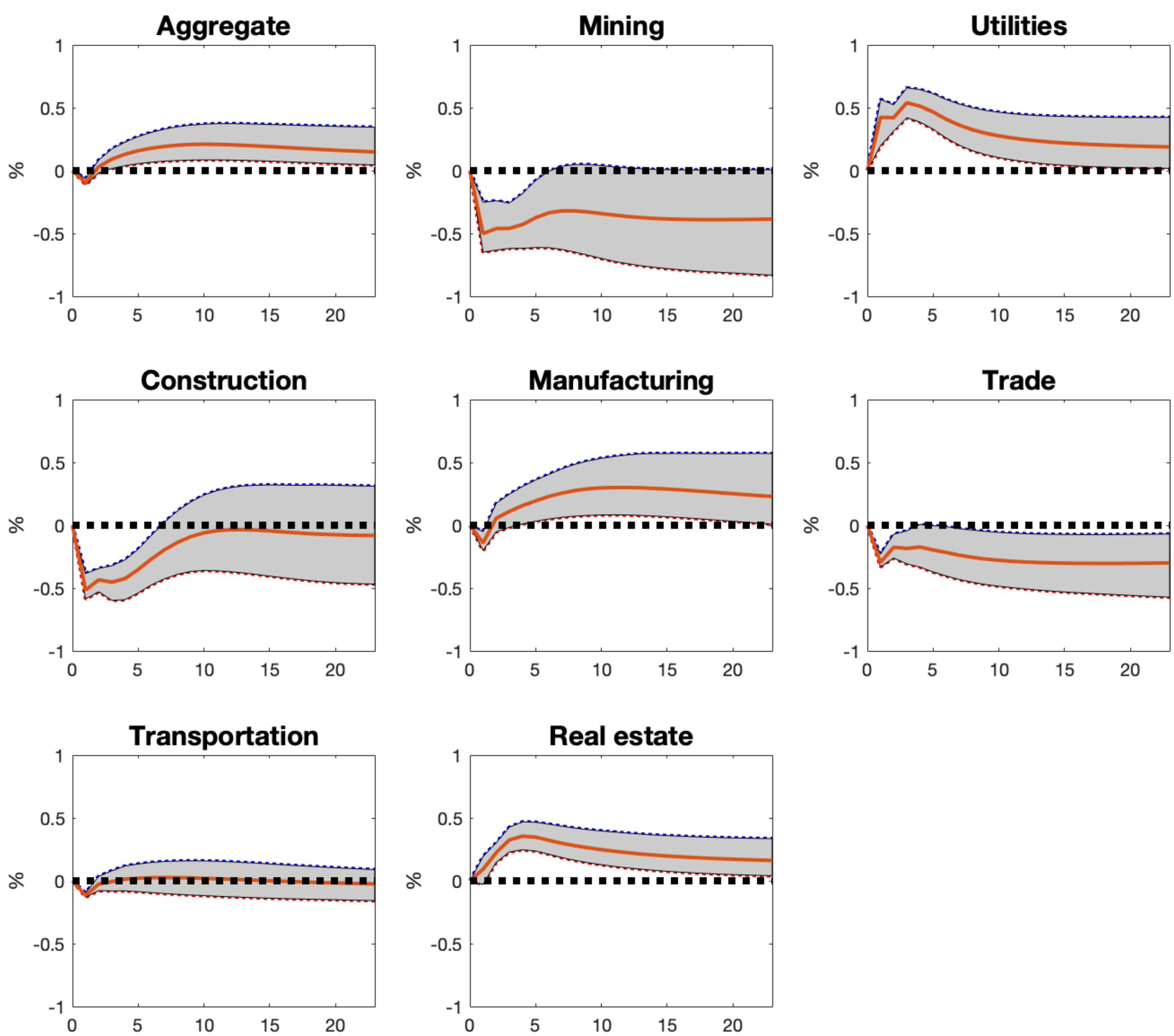
Note: The Median, 16th, and 84th Bayesian percentiles. Monthly horizon.

Figure 28: The United Kingdom - Industrial Impulse Response Functions During Non-ZLB



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

Figure 29: Japan - Industrial Impulse Response Functions During Non-ZLB



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

A Appendix

A.1 Industry Definitions

The following table summarizes the categories of the industries:

Table A.1: Industry definition

Country	The US	The UK	Japan
Codes	NAICS	UK SIC	JSIC
industries			
Agriculture	11	A	N.A.
Mining	21	B	C
Utilities	22	D, E	F
Construction	23	F	D
Manufacturing	31-33	C	E
Durable goods	321, 327, 33	CC16, CH, CI, CJ, CK,CL,CM	12,13,22-31 323-326
Non-durable goods	31, 322-326	CA, CB, CC17, CC18, CD, CE, CF, CG	09-11,14-21
Trade	42, 44-45	G	I
Transportation	48-49	H	H
Information	51	J	G
Finance	52	K	J
Real estate	53	L	K
Professional service	54-56	M,N	L
Education	61	P	O
Healthcare	62	Q	P
Arts, entertainment, & recreation	71	R	N
Accommodation & food	72	I	M
Other Services	81	S	Q,R
Government	92	O	N.A.

A.2 Unit-Root and Stationarity Tests

I operate both unit root and stationarity tests. For the unit root test, I use augmented Dickey-Fuller (ADF) and ADF-GLS tests. For the stationarity test, I use the KPSS test. All of these tests are done for each series for each country. The number of lags for the ADF test is chosen by AIC, the number for ADF-GLS is chosen by Modified AIC (Ng and Perron, 2001), and the number for the KPSS test is determined by $[12(\frac{T}{100})^{0.25}]$. I took the logarithm and then multiplied by 100 of all of the series except stock market implied volatility, since the specification is how each variable enters the VAR model. For both tests, constant and trend terms are included. The following tables (tables A.2, A.3, and A.4) summarizes those tests results.

Table A.2: The United States - Unit-Root and Stationarity tests

	Total			Agriculture			Mining			Utilities			Construction		
Test	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS
Statistic	-7.69	-0.99	0.15	-2.17	-1.81	0.09	-0.80	-1.97	0.11	-2.71	-1.52	0.08	-3.39	-0.90	0.14
p-value	0.00		0.05	0.50		0.10	0.95		0.10	0.25		0.10	0.07		0.05
Support	I(0)	I(1)	I(1)	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Overall support		Mix			Mix			Mix			Mix			Mix	
	Manufacturing			Trade			Transportation			Information			Finance		
TestI(1)	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS
Statistic	-2.84	-1.64	0.14	-3.29	-0.81	0.15	-1.44	-1.49	0.10	-1.00	-0.75	0.15	-1.87	-0.90	0.14
p-value	0.20		0.06	0.09		0.05	0.83		0.10	0.93		0.04	0.64		0.06
SupportDF-GLS	I(1)	I(1)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)
Overall support		Mix			I(1)			Mix			I(1)			Mix	
	Real estate			Professional service			Education			Healthcare			Arts, etc		
TestI(1)	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS
Statistic	-3.21	-2.17	0.13	-9.29	-2.21	0.13	-2.11	-1.39	0.13	-0.33	-0.67	0.15	-2.20	-2.15	0.10
p-value	0.10		0.08	0.00		0.07	0.53		0.08	0.99		0.05	0.49		0.10
Support	I(1)	I(1)	I(0)	I(0)	I(1)	I(0)	I(1)	I(1)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)
Overall support		Mix			Mix			Mix			I(1)			Mix	
	Accommodation			Other service			Government			Durable goods			Non-durable goods		
TestI(1)	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS
Statistic	-2.89	-2.73	0.12	-2.30	-0.82	0.15	-1.77	-1.89	0.10	-4.06	-3.053*	0.10	-3.23	-1.55	0.13
p-value	0.18		0.10	0.44		0.05	0.69		0.10	0.02		0.10	0.10		0.09
Support	I(1)	I(1)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)	I(0)	I(0)	I(1)	I(1)	I(0)
Overall support		Mix			I(1)			Mix			I(0)			Mix	
	Agg. Manufacturing			Agg. Service			ln(CPI)			ln(AT)			VOL		
TestI(1)	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS
Statistic	-2.50	-1.35	0.13	-3.40	-1.23	0.15	-2.94	-2.50	0.10	-0.69	-0.71	0.16	-1.63	-1.64	0.13
p-value	0.35		0.08	0.07		0.04	0.16		0.10	0.96		0.04	0.75		0.08
Support	I(1)	I(1)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)
Overall support		Mix			I(1)			Mix			I(1)			Mix	

Table A.3: The United Kingdom - Unit-Root and Stationarity tests

	Total			Agriculture			Mining			Utilities			Construction		
Test	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS
Statistic	-4.84	-1.13	0.21	-3.51	-1.94	0.07	-1.21	-0.62	0.26	-2.56	-1.45	0.18	-2.40	-0.99	0.20
p-value	0.00		0.01	0.04		0.10	0.90		0.01	0.32		0.02	0.39		0.02
Support	I(0)	I(1)	I(1)	I(0)	I(1)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Overall support		Mix			Mix			I(1)			I(1)			I(1)	
	Manufacturing			Trade			Transportation			Information			Finance		
Test	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS
Statistic	-4.17	-2.37	0.10	-1.98	-0.65	0.23	-5.38	-0.81	0.16	-1.46	-1.08	0.22	-3.18	-2.10	0.14
p-value	0.01		0.10	0.60		0.01	0.00		0.04	0.84		0.01	0.09		0.06
Support	I(0)	I(1)	I(0)	I(1)	I(1)	I(1)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)
Overall support		Mix			I(1)			Mix			I(1)			Mix	
	Real estate			Professional service			Education			Healthcare			Arts, etc		
Test	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS
Statistic	-0.88	-0.98	0.13	-4.00	-1.51	0.13	-3.05	-1.16	0.14	0.12	-0.68	0.24	-3.08	-1.69	0.10
p-value	0.95		0.08	0.01		0.08	0.12		0.07	1.00		0.01	0.12		0.10
Support	I(1)	I(1)	I(0)	I(0)	I(1)	I(0)	I(1)	I(1)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)
Overall support		Mix			Mix			Mix			I(1)			Mix	
	Accommodation			Other service			Government			Durable goods			Non-durable goods		
TestI(1)	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS
Statistic	-3.09	-1.46	0.14	-2.76	-2.19	0.13	-1.80	-1.49	0.13	-3.89	-2.58	0.05	-2.05	-0.81	0.21
p-value	0.11		0.06	0.22		0.09	0.69		0.08	0.02		0.10	0.56		0.01
Support	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)	I(0)	I(1)	I(0)	I(1)	I(1)	I(1)
Overall support		Mix			Mix			Mix			Mix			I(1)	
	Agg. Manufacturing			Agg. Service			ln(CPI)			ln(AT)			VOL		
TestI(1)	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS
Statistic	-1.65	-1.32	0.20	-3.92	-1.60	0.19	-2.95	-2.12	0.23	-3.82	-1.58	0.17	-3.67	-3.63	0.12
p-value	0.76		0.02	0.01		0.02	0.15		0.01	0.02		0.03	0.03		0.10
Support	I(1)	I(1)	I(1)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)	I(0)	I(0)
Overall support		I(1)			Mix			I(1)			Mix			I(0)	

Table A.4: Japan - Unit-Root and Stationarity tests

	Aggregate			Mining			Utilities			Construction			Manufacturing		
Test	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS
Statistic	-2.16	-1.85	0.15	-2.33	-1.73	0.17	-2.85	-1.45	0.28	-1.25	-0.97	0.30	-2.59	-2.50	0.10
p-value	0.51		0.05	0.43		0.03	0.18		0.01	0.90		0.01	0.30		0.10
Support	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)
Overall support		I(1)			I(1)			I(1)			I(1)			Mix	
	Trade			Transportation			Information			Finance			Real estate		
Test	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS
Statistic	-2.65	-1.77	0.11	-1.65	-2.02	0.19	-1.49	-1.70	0.19	-1.65	-1.97	0.19	-3.19	-1.03	0.14
p-value	0.27		0.10	0.76		0.02	0.83		0.02	0.76		0.02	0.09		0.06
Support	I(1)	I(1)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)
Overall support		Mix			I(1)			I(1)			I(1)			Mix	
	Professional service			Education			Healthcare			Arts, etc			Accommodation		
Test	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS
Statistic	-2.02	-2.29	0.12	-1.70	-1.57	0.20	-2.06	-1.43	0.15	-2.18	-1.81	0.11	-1.83	-1.48	0.15
p-value	0.58		0.09	0.74		0.02	0.56		0.05	0.50		0.10	0.67		0.05
Support	I(1)	I(1)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)	I(1)	I(1)	I(1)
Overall support		Mix			I(1)			I(1)			Mix			I(1)	
	Other services			Durable goods			Non-durable goods			Agg. Manufacturing			Agg. Service		
TestI(1)	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS
Statistic	-3.28	-1.89	0.16	-2.59	-2.39	0.09	-2.17	-2.52	0.16	-2.03	-2.62	0.15	-2.20	-1.40	0.14
p-value	0.07		0.04	0.30		0.10	0.51		0.04	0.57		0.05	0.49		0.06
Support	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)
Overall support		I(1)			Mix			I(1)			I(1)			Mix	
	ln(CPI)			ln(AT)			VOL								
TestI(1)	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS						
Statistic	-1.17	-1.03	0.23	-1.54	-0.95	0.34	0.37	0.00	0.08						
p-value	0.91		0.01	0.81		0.01	0.00		0.00						
Support	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)	I(1)						
Overall support		I(1)			I(1)			Mix							

A.3 Complete Description of Identification

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

$$\Sigma_u = BB' = BI_4B' = BQQ'B' \tag{11}$$

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

$$Q = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & cos(\theta) & -sin(\theta) \\ 0 & 0 & sin(\theta) & cos(\theta) \end{bmatrix} \tag{12}$$

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

$$\underbrace{\begin{bmatrix} u_{SO} \\ u_{CPI} \\ u_{AT} \\ u_{VOL} \end{bmatrix}}_{\substack{\text{Reduced form error} \\ u_t}} = \underbrace{\begin{bmatrix} * & * & 0 & 0 \\ * & * & 0 & 0 \\ * & * & + & + \\ * & * & -,0 & + \end{bmatrix}}_{BQ} \underbrace{\begin{bmatrix} \epsilon_{SO} \\ \epsilon_{CPI} \\ \epsilon_{AT} \\ \epsilon_{VOL} \end{bmatrix}}_{\substack{\text{Structural error} \\ \epsilon_t}} \qquad \text{(2 revisited)}$$

A.4 Complete Description of Bayesian Estimation

First, I impose the priors of $vec(A)$ and Σ_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 Σ_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 $n = 5$. For the prior variance of the coefficients parameter, $V_{vec(A)}$, I impose the form of Minnesota prior. This enables the prior distribution to be tight and that is important to overcome the curse of dimensionarity, especially for estimating global VAR model in section 6.1.2. 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:

$$v_{jk,i} = \begin{cases} (\lambda/i)^2 & \text{if j=k} \\ (\lambda\alpha\sigma_j/i\sigma_k)^2 & \text{if j}\neq\text{ k} \end{cases} \tag{13}$$

where $\lambda = 0.2$, $\alpha = 0.1$. σ_j and σ_k are obtained from equation by equation OLS estimates of the VAR model. Then $V_{vec(A)}$ is:

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

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

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

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

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

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

and

$$\tau = T + n.$$

Moreover, Σ_u is the OLS estimate, $\mathbf{Z}_t = Z_t \otimes I_4$ and $Z = [Z_0, \cdots, Z_{T-1}]$ with $Z_{t-1} = (1, y_{t-1}', y_{t-2}')'$.

Here the posterior distribution of $vec(A)$ is conditional on Σ_u and the posterior distribution of

Σ_u is conditional on $vec(A)$. Therefore, to draw sample parameters from the joint posterior distribution, Gibbs sampler is required. A burn-in sample of 20,000 draw is discarded following the literature[23] and then I take the following steps to generate IRFs.

Step 1: Draw reduced form parameters ν^{*r}, $A_i^{*r}s$, and Σ_u^{*r} and compute the Cholesky decomposition of Σ_u^{*r}.

Step 2: For each ν^{*r}, $A_i^{*r}s$, and Σ_u^{*r}, draw N random Given's rotation matrix, $Q^{i\in N}$. For each combination of (ν^{*r}, $A_i^{*r}s$, Σ_u^{*r}, and Q^i), calculate the IRF.

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

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

Here I set N = 1000 and M = 1000. I sort all of the successful IRFs in a descending order and report the upper 84% and bottom 16% of them as a 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 Impacts of National UMP Compared to CMP Studies

It is of interest to know the magnitude of UMP compared to the magnitude of CMP. The table below lists several CMP studies and summarizes the quantitative results of CMP from a one standard deviation shock to the policy rate.

Table A.5: Comparison of National Effects Across CMP Studies

Authors	Country	Estimate			Sample periods	Output variable	Note
		GDP in %	CPI in %	1 STD CMP shock			
This paper	the US	0.16	0.11	2.86	2008Q1-2017Q4	Quarterly GVA	
	the UK	0.12	0.09	2.23	2008M1-2018M6	Monthly GDP	
	Japan	0.23	0.07	1.80	2003M1-2018M2	Monthly quantity index	
Christiano et al. (1999)	the US	0.50	0.15	-0.75	1965Q3-1995Q2	GDP	
Jordà (2005)	the US	0.23	0.13	-0.60	1960M1-2001M2	non-agricultural payroll employment	Local Projection method, price = PCE
Bernanke and Mihov (1998)	the US	0.20	0.30	-0.38	1965M1-1996M12	interpolated GDP	price = GDP deflator
Bagliano and Favero (1998)	the US	0.17	0.07	-0.10	1988M11-1996M3	interpolated GDP	
Dale and Haldane (1995)	the UK	1.00	-1.00	-0.01	1974M6-1992M10	retail sale and indsutrial production	
Mojon and Peersman (2001)	EU	0.10	0.10	-0.30	1980Q1-1998Q4	Real GDP	
Kim (1999)	the US	0.45	0.60	-0.16	1961M3-1994M3	industrial production	
	the UK	0.30	1.00	-0.07	1961M3-1997M3	industrial production	
	Japan	0.30	0.50	-0.30	1965M3-1996M6	industrial production	
Average		0.30	0.44	-0.30			
Median		0.30	0.40	-0.30			

The range of effect lies between 0.1% to 1% for output and between -1% to 1% on price. The averages (medians) are 0.3% (0.3%) for output and 0.44% (0.4%) for price. Compared to this paper's results and other studies from UMP literature, UMP policy seems not as effective as CMP in terms

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

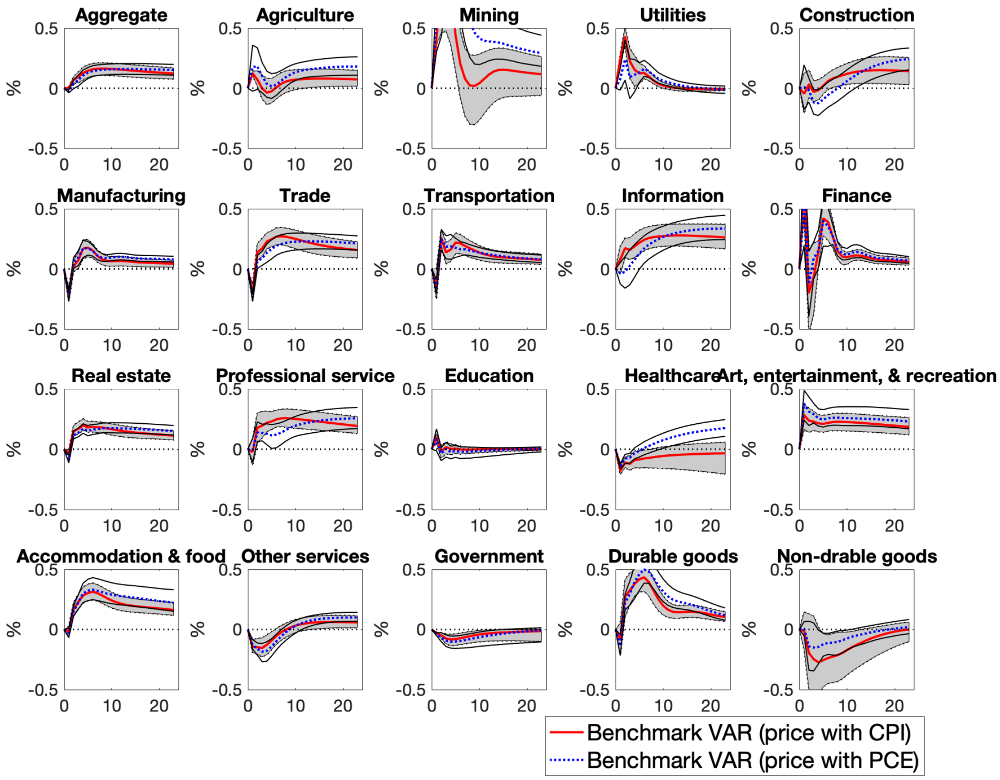
of how one standard deviation shock to the monetary policy instruments stimulate the outcome variables. In terms of stimulating output, UMP policy does not seem so weak. Its effect is about $66\%(=\frac{0.2\%}{0.3\%})$ of CMP. However, UMP's effect on price seems weak and the effect is only about $13\%(=\frac{0.06\%}{0.44\%})$ of CMP on average. This finding is probably due to the periods covered for those studies which are during the high inflationary periods and the model captured the fluctuations. The studies by Bagliano and Favero (1998) and Mojon and Peersman (2001) only include periods after the great moderation and effects are 0.07 and 0.10, which is comparable to the UMP studies. Therefore, the UMP impacts of price may not be so bad. Even though I could not directly compare the effect of UMP with CMP, since the policy instruments are different, it seems that effectiveness of UMP is not bad.

A.6 Industrial Impacts of UMP When Personal Consumption Expenditure is Used

The target price variable of the monetary policy for the Federal Reserve is personal consumption expenditure (PCE). In this paper, I use CPI[24] for the price variable by following Gambacorta et al. (2014). However, the use of CPI can be misspecified. In this section, I estimate the model including the PCE instead of CPI to see whether or not results are radically altered. Figure 30 show the results.

[24]The target variable for the Bank of England and the Bank of Japan is CPI

Figure 30: The United States - Industrial Impulse Response Functions when Personal Consumption Expenditure is used



Note: The Median, 16th, and 84th Bayesian percentiles. Quarterly horizon.

There are some industries whose IRFs are slightly altered such as agriculture, mining, and healthcare. However, generally the deviation is within the error band and the results are not so qualitatively different.

A.7 Complete Description of GVAR estimation

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

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

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 non i industrial output) and $y^*_{i,t}$ is constructed as a weighted average of domestic variables $\forall j \neq i$:

$$y^*_{i,t} = \sum_{j \neq i} w_{i,j} y_{j,t} \qquad\qquad \sum_{j \neq i} w_{i,j} = 1 \tag{15}$$

The weight $w_{i,j}$ is assumed to be constant during the estimation periods. Traditionally bilateral trade flow is used (for example Vansteenkiste and Hiebert, 2011; Galesi and Lombardi, 2009), since GVAR models are often used for assessing international spillover effects. However, since the focus of the chapter is industrial level interaction, I use an IO table for the weight[25].

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

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

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 a GDP share of industry i.

Given the specifications of equation (14) 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 (14) is going to be:

$$G_{i,0} y_{i,t} = c_i + \sum_{j=1}^{p_i} G_{i,j} y_{i,t-j} + \sum_{j=0}^{q_i} C_{i,j} x_{t-j} + u_{i,t} \tag{17}$$

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:

$$G_0 y_t = c + \sum_{j=1}^{p} G_j y_{t-j} + \sum_{j=0}^{q} C_j x_{t-j} + u_t \tag{18}$$

Likewise, transform equation (16) using the fact that $\tilde{y}_t = W^* y_t$ where W^* is a link matrix based on the industrial GDP share:

$$x_t = c_x + \sum_{j=1}^{p_x} D_j x_{t-j} + \sum_{j=0}^{q_x} F_j W^* y_{t-j} + u_{xt} \tag{19}$$

By combining the equations (18) and (19), we can construct a structural Global VAR model:

$$H_0 Z_t = h_0 + \sum_{j=1}^{p} H_j Z_{t-j} + e_t \tag{20}$$

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

where $Z_t = (y_t', x_t')'$, $H_0 = \begin{bmatrix} G_0 & -C_0 \\ -FW^* & I \end{bmatrix}$, $h_0 = \begin{bmatrix} c \\ c_x \end{bmatrix}$, $H_j = \begin{bmatrix} G_j & C_j \\ F_jW^* & D_j \end{bmatrix}$, 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 a reduced form Global VAR (p) model:

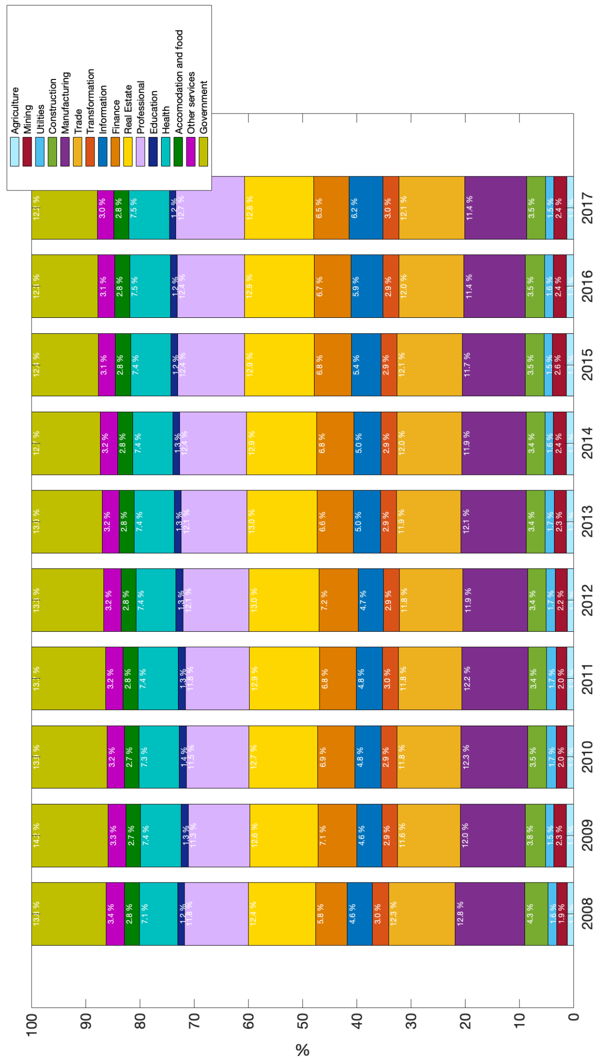
$$Z_t = k_0 + \sum_{j=1}^{p} K_j Z_{t-j} + \nu_t \tag{21}$$

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

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. I define $y_{it} = IO_{it}$ and $x_t = [CPI_t \quad AT_t \quad VOL_t]'$. Hypothetically, directly estimating equation (21) 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 the problem, I follow the conventional way to estimate a GVAR: estimate the domestic equation (14) and the common equation (16) individually using OLS. Finally, the identification and the Bayesian inference is the same as in section 3.3 except that this estimate is the mean of the parameters of the prior distribution.

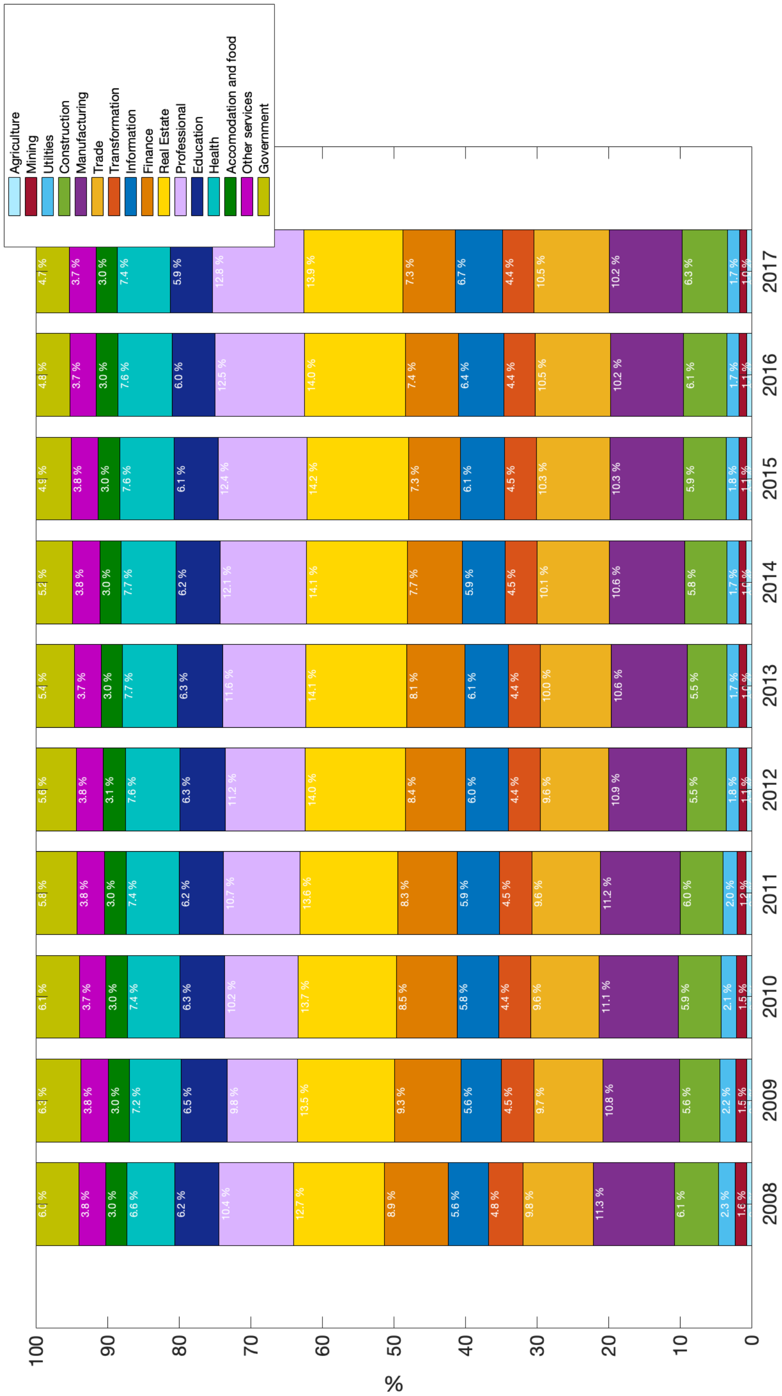
B Appendix: Figures

Figure B.31: The United States - Industrial Composition



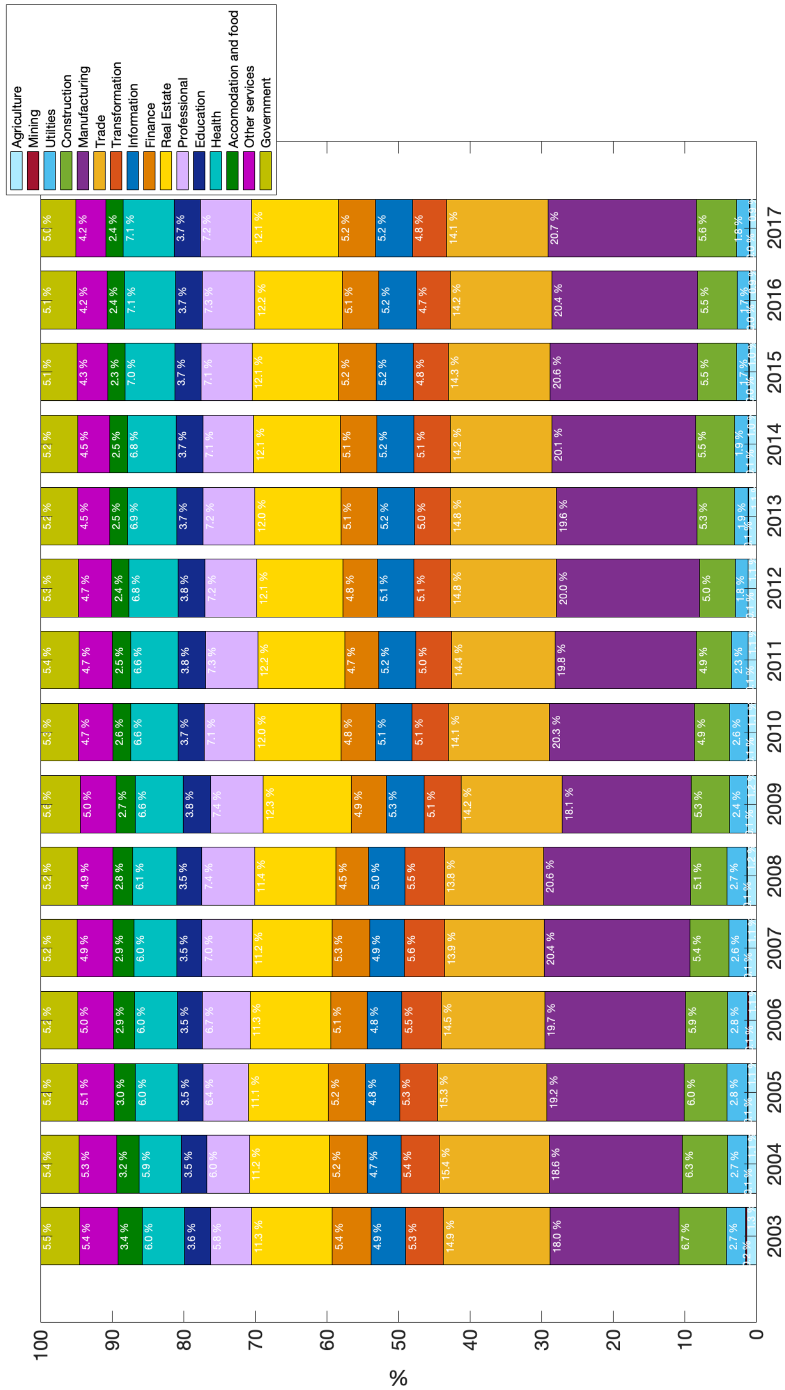
Source: The Bureau of Economic Analysis

Figure B.32: The United Kingdom - Industrial Composition



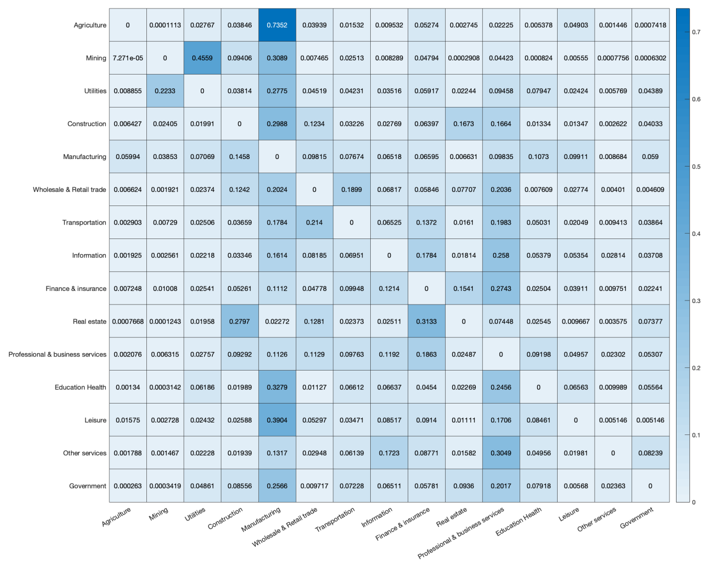
Source: The Office for National Statistics

Figure B.33: Japan - Industrial Composition



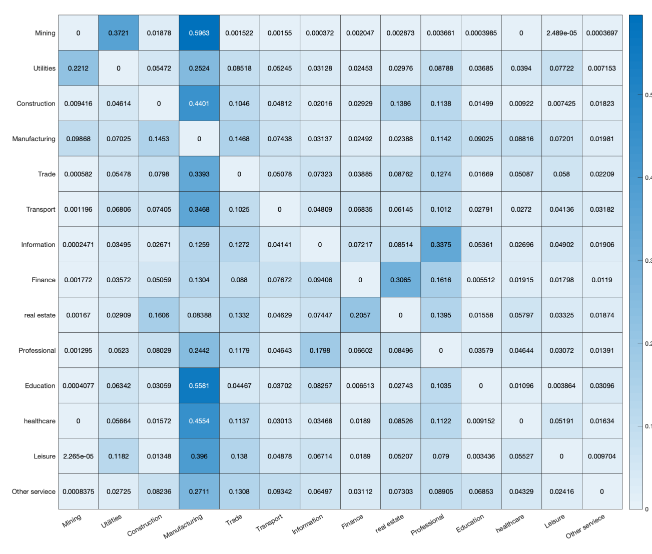
Source: The Cabinet of Japan

Figure B.34: The UK - The Weighting Matrix



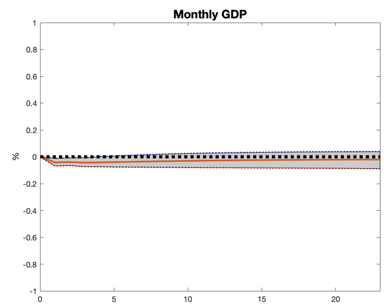
Source: The Office for National Statistics

Figure B.35: Japan - The Weighting Matrix



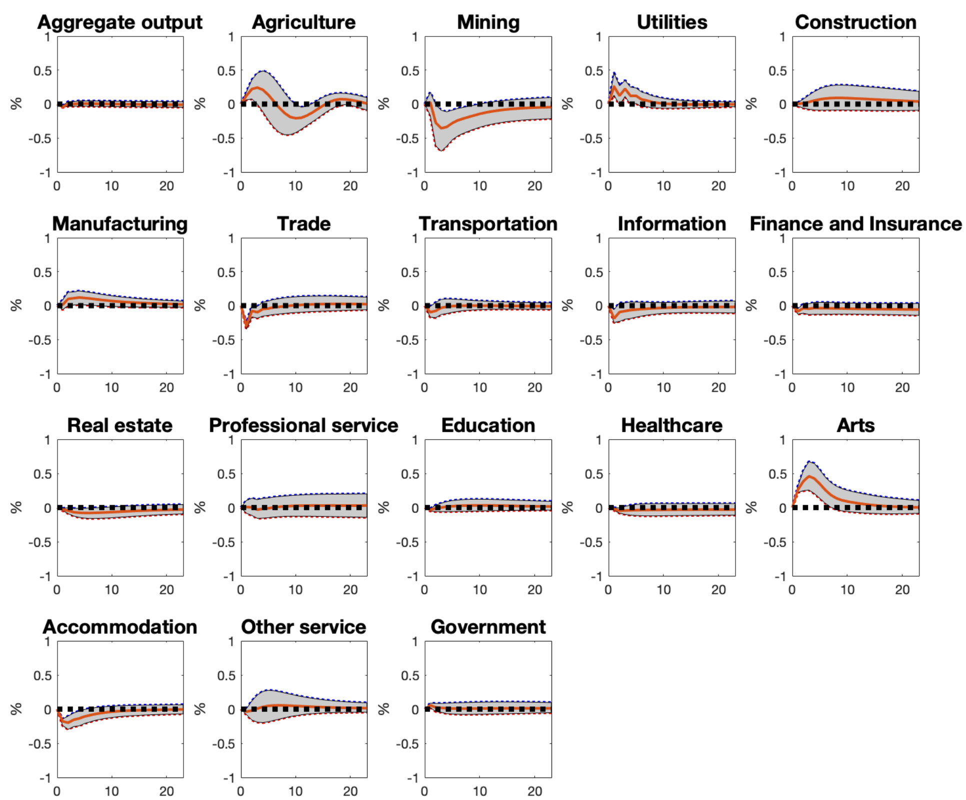
Source: The Ministry of Economy, Trade and Industry

Figure B.36: The United States - National Impulse Response Functions During Non-ZLB with Policy Rate



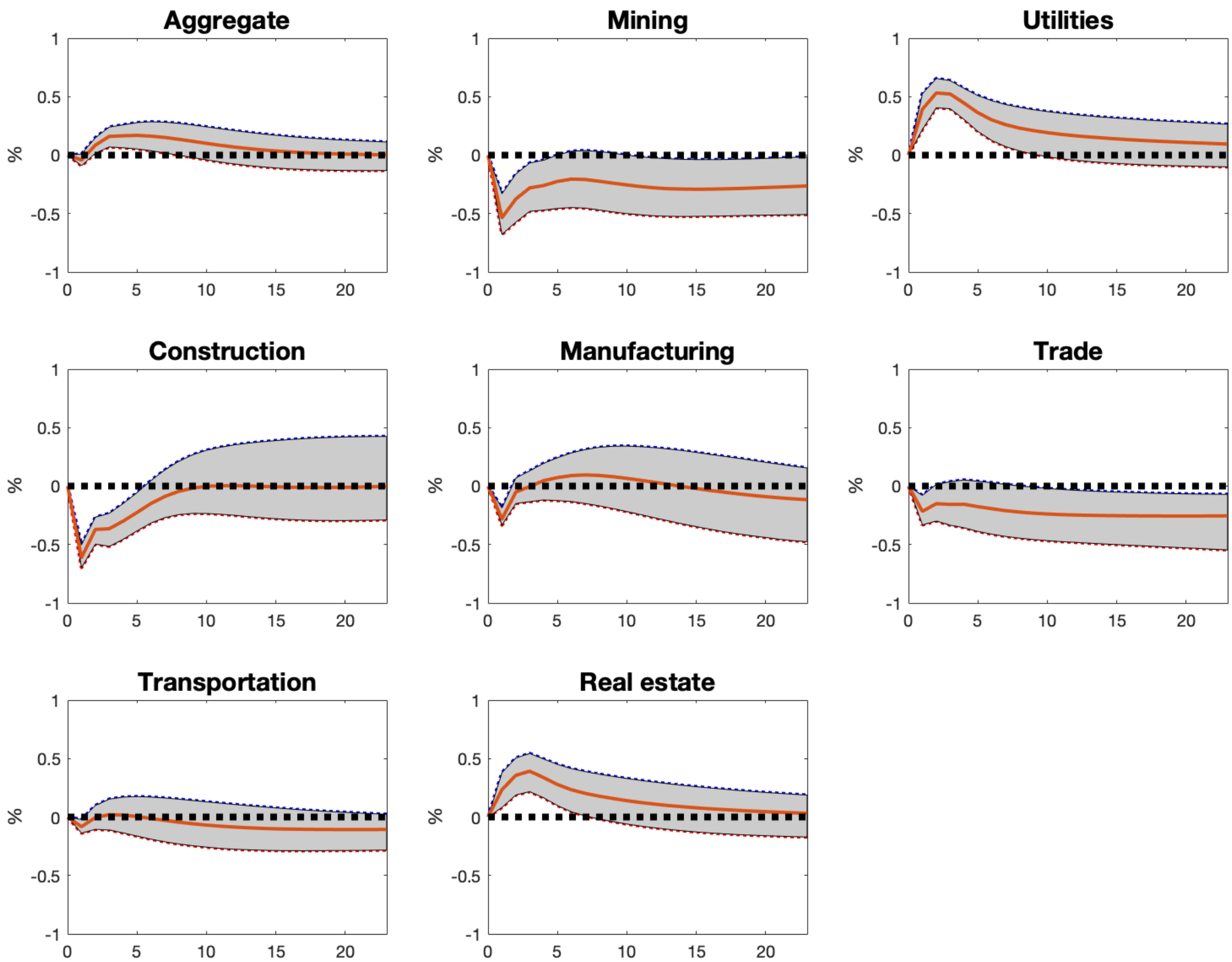
Note: The Median, 16th, and 84th Bayesian percentiles. Monthly horizon.

Figure B.37: The United Kingdom - Industrial Impulse Response Functions During Non-ZLB with Policy Rate



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

Figure B.38: Japan - Industrial Impulse Response Functions During Non-ZLB with Policy Rate



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