Essays on international economics and spillover effects

A dissertation submitted to the department of economics,
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for the degree of doctor of philosophy

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ABSTRACT

This dissertation consists of three essays. In particular, I apply time-series methods including a multivariate GARCH model, factor-augmented vector auto regression, and vector auto regression with sign restrictions.

In Chapter 1, "On the link between the US economic policy uncertainty," I analyze the effect of economic policy uncertainty shocks stemming from the United States on exchange rates. The findings suggest that economic policy uncertainty generated in the US has some spillover effects on foreign currencies, and the sign of such spillovers depends on the different currency yielding. Moreover, I find that such spillover effects are pronounced during economic recessions. This chapter was accepted by *Economics Letters*.

In Chapter 2, "Spillover effects of a US policy uncertainty shock: its impact on Asian and global financial market," I analyze the spillover effects of the US economic policy uncertainty on broader financial markets: stock markets and commodity markets, in addition to foreign exchange markets. This empirical exercise shows that the US economic policy uncertainty significantly affects each global latent factors separately extracted from equity markets, foreign exchange markets, and commodity markets. By country level analysis, some heterogeneities of responses are observed among selected countries. As for equity prices, US economic policy shocks adversely affect, however, its impact on Chinese equity market is relatively small. As for exchange rate market, while many currencies depreciate in response to positive economic policy uncertainty shocks, US dollar and Japanese yen appreciate reflecting their safe haven nature. Chinese yuan, whose nominal exchange rate is closely linked to US dollar, also appreciates in response to uncertainty shocks. This chapter was presented in 2016 YNU-ECU International Conference, and has been revised and resubmitted to *North American Journal of Economics and Finance* (currently under review).

In Chapter 3, "Disentangling the nexus between the stock price and the oil price: sign restriction approach," I analyze the underlying shocks that drive US stock prices and oil prices. In particular, by applying the sign restriction approach to the sample period where the US monetary policy confronted with zero lower bound, this study I examine the effect of unconventional monetary policy on the stock prices and oil prices. The findings in this chapter suggest that US unconventional monetary policy played an important role in boosting stock prices and oil prices from 2009 to 2012. Further, the findings suggest that the divergence between the stock price and the oil price can be attributed to oil supply shocks.

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I had the honor to work alongside my advisor Kiyotaka Sato over these years, and his guidance, direction and patience have been crucial to the production of the research included in this document. His dedication, wisdom and attention to detail have trained me as an economist and as a person, I will always be extremely grateful to him. I am also very grateful to my advisor Tsunao Okumura, Craig Parsons and other faculty members at Yokohama National University for many helpful conversations that changed how I think about research. The staff of the Department of Economics has always been helpful and kind to me way beyond expectations. They provided ideal environment for research.

Content

Chapter 1:

On the link between the US economic policy uncertainty and exchange rates

Abstract

Employing dynamic conditional correlation GARCH (DCC-GARCH) model, this chapter analyzes spillover effects of the US economic policy uncertainty shock on real effective exchange rates with the data from January 2000 to December 2014. We find that the correlations between the US EPU and the returns of the high-yielding currencies are consistently negative throughout the sample period, while the correlation between the US EPU and the returns of Japanese yen is consistently positive. Moreover, we find that the correlations tend to be intensified during two post-2000 recession episodes.

Keywords:

Economic policy uncertainty; Spillover; Dynamic conditional correlation; Real effective exchange rate

JEL Classification Code: F3

1.1 Introduction

It is widely recognized that uncertainty has negative effects on economic activity. For example, Bernanke (1983) researched that when firms face uncertainty, they reduce investments and wait for further information as investment costs are irreversible. Related to this, effects of economic policy uncertainty (EPU), which is uncertainty related to monetary policy, fiscal policy and other relevant policies, are also researched. With regard to its effects on asset prices, Pastor and Veronesi (2012) showed theoretically that government policy uncertainty lowers equity returns. Other recent works include Brogaard and Detzel (2015), which empirically showed that the US EPU has negative effects on US equity markets mainly by increasing risk premium.

While literature in this field is growing, there is limited research about spillover effects of advanced economies' EPU. Given this background, this chapter sheds light on spillover effects of the US EPU on selected economies' exchange rates. One of our research's aims is to investigate effects of the US EPU on carry trade activities. For this purpose, we include four high-yielding currencies as well as G3 currencies (US dollar, Euro and Japanese yen).

Novelty of this chapter is that it analyzes time-varying nature of spillover effects of the US EPU on real effective exchange rates (REER).Our findings show that the correlations between the US EPU and returns of high-yielding currencies are consistently negative, while the correlations between the US EPU and the return of Japanese yen is consistently positive. Moreover, we also find that correlations between the US EPU and some REER are intensified during the US recessions.

The paper proceeds as follows. Section 1.2 introduces data and an empirical method employed. Section 1.3 discusses the results and conducts further analysis. Section 1.4 concludes.

1.2 Data and Empirical methods

Our analysis employs monthly data of an EPU index and REER returns from January 2000 to 2014[1]. As for EPU data, we adopt the index developed by Baker et al. (2013)[2]. The index is the news-based index, which captures wide range of policy uncertainty terms appeared in the US newspapers. As figure 1 displays, the index captures salient economic events such as 9/11, Lehman Brothers bankruptcy, and the debt-ceiling dispute. As for REER, we adopt the broad indices complied by Bank for International Settlements and convert them into monthly returns.

Table 1 reports descriptive statistics of the data. The two unit root tests, Augmented Dickey-Fuller (ADF) test and Phillips-Perron (PP) test, indicate that the data are stationary. As for pairwise

[1] We do not include pre-2000 data because some of our sample countries have experienced very volatile period, such as Asian currency crisis and Mexican peso crisis.
[2] Data are obtained at http://www.policyuncertainty.com/us_monthly.html.

correlations with US EPU, all high-yielding currencies show negative correlations, while G3 currencies show positive correlations.

As Jones and Olson (2013) argues, effects of the US EPU can be time-varying. Given this, we employ dynamic conditional correlation GARCH (DCC-GARCH) model developed by Engel (2002). DCC-GARCH model produces time-varying conditional correlations and allows us to analyze evolution of correlations in different phases.

This chapter analyzes bivariate dynamic conditional correlation between REER returns and the US EPU. First, conditional mean of REER returns and the US EPU are derived with equation (1) and equation (2):

$$r_{i,t} = \alpha_i + \beta_{i,1} r_{i,t-1} + \beta_{i,2} u_{i,t-1} + e_{i,t} \quad (1)$$

$$u_t = \alpha_u + \beta_u u_{t-1} + e_{u,t} \quad (2)$$

where r_i denotes the REER return of a currency, u_t denotes the US EPU and e_t denotes error terms of the equations. The parameters are estimated by ordinary least square (OLS).

Table 2 summarizes estimation results of equation (1) and (2). As table 2 reports, coefficients of the own lagged variables are statistically significant in all equations. Breusch–Pagan tests show that heteroscedasticity are present for most of variables, and support the use of GARCH-type models.

In DCC-GARCH model, the residual vector e_t is assumed to follow normal distribution.

$$e_t = \begin{bmatrix} e_{i,t} \\ e_{u,t} \end{bmatrix} \sim N(0, D_t R_t D_t) \quad (3)$$

where D_t =diag$\{\sqrt{h_{i,t}}, \sqrt{h_{u,t}}\}$is a 2×2 matrix containing time-varying standard deviations from univariate GARCH models. They are governed by following GARCH processes.

$$h_{i,t} = \gamma_i + \kappa_i e_{i,t-1}^2 + \lambda_i h_{i,t-1} \quad (4)$$

$$h_{u,t} = \gamma_u + \kappa_u e_{u,t-1}^2 + \lambda_u h_{u,t-1} \quad (5)$$

In equation (3), R_t is a 2×2 matrix of time-varying conditional correlations computed with a 2×2 time-varying covariance Q_t:

$$R_t = diag\{Q_t\}^{-1} Q_t diag\{Q_t\}^{-1} \quad (6)$$

$$Q_t = w + A\varepsilon_{t-1}\varepsilon_{t-1}' + BQ_{t-1} \quad (7)$$

where $\varepsilon_t = D_t^{-1} e_t$.

Following Engel (2002), the parameters are estimated with a two-step maximum likelihood estimation method. Table 3 reports the estimated parameters.

1.3 Results

Figure 2 displays dynamic conditional correlation obtained in equation (6). The correlations between high-yielding currencies and the US EPU are consistently negative throughout the sample period. That is, high-yielding currencies tend to appreciate when uncertainty remains low and tend to depreciate when uncertainty is high. This observation is consistent with Brunnermeier et al. (2009), which showed that currency crashes of high carry currencies are positively correlated with implied stock market volatility.

In contrast to high-yielding currencies, Japanese yen consistently show positive correlations with the US EPU. This suggests that they tend to appreciate (depreciate) when uncertainty is high (low). Such a contrast between the high-yielding currencies and Japanese yen reflects carry trade activities. US dollar and Euro show volatile correlations with the US EPU. Importantly, however, in the recent financial crisis, the former shows positive correlation while the latter shows rather negative correlation. This suggests that, amid highly uncertain global financial crisis, US dollar behaved as a safe-haven currency, while Euro did not perform such functions.

An important question is how correlations evolve in business cycles. Employing a smooth transition vector autorgression model, Caggiano et al. (2014) showed that effects of uncertainty shocks are intensified during recessions in the US economy. To investigate how correlations behave during recessions, we consider the following equation:

$$DC_{i,t} = \alpha_i + \beta_i \, DC_{i,t-1} + \gamma_i \, NBER_t + e_{i,t} \qquad (8)$$

where DC_t denotes a dynamic conditional correlation obtained in (6) and *NBER* denotes a dummy variable for the US recession periods defined by National Bureau of Economic Research. We estimate this equation by OLS.

Table 4 summarizes estimated coefficients of equation (8). It indicates that the coefficients of NBER recession dummies are significantly negative for some high-yielding currencies. Since EPU tends to be relatively high during recessions, such high-yielding currencies tend to depreciate strongly in response to higher EPU. Corresponding to that, the coefficient of NBER recession dummy is significantly positive for the US dollar, suggesting that US dollar strongly appreciates in response to higher EPU.

Our findings supplement existing literature on exchange rates and uncertainty shocks. With regard to exchange rates, the violation of uncovered interest parity (UIP) is often discussed. Our findings suggest that high-yielding currencies tend to appreciate in real term when the US EPU remains low, but tend to depreciate in real term when the US EPU is elevated. That is, exchange rates that have deviated from UIP theory tend to be adjusted over the US EPU cycles. With regard to spillover effects of uncertainty shock, Carrière-Sawllow and Céspedes (2013) showed that impacts of exogenous uncertainty shocks on emerging economies are larger than that on advanced economies due to credit constraints. In this respect, we show that the high-yielding currencies tend to depreciate strongly given high US EPU in the US recession periods. As depreciation of the domestic currency increases burden of foreign currency denominated debt, this channel may amplify the effects of credit constraint.

1.4 Conclusion

By employing a bivariate DCC-GARCH model, this chapter has analyzed time-varying correlation coefficients between the US EPU and returns of selected REER. We find that correlation between the US EPU and returns of high-yielding currencies are consistently negative. In contrast, we find that the correlations between the US EPU and the return of Japanese yen is consistently positive. This suggests that, when US EPU remains low, the high-yielding currencies tend to appreciate and Japanese yen tends to depreciate. In contrast, in the situations which US economic policies are uncertain, the high-yielding currencies tend to depreciate and the Japanese yen tends to appreciate. US dollar and Euro show volatile correlations with the US EPU. In the recent financial crisis, however, the former behaved as a safe-haven showing positive correlation with the US EPU, while the latter did not perform such functions. This chapter also has analyzed how the correlations behave over the business cycle. Our findings show that the correlations between the US EPU and some REER are intensified during the US recession periods.

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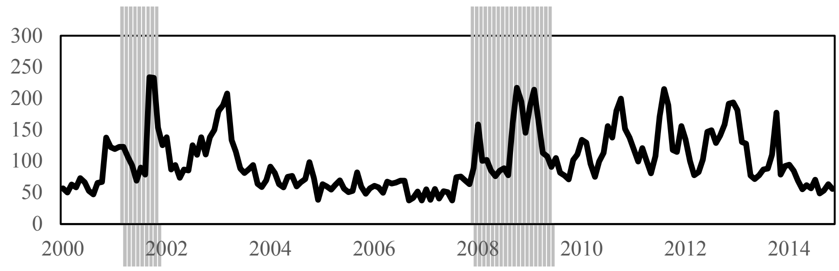
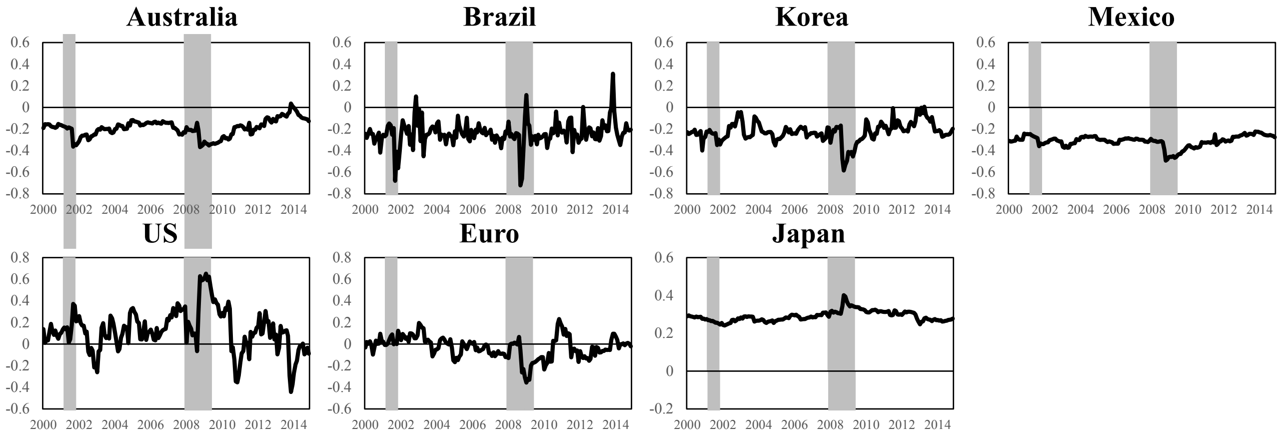
Figure 1: The US economic policy uncertainty（US EPU）



Note: US EPU is a news based index developed by Baker et al. (2013). The gray bands indicate recession periods defined by NBER.

Figure 2: Dynamic Conditional Correlation



Note: The gray bands indicate recession periods defined by NBER.

Table 1: Descriptive statistics of data (sample period Jan. 2000 to Dec.2014)

	Australia	Brazil	Korea	Mexico	US	Euro	Japan	US EPU
Mean	0.15	0.14	0.04	-0.08	-0.05	0.03	-0.35	99.27
S.dev	2.40	3.46	2.06	2.26	1.21	1.50	2.36	45.25
Max.	5.27	10.77	7.71	8.20	5.44	5.11	10.60	234.09
Min.	-13.94	-13.84	-13.67	-13.57	-3.59	-3.50	-6.96	37.27
Skewness	-1.35	-0.64	-1.88	-1.19	0.33	0.40	0.49	1.00
Kurtosis	5.84	2.05	11.71	7.24	1.96	0.58	2.33	0.34
ADF test	-5.14***	-6.03***	-5.00***	-7.00***	-4.74***	-5.09***	-6.54***	-3.50**
PP test	-9.23***	-8.97***	-8.71***	-10.61***	-9.16***	-10.32***	-10.41***	-4.57***
Correlation with US EPU	-0.06	-0.12	-0.24	-0.17	0.08	0.07	0.15	1.00

Note: For each country, data are returns of REER. In the table, ***, **, * denote 1%, 5% and 10% significant level respectively. ADF tests are conducted with 5 lags.

Table 2: Estimated parameters for equation (1) and equation (2)

	Australia	Brazil	Korea	Mexico	US	Euro	Japan	US EPU
Constant	-0.081	-0.640	0.097	-0.495	0.099	-0.243	0.275	21.087***
	(0.406)	(0.587)	(0.356)	(0.407)	(0.208)	(0.266)	(0.419)	(5.041)
R_{t-1}	0.344***	0.385***	0.374***	0.208**	0.341***	0.225**	0.268***	
	(0.070)	(0.070)	(0.072)	(0.076)	(0.072)	(0.073)	(0.073)	
U_{t-1}	0.009*	0.007	-0.001	0.004	-0.001	0.003	-0.005	0.788***
	(0.004)	(0.005)	(0.003)	(0.004)	(0.002)	(0.002)	(0.004)	(0.046)
R^2	0.139	0.148	0.147	0.043	0.115	0.06	0.07	0.623
Breusch–Pagan test	5.04*	23.7***	15.3***	7.6**	5.64*	6.88**	1.94	4.72**

Note: Dependent variables are corresponding countries' REER returns or US EPU expressed in equations. In the table, ***, **, * denote 1%, 5% and 10% significant level respectively. Standard deviations are in parentheses.

Table 3: Estimated parameters for DCC-GARCH

	Australia	Brazil	Korea	Mexico	US	Euro	Japan
Γ	0.846	2.23	0.440	0.764	0.178	0.117	0.170
	(0.552)	(1.40)	(0.308)	(0.711)	(0.394)	(0.300)	(0.196)
Κ	0.158	0.242	0.228	0.333	0.046	0.045	0.053
	(0.236)	(0.170)	(0.162)	(0.266)	(0.367)	(0.189)	(0.07)
Λ	0.672	0.536	0.649	0.613	0.816	0.895	0.917
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.02)
A	0.028	0.133	0.058	0.022	0.133	0.075	0.012
	(0.030)	(0.020)	(0.052)	(0.038)	(0.027)	(0.055)	(0.058)
B	0.903	0.226	0.739	0.910	0.725	0.750	0.925
	(0.143)	(0.383)	(0.272)	(0.221)	(0.076)	(0.228)	(0.346)
A+B	0.931	0.359	0.797	0.932	0.858	0.825	0.937

Note: In the table, γ, κ and λ are for equation (4); A and B are for equation (7) respectively. Standard deviations are in parentheses.

Table 4: Estimated parameters for equation (8)

	Australia	Brazil	Korea	Mexico	US	Euro	Japan
Constant	-0.014*	-0.142***	-0.046***	-0.026**	0.013	-0.003	0.019*
	(0.005)	(0.018)	(0.011)	(0.009)	(0.009)	(0.004)	(0.008)
DCC_{t-1}	0.911***	0.386***	0.772***	0.910***	0.830***	0.841***	0.934***
	(0.028)	(0.069)	(0.045)	(0.027)	(0.041)	(0.041)	(0.026)
$NBER_t$	-0.019**	-0.029	-0.034**	-0.014***	0.051*	-0.012	0.003
	(0.006)	(0.023)	(0.012)	(0.004)	(0.022)	(0.011)	(0.002)
R^2	0.878	0.165	0.685	0.880	0.742	0.724	0.892

Note: Dependent variables are estimated dynamic conditional correlations in equation (6). In the table, ***, **, * denote 1%, 5% and 10% significant level respectively. Standard deviations are in parentheses.

Chapter 2:

Spillover effects of a US policy uncertainty shock: its impact on Asian and global financial market

Abstract

This chapter investigates spillover effects of US economic policy uncertainty shocks on Asian and global financial markets employing a factor-augmented vector autoregression (FAVAR). Our empirical exercise shows that US economic policy uncertainty significantly affects latent factors extracted from equity prices, exchange rates, and commodity prices. By country-level analysis, we find some heterogeneities in responses to an increase in US economic policy uncertainty. As for equity, US economic policy uncertainty adversely affects equity prices. However, its impact on Chinese equity market is relatively small. As for foreign exchange markets, while many currencies depreciate in response to an increase in US economic policy uncertainty, US dollar and Japanese yen appreciate reflecting their safe haven status. Chinese yuan, whose nominal exchange rate is closely linked to US dollar, also appreciates in response to uncertainty shocks.

Keywords:
Spillover, Economic Policy Uncertainty, Factor-Augmented Vector Auto Regression (FAVAR), Asian financial market

JEL Classification Code: G15, G18

2.1 Introduction

Recently, there has been growing interest in understanding the role that economic policy uncertainty plays in driving macroeconomic fluctuations. In principle, economic policy uncertainty, which includes uncertainty related to fiscal policy, monetary policy or regulations can adversely affect economic activities. For example, as Bernanke (1983) and Dixit (1994) point out that high uncertainty gives firms an incentive to delay their investment when investment projects are costly to reverse.

Some recent empirical studies also confirm the significant role of policy uncertainty shocks. For example, utilizing firm-level data, Handley and Liamo (2015) showed that trade policy uncertainty plays an important role on firms' investment. Baker et al. (2016) showed that US economic policy uncertainty measured based on US newspapers adversely affects US production, investment, and employment. Similarly, Jones and Olson (2013) found that an increase in US economic policy uncertainty has a negative impact on domestic output. Despite substantial advances in the literature, there is limited research that analyzes how major economies' economic policy uncertainty affects global financial markets. As both financial linkage and economic linkage have been strengthened among countries, understanding the transmission mechanism of economic policy uncertainty generated from major economies to global financial markets is essential.

The aim of this chapter is to contribute toward the study of the international spillover effects of US economic policy uncertainty. In this chapter, we shed light on how US policy uncertainty transmits to global financial markets, focusing on its impact on Asian equity markets and exchange rate markets. As there exist significant cross-country differences among Asian countries in the openness of financial markets, the degree of economic development, or exchange rate policies, understanding heterogeneity of responses to US policy uncertainty shocks is important.

The novelty of our research is outlined with the following points. First, this chapter sheds light on spillover effects of US economic policy uncertainty on Asian and global financial markets. While a growing body of research analyzes the impact of economic policy uncertainty on US economic activities or US financial markets, research that analyzes its international spillover effects on global financial markets is still limited. Second, we employ a Factor-Augmented VAR (FAVAR) approach in our spillover research. FAVAR fits our research purpose since it accommodates a large number of financial variables in addition to economic policy uncertainty, allowing for interaction between an economic policy uncertainty and underlying factors of financial variables. To our best knowledge, this is the first attempt of studying spillover effects of economic policy uncertainty shocks on global financial markets with FAVAR.

Main findings of our research are as follows. First, we find that the US economic policy uncertainty significantly affects latent factors of equity prices, exchange rates, and commodity prices. Second, in the country-level analysis, we find that there exist some heterogeneity among countries. As for equity markets, adverse effects of US economic policy on equity markets are widely observed, but its impact on China is relatively small. As for exchange rate markets, while many currencies depreciate in response to increase in US economic policy uncertainty, US dollar and Japanese yen appreciate reflecting their safe haven status. Chinese yuan, whose nominal exchange rate is closely linked to US dollar, also appreciates in response to increase in US economic policy uncertainty.

The structure of this chapter is outlined as follows. In Section 2.2, we explain dataset used in empirical analysis. In Section 2.3, we cover our econometric framework employed for our empirical exercise (i.e. FAVAR). In Section 2.4, we summarize and discuss estimation results obtained from empirical exercise. In Section 2.5, we conduct some robustness checks of those results. Finally, Section 2.6 concludes our research.

2.2 Dataset

We start this section by describing a measurement of economic policy uncertainty, key data in our empirical research.[3] In this chapter, we employ the news-based economic policy uncertainty index developed by Baker et al. (2016), which captures a wide range of policy uncertainty terms that appeared in the US newspapers. In their paper, they investigated the impact of US economic policy uncertainty shocks and found that an increase in economic policy uncertainty index foreshadows declines in investment, output, and employment. Figure 1 displays the economic policy uncertainty index for the United States. The index captures some important events such as September 11th in 2001, Lehman Brothers' bankruptcy in 2008, and debt ceiling debates in 2011.

Since our research focus is international spillover effects of US economic policy uncertainty shocks on global financial markets, we employ a balanced panel of equity prices and exchange rates of 19 selected economies and several commodity indices with the sample period of January 2000 to December 2015.[4][5] In our empirical exercise, we analyze financial variables in real terms rather than in nominal terms because of some advantages. That is, variables expressed in real terms (e.g., real equity prices) have more direct information on real economic activities than variables expressed in nominal terms do (e.g., nominal equity prices).[6] Put differently, analyzing

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[3] Data are obtained at http://www.policyuncertainty.com/us_monthly.html.

[4] Selected economies are Australia, Chile, China, Japan, Korea, Mexico, Norway, Poland, Sweden, Switzerland, Turkey, United Kingdom, United States, Euro Area, Brazil, India, Indonesia, Russia, and South Africa. See Appendix for the commodity indices used in the exercise.

[5] We do not include pre-2000 data since financial markets of some emerging market economies experienced quite large fluctuations in 1990s.

[6] For example, see Cochrane (1991) for the link between economic activities and real stock returns.

variables in real terms improves comparability of financial variables denominated in different currencies. This point is particularly important for some emerging market economies that have experienced high inflation.

In the data series, we construct real equity prices by deflating a country's nominal equity index with its consumer price index.[7] As for exchange rates, we employ broad-based real effective exchange rate indices compiled by Bank for International Settlement (BIS). We obtain commodity indices by deflating nominal commodity indices with the US consumer price index. For all financial variables, we take a first-difference of log-level data to obtain returns. Following common practice, all variables are normalized before extracting factors by principal components analysis in the next section.[8]

2.3 Empirical analysis with FAVAR model

To analyze the spillover effects empirically, we employ a vector autoregression (VAR) approach. Since economic policy uncertainty and financial variables are expected to influence each other, it is appropriate to employ a VAR model and treat them as endogenous variables. Specifically, we employ factor-augmented VAR (FAVAR) developed by Bernanke et al. (2005).[9] FAVAR approach has some advantages compared with small-scale VAR models. First, while small-scale VAR models can accommodate only a limited number of variables due to "the curse of dimensionality," FAVAR models allow us to analyze a large number of variables. Importantly, by incorporating some variables omitted in small-scale VAR that potentially affect the system, FAVAR improves omitted variable biases. As Bernanke et al. (2005) report, FAVAR models often improve some implausible empirical results obtained by small-scale VAR such as price puzzle. FAVAR is widely used to gauge monetary policy effects, but its application to financial markets is limited.[10]

Our econometric framework is described by following equations. Let X_t be a vector of global financial variables. We assume that those financial variables are explained by a small set of unobservable factors F_t plus a vector of idiosyncratic noises u_t.

$$X_t = \Lambda F_t + u_t. \qquad (1)$$

[7] Nominal equity prices are obtained from the IMF's IFS database and price data are obtained from OECD database.
[8] The US economic policy uncertainty index is also normalized.
[9] For parameter estimations, they examined a two-step procedure and a joint estimation using likelihood-based Gibbs sampling techniques, and they reported that the two procedures produce similar results. In our research, we employ the two step procedure because of its computational simplicity.
[10] Claeys and Vasicek (2014) employs FAVAR to analyze the spillovers of sovereign bond markets in Europe.

Following Stock and Watson (2002), we employ the principal component approach to estimate the factors F_t in the factor model (1). In doing so, as done in Ang and Piazzesi (2003) or Fernald et al. (2014), we divide financial variables into categories above and extract the principal components from each group to get “commodity” factors, “exchange rate” factors and “equity” factors. This approach aids intuition by ensuring that each factor has a clear interpretation.[11] In the benchmark case, we utilize the first factors (first principal components) extracted from each category.[12]

Having obtained latent factors, we can estimate equation (2), a reduced form of factor-augmented vector autoregression system that incorporates the extracted financial factors F_t and economic policy uncertainty R_t. In estimating, we select the number of lag based on Akaike Information Criteria (AIC) and Schwarz information criterion (SIC).

$$\begin{bmatrix} R_t \\ F_t \end{bmatrix} = A(L) \begin{bmatrix} R_{t-1} \\ F_{t-1} \end{bmatrix} + \eta_t. \quad (2)$$

By multiplying factor-level impulse responses derived from (2) with the coefficients of factors in equation (1), we can set up impulse response functions of each selected variable X_t to structural shocks. For identification of shocks, we assume a recursive ordering, with the economic policy uncertainty R_t first, followed by the commodity factor, the exchange rate factor, and the equity factor.[13] That is, we assume that financial variables move endogenously in response to economic policy uncertainty within the month, but that financial variables affect economic policy uncertainty with a lag of one month or more.

2.4 FAVAR model results

2.4.1 Interpreting latent factors

We begin by interpreting latent factors extracted from the three categories of financial variables. Table 1, 2 and 3 report factor loadings as well as variance shares of the factors.[14] Figure 2 displays the latent factors, along with their cumulative changes. In the figure, it can be seen that the three factors are considerably correlated, as they show large decline around the global

[11] In Section 5, for the robustness check, we also consider the case in which factors are extracted from a single set of financial variables (i.e., not separately from each category).

[12] The results of country-level exercise presented in Section 4.3 may be affected by the number of factors included. Thus, in Section 5, for the robustness check, we examine the case in which second principal components are also included.

[13] The ordering of financial factors are based on the idea that commodity prices are most exogenous and equity prices are least exogenous among the three categories. However, results reported in the paper are robust to the choice of ordering.

[14] Table 1, 2, and 3 also report information on second factors (second principal components). Second principal components are used in the robustness check exercise in Section 5.

financial crisis. However, there is some heterogeneity exists among the three factors. For example, the equity factor exhibits a large decline in early 2000 reflecting the burst of the dot-com bubble. Such a decline is also observed in the commodity factor and the exchange rate factor but to a lesser extent. As for the commodity markets, the factor exhibits stronger recovery after global financial crisis, due to a surge in oil prices and other commodity prices. After that, the commodity factor and the exchange rate factor show a sharp decline since 2014. In the meanwhile, equity factor remains stable and shows only a limited decline.

2.4.2 Impulse response and variance decomposition

In accordance with the AIC and SIC lag selection criteria, we estimate the benchmark FAVAR model, which incorporates the extracted factors, with one month lag (Table 4). Figure 3 displays impulse responses of US economic policy uncertainty and the three financial factors to the structural shock that corresponds to a one standard deviation increase in US economic policy uncertainty. In all cases, a rise in economic policy uncertainty negatively affects the three factors of financial variables. Those impacts are statistically significant in the first and second month of the shock and diminish afterward.

Other than impulse response functions, another exercise typically performed in the VAR context is forecast error variance decomposition. Table 5 displays variance decomposition of economic policy uncertainty and the three factors. It shows that structural shock of economic policy uncertainty explains certain share of the variation in the three factors of financial variables. For example, as for equity price, innovations to economic policy uncertainty explain about 15 percent of the variance. Among the three factors, the commodity price factor exhibits a lesser degree of dependence on economic policy uncertainty, as economic policy uncertainty only explain about 5 percent of its variance.

2.4.3 Country level analysis: impacts on Asian and US financial markets

This sub-section describes the effects of economic policy uncertainty on each country. In particular, we focus on five large Asian economies (China, Japan, Korea, India, Indonesia) and the United States and explore heterogeneity of responses.

The left column of Table 6 reports selected countries' (indices') one-year cumulative impulse responses to economic policy uncertainty shocks by categories. As for equity price, an increase in US economic policy uncertainty adversely affects real equity returns. Among selected economies, however, China exhibits a smaller negative impulse response. As discussed later, Chinese equity market is mainly driven by an idiosyncratic factor, and US economic policy uncertainty does not play a critical role in determining prices.

Impulse responses of exchange rates are quite heterogeneous. Among selected economies, the majority of them, including Korea, India, Indonesia, exhibit depreciation. Among others, Japan and the US show a sizable appreciation. This reflects safe haven status of those currencies. That is, in uncertain phase, investors tend to avoid risky assets such as emerging market currencies and hold safer assets instead. In addition to those two currencies, China, whose nominal exchange rate is closely linked to US dollar, similarly shows some appreciation.

In addition to impulse responses, it is useful to explore the extent to which estimated latent factors explain financial variables. The right column of Table 6 reports R^2 of equation (1). R^2 of equation (1) indicates to which extent common factors explain each variable. Looking at median values of each sub-category, it suggests that common factors explain a sizeable fraction of equity prices and commodity prices as their median R^2 exceed 60%. In the meanwhile, as for REER, common factors only explain to a limited extent as its R^2 remains around 20%. This suggests that real effective exchange rates are driven by idiosyncratic components, which partly reflect varied exchange rate policies of emerging market economies.

A country breakdown highlights some heterogeneities. As for real equity prices, China exhibits quite low R^2. This reflects weaker linkage between the international equity markets and Chinese equity market, in which cross-border investment is restricted. Put differently, Chinese equity is mainly driven by an idiosyncratic factor. Among real effective exchange rates, Indonesia exhibits quite low R^2, indicating that it is mainly driven by an idiosyncratic factor. This reflects inflexible nature of the currency.

2.5 Robustness check:

2.5.1 Inclusion of second factors

Our benchmark specification in Section 2.4 utilizes first principal components extracted from each category to build FAVAR model. However, information not captured by the first principal components can make a change to the country-level results shown in Section 2.4. Thus, in this subsection, we conduct a robustness check by re-estimating FAVAR model utilizing the first and second principal components extracted from each category and compare country-level responses to one standard deviation increase in US economic policy uncertainty.[15] In estimating FAVAR model, we select lag of 1 based on AIC and SIC. For identification, we assume a recursive ordering; the economic policy uncertainty is positioned first followed by the first and second principal components of commodities, the first and second principal components of exchange rates, and the first and second principal components of equities.

The second left column of Table 7 displays country-level impulse responses to the structural

[15] Information on second principal components are reported in the right columns of Table 1, 2 and 3.

shock that corresponds to a one standard deviation increase in US economic policy uncertainty. The results look broadly similar to the results obtained from the benchmark FAVAR model in Section 2.4. Thus, our earlier results are largely robust to the inclusion of second principal components.

2.5.2 Pooled factor data

Our specification in Section 2.4 follows Ang and Piazzesi (2003) and Fernald et al. (2014) in extracting factors from indicator variables associated with each category (commodities, exchange rates, and equities). An advantage of this approach is that it gives a clear interpretation of factors because each factor represents information related to each corresponding categories. An alternative approach is to pool all of the indicator variables and estimate the latent factors of the model directly from this single set of indicators (Bernanke et al., 2005). This alternative approach possibly alters the results since factors extracted from pooled dataset may contain different information.

As a robustness check, we thus re-estimate benchmark FAVAR model based on this approach and compare country-level results. Specifically, we extract latent factors directly from the entire dataset by the principal component approach. To determine the number of factors, we employ IC_{p1} and IC_{p2} criteria proposed by Bai and Ng (2002). Since IC_{p1} indicates four factors and IC_{p2} indicates three factors, we examine both cases. For both the three-factor case and the four-factor case, we select lag of 1 based on AIC and SIC and assume a recursive ordering for the variables in which the economic policy uncertainty is positioned first followed by principal components (a first principal component is ordered first among principal components).

Right columns of Table 7 display country-level impulse responses to the structural shock that corresponds to a one standard deviation increase in US economic policy uncertainty. Those results look broadly similar to the results obtained from the benchmark FAVAR model in Section 2.4. Thus, our earlier results are largely robust to the choice of the methodologies for extracting factors.

2.6 Conclusion

To better understand how US economic policy uncertainty is transmitted to global financial markets, this chapter estimates the FAVAR model that incorporate economic policy uncertainty and global financial variables. Our empirical exercise shows that US economic policy uncertainty is an important driver of global financial markets. By extracting latent factors from the three categories (i.e., commodity, exchange rate, and equity), we find that the US economic policy uncertainty significantly affects those factors. Variance decomposition exercise also confirms that US economic policy uncertainty is an important source of fluctuations in financial markets.

Country-level impulse responses show some heterogeneity among selected economies. US economic policy uncertainty adversely affects real equity price. However, its impact on Chinese equity market is relatively small. As for exchange rates, US dollar, Japanese yen, and Chinese yuan appreciate in response to an increase in US economic policy uncertainty. On the other hand, other Asian currencies, as well as currencies of many emerging market economies, depreciate in response to an increase in US economic policy uncertainty.

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Figure 1. US Economic Policy Uncertainty index

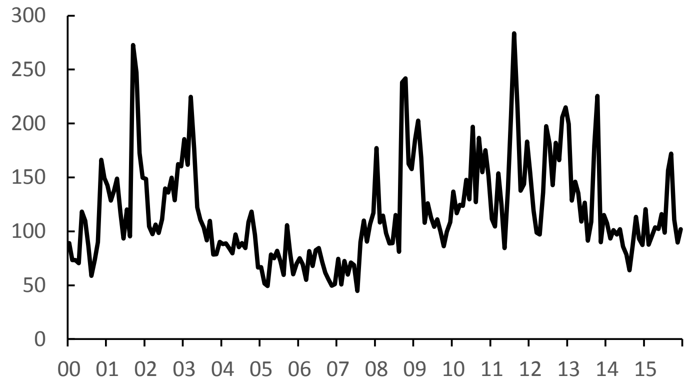
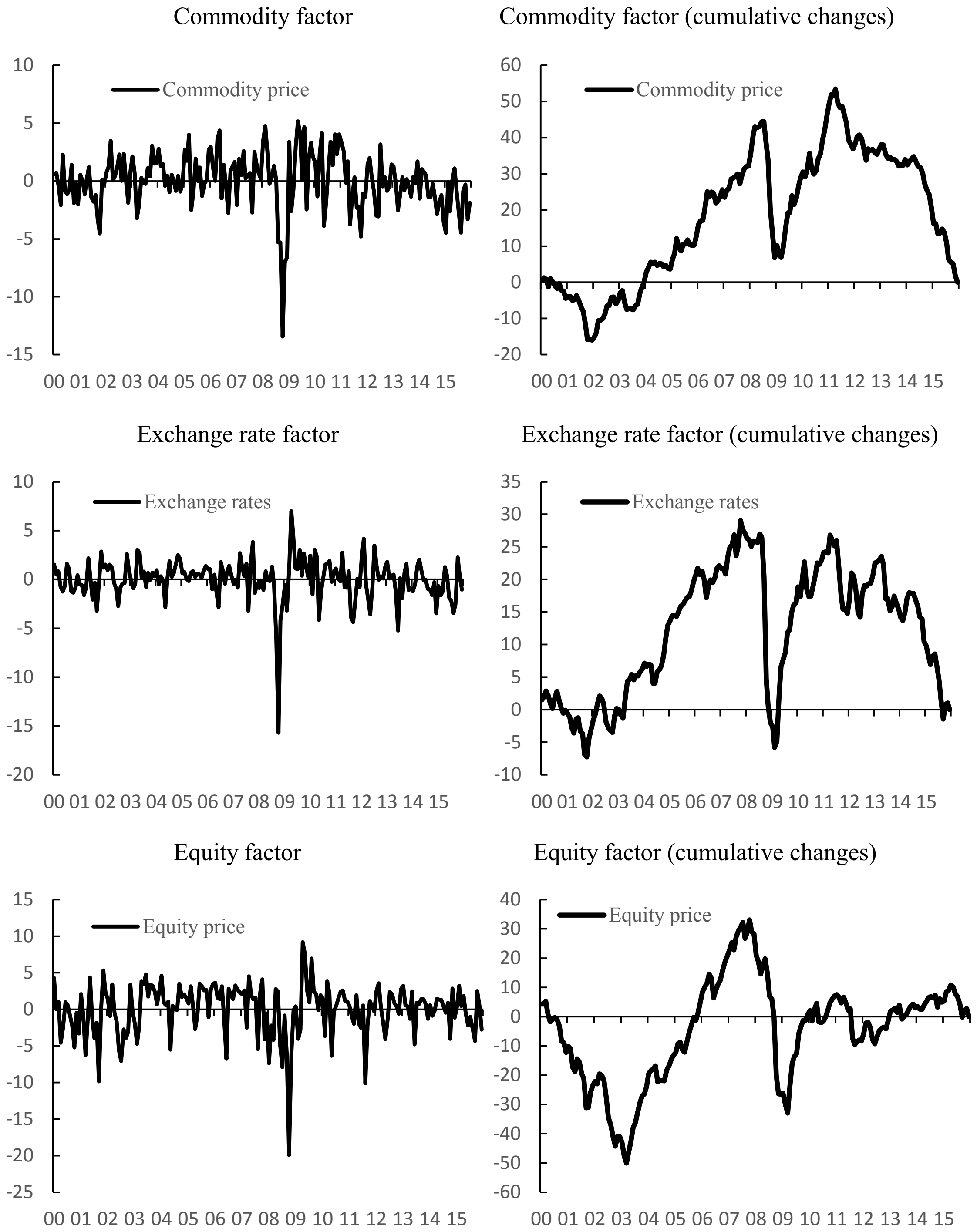
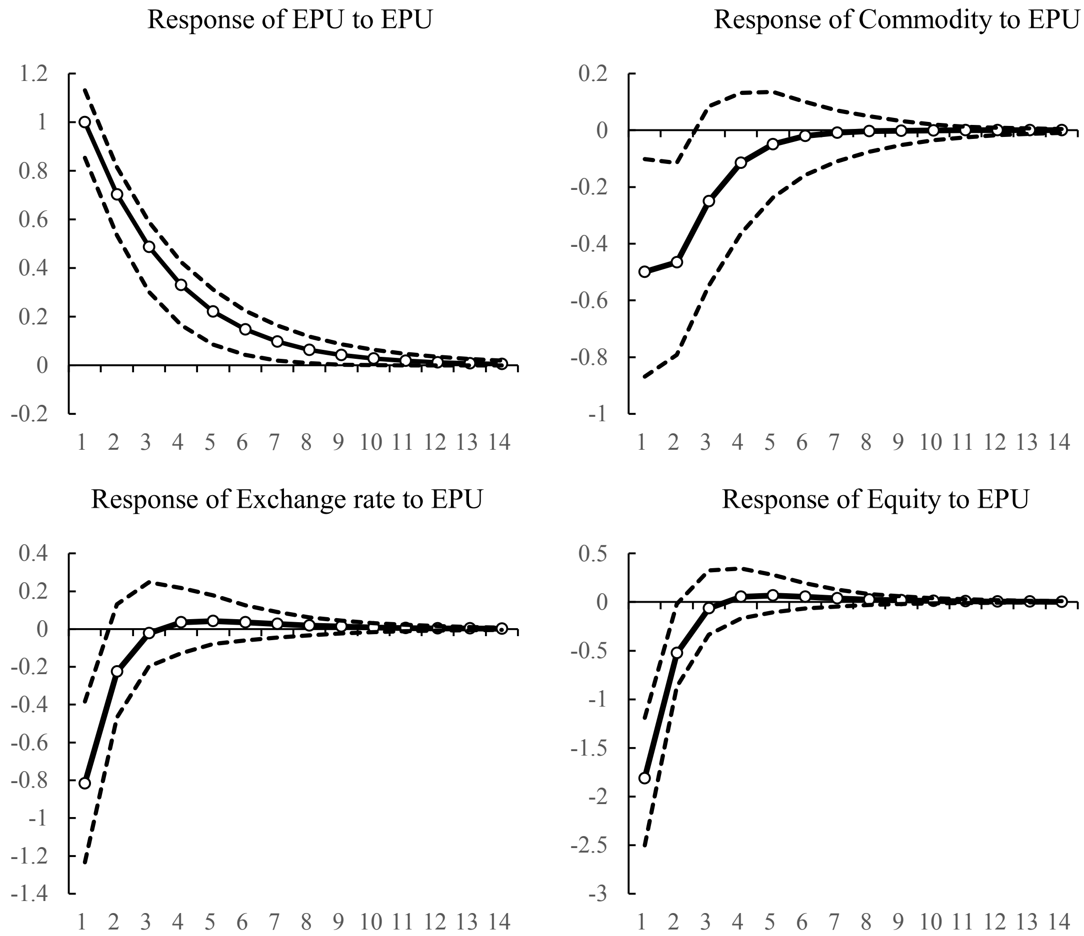


Figure 2. Estimated Factors



Note: The left panels display the first factors of each category. The right panels display their cumulative changes.

Figure 3. Impulse Responses of FAVAR model



Note: The figures display the impulse response functions of the factors to the structural shock that corresponds to a one standard deviation increase in US economic policy uncertainty (EPU). Dash lines indicate bootstrapped 90 percentile error bands around the point estimates. Periods are months.

Table 1. Factors extracted from commodity variables

Index	Factor loadings of 1st PC variance share: 0.702	Factor loadings of 2nd PC variance share: 0.149
all commodity price index	0.369	0.306
non-fuel price index	0.387	-0.238
food and beverage price index	0.303	-0.448
food price index;	0.294	-0.437
beverage price index	0.199	-0.269
industrial product index	0.350	0.012
agricultural raw material index	0.257	0.071
metals price index	0.325	-0.011
fuel price index.	0.321	0.431
crude oil price index	0.315	0.441

Table 2. Factors extracted from exchange rate variables

Index	Factor loadings of 1st PC variance share: 0.237	Factor loadings of 2nd PC variance share: 0.151
Australia	0.364	0.138
Brazil	0.312	-0.126
Chile	0.213	-0.096
China	-0.210	-0.418
Euro area	0.009	0.494
India	0.180	-0.294
Indonesia	0.136	-0.012
Japan	-0.228	0.186
Korea	0.322	-0.054
Mexico	0.349	-0.178
Norway	0.163	0.156
Poland	0.274	0.012
Russia	0.120	-0.158
South Africa	0.237	0.002
Sweden	0.190	0.247
Switzerland	-0.065	0.265
Turkey	0.217	-0.253
United Kingdom	0.019	-0.072
United States	-0.305	-0.362

Table 3. Factors extracted from equity variables

Index	Factor loadings of 1st PC variance share: 0.587	Factor loadings of 2nd PC variance share: 0.074
Australia	0.248	-0.126
Brazil	0.239	0.238
Chile	0.192	0.310
China	0.091	0.336
Euro area	0.263	-0.285
India	0.225	0.233
Indonesia	0.204	0.366
Japan	0.212	-0.216
Korea	0.235	0.112
Mexico	0.237	0.106
Norway	0.257	-0.010
Poland	0.236	0.037
Russia	0.198	0.277
South Africa	0.239	0.040
Sweden	0.254	-0.180
Switzerland	0.242	-0.386
Turkey	0.204	0.075
United Kingdom	0.257	-0.280
United States	0.264	-0.181

Table 4. Model selection criteria for FAVAR model

	1	2	3	4	5	6	7	8
AIC	3.86	3.91	3.94	3.96	4.02	4.07	4.16	4.16
SIC	4.22	4.54	4.85	5.16	5.50	5.83	6.20	6.48

Note: The table reports AIC and SIC values of the benchmark FAVAR model for each lag.

Table 5. Forecast error variance decomposition

US economic policy uncertainty

	US EPU	Commodity	Exchange rate	Equity
1	1.0000	0.0000	0.0000	0.0000
5	0.9682	0.0239	0.0057	0.0022
10	0.9653	0.0256	0.0069	0.0023

Commodity

	US EPU	Commodity	Exchange rate	Equity
1	0.0272	0.9728	0.0000	0.0000
5	0.0467	0.9010	0.0520	0.0003
10	0.0467	0.9008	0.0522	0.0003

Exchange rate

	US EPU	Commodity	Exchange rate	Equity
1	0.0882	0.2932	0.6186	0.0000
5	0.0799	0.2877	0.6299	0.0025
10	0.0802	0.2876	0.6298	0.0025

Equity

	EPU	Commodity	Exchange rate	Equity
1	0.1593	0.1515	0.3200	0.3692
5	0.1520	0.1405	0.3708	0.3368
10	0.1521	0.1404	0.3707	0.3367

Note: Tables show forecast error variance decompositions of US economic policy uncertainty (EPU) and the factors. Periods are months.

Table 6. Impulse responses to the economic policy uncertainty shocks

Category	Country	1-year cumulative responses	R^2
Equity price	Median of 19 economies	-0.50	0.667
	United States	-0.56	0.826
	China	-0.19	0.098
	Japan	-0.45	0.531
	Korea	-0.50	0.656
	India	-0.48	0.600
	Indonesia	-0.43	0.491
Exchange rate	Median of 19 economies	-0.16	0.204
	United States	0.27	0.421
	China	0.18	0.198
	Japan	0.20	0.235
	Korea	-0.28	0.468
	India	-0.16	0.146
	Indonesia	-0.12	0.083
Commodity price	All commodity index	-0.45	0.791
	Non-fuel index	-0.55	0.869
	Industrial inputs index	-0.49	0.712
	Food price index	-0.43	0.502
	Crude oil	-0.45	0.579

Note: 1-year cumulative responses to the structural shock that corresponds to a one standard deviation increase in US economic policy uncertainty (EPU). Figures are expressed in standard deviation. R^2 is for equation (1).

Table 7. Impulse responses to the economic policy uncertainty shocks

Category	Country	1-year cumulative responses: benchmark FAVAR model	1-year cumulative responses: FAVAR (second factors inclued)	1-year cumulative responses: FAVAR with three pooled factors	1-year cumulative responses: FAVAR with four pooled factors
Equity	Median of 19 economies	-0.50	-0.51	-0.46	-0.46
	United States	-0.56	-0.59	-0.51	-0.50
	China	-0.19	-0.17	-0.18	-0.18
	Japan	-0.45	-0.48	-0.50	-0.49
	Korea	-0.50	-0.51	-0.39	-0.39
	India	-0.48	-0.48	-0.38	-0.37
	Indonesia	-0.43	-0.42	-0.39	-0.39
Exchange rate	Median of 19 economies	-0.16	-0.18	-0.27	-0.27
	United States	0.27	0.14	0.22	0.22
	China	0.18	0.03	0.06	0.06
	Japan	0.20	0.30	0.42	0.42
	Korea	-0.28	-0.34	-0.46	-0.46
	India	-0.16	-0.30	-0.35	-0.34
	Indonesia	-0.12	-0.14	-0.12	-0.11
Commodity	All commodity index	-0.45	-0.48	-0.48	-0.49
	Non-fuel index	-0.55	-0.49	-0.53	-0.53
	Industrial inputs index	-0.49	-0.51	-0.54	-0.54
	Food price index	-0.43	-0.31	-0.33	-0.32
	Crude oil	-0.45	-0.57	-0.48	-0.50

Note: 1-year cumulative responses to the structural shock that corresponds to a one standard deviation increase in US economic policy uncertainty (EPU). Figures are expressed in standard deviation.

Appendix. Description of data

Category	Coverage	Sources
US economic policy uncertainty	News-based economic policy uncertainty index.	Backer, Bloom and Davis (2016)
Commodity	Real commodity prices: all commodity price index; non-fuel price index; food and beverage price index; food price index; beverage price index; industrial product index; agricultural raw material index; metals price index; fuel price index and crude oil price index.	International Monetary Fund (IMF), Organization for Economic Cooperation and Development (OECD)
Exchange rate	Real effective exchange rates (broad indices): Australia; Chile; China; Japan; Korea; Mexico; Norway; Poland; Sweden; Switzerland; Turkey; United Kingdom; United States; Euro Area; Brazil; India; Indonesia; Russia; and South Africa.	Bank for International Settlement (BIS)
Equity	Real equity prices: Australia; Chile; China; Japan; Korea; Mexico; Norway; Poland; Sweden; Switzerland; Turkey; United Kingdom; United States; Euro Area; Brazil; India; Indonesia; Russia; and South Africa.	International Monetary Fund (IMF), Organization for Economic Cooperation and Development (OECD)

Note: Real commodity prices are obtained by deflating nominal indices by US consumer price index. Real equity prices are obtained by deflating nominal equity prices with corresponding consumer price indices. Nominal data for commodity prices and equity prices are obtained from IMF. Consumer price indices are obtained from OECD.

Chapter 3:

Disentangling the nexus between the stock price and the oil price: a sign restriction approach

Abstract

This chapter proposes a simple approach that disentangles stock price and oil price movement. Employing a sign restriction vector auto regression, this chapter identifies economic news shocks, oil supply shocks, and monetary policy shocks observed in financial markets. In particular, by applying this approach to sample period where the US policy rate was at the zero lower bound, we examine the extent to which US unconventional monetary policy affect stock prices and oil prices. Our empirical exercise shows that unconventional monetary policy played an important role in boosting the stock price and oil price from 2009 to 2012. Further, we find that stock price and oil price divergence from 2013 to 2015 is driven by oil supply shocks.

Keywords:

Oil; Sign restriction VAR; Unconventional Monetary policy

JEL Classification Code: G15

3.1 Introduction

The relationship between stock prices and oil prices are actively investigated by economists. Employing a vector auto regression (VAR) model, Sadorsky (1999) found that positive shocks to oil prices depress real stock returns. He also found that oil price movements explain a larger fraction of the forecast error variance in real stock returns than do interest rates. Kilian and Park (2009) showed that the reaction of US real stock returns to an oil price shock differs depending on whether the change in the price of oil is driven by demand or supply shocks in the oil market. They analyzed that shocks to the production of crude oil are less important for understanding changes in stock prices than shocks to the global aggregate demand for industrial commodities or shocks to the precautionary demand for oil that reflect uncertainty about future oil supply shortfalls.

A recent literature argues the importance of monetary policy on stock prices and oil prices. Anzuini et al. (2013) analyzed the relationship between commodity prices and US monetary policy by employing VAR system with the data from January 1970 to December 2008. They found that conventional monetary policy easing pushes commodity prices up, while its effect is not overwhelmingly large. Although increasing number of research investigates the role of monetary policy in determining commodity prices, there is limited research that sheds light on the effect of recent unconventional monetary policy on commodity prices. Ratti and Vespignani (2013) showed that unanticipated increases in real global M2 led to statistically significant increases in real oil prices. Specifically, they argued that the historical impact of real global M2 on the real price of crude oil is important in the recovery of oil prices over 2009 to 2011.

In this chapter, we aim to investigate underlying factors that define fluctuation of stock prices and oil prices. In particular, we focus on data from 2008 to 2015, where the US policy rate hit zero lower bound, and shed light on the effects of news shocks, monetary policy shocks and oil shocks on stock prices and oil prices.

The novelty of our research is two-folds. First, this chapter incorporates a monetary policy effect in analyzing the nexus between stock prices and oil prices. In particular, this chapter sheds the lights on the effects of unconventional monetary policies, which have been actively conducted after global financial crisis, on stock prices and oil prices. To gauge monetary policy stance under zero lower bound environment, we employ long-term US treasury yield. Second, this chapter employs a novel sign restriction VAR. A sign restriction approach allows us to extract structural shocks consistent with economic theories directly. While this approach is widely used for analyzing monetary policies, its applications on analyzing oil prices or financial market, in general, are limited[16].

[16] Kilian and Murphy (2012) demonstrate that sign restrictions alone are insufficient to infer the responses of the real price of oil to demand and supply shocks. Unlike their research, however, our empirical research focuses on market data.

Our empirical exercise shows that unconventional monetary policy played an important role in boosting the stock price and oil price from 2009 to 2012. Further, we also find that oil supply shocks drive stock price and oil price divergence from 2013 to 2015.

The paper proceeds as follows. Section 3.2 explores data set we employ for an empirical exercise. Section 3.3 delves into the link between the oil price and the stock price using a bivariate sign restriction VAR. Section 3.4 extends base models and identify news shock, oil supply shocks, and monetary policy shocks. Section 3.5 concludes.

3.2 Dataset

This section explains data we employ for empirical research and explores the correlation between stock returns and oil price returns. As our research purpose is to delve into the comovement between stock price and oil price, this chapter employs weekly data of nominal return of S&P 500 index, a nominal return of West Texas Intermediate (WTI) oil prices.[17] In addition to these variables, we include a variable that gauges stance of unconventional monetary policy, as the impact of unconventional monetary policy on stock price and oil price is main research interest.

A critical part of our empirical exercise is a choice of the measurement of unconventional monetary policy stance. Unlike conventional monetary policy which uses a policy rate as the main policy instrument, there is no clear measure for unconventional policies. Gambacorta et al. (2014), for example, employs central banks' balance sheet size to gauge accommodativeness of unconventional monetary policy. However, this metric does not fit our empirical research, as current asset prices are determined in a forward looking manner, reflecting expected future path of central banks' balance sheet size. Thus, this chapter employs an alternative measure of unconventional monetary policy, namely 10-year US Treasury bond yield, which is often employed as a metric of unconventional monetary policy (Rogers et al., 2014; Matheson and Stavrev, 2014). 10-year US Treasury bond yield reflects expected the future path of the policy rate and associated term premium, therefore works as a forward looking measurement of unconventional monetary policy stance. For example, Rogers et al. (2014) found that consecutive introductions of unconventional monetary policy lowered 10-year US Treasury bond yield mainly through compression of term premium. Matheson and Stavrev (2014), employing a sign restriction VAR, examined the effects of monetary shock on 10-year US Treasury bond yield during the period where federal reserve policy rate was subject to zero lower bound.

With regard to sample period, we focus on the period in which the policy rate hit zero lower bound. Following Gambacorta et al. (2014), we use data from January 2008 to December 2015[18]. While much

[17] We employ log first difference for return computation.
[18] Gambacorta et al (2014) analyzes the effectiveness of unconventional monetary policy using data from January 2008. We extend the sample period only to December 2015 as US monetary policy has normalized since then.

previous research employs monthly data (Kilian, 2009; Killian and Park, 2009), we utilize weekly data since all variables employed in this chapter are readily observed at a higher frequency in financial markets. This allows us to address the problem of relatively short sample periods. Summary of data is displayed in Table 1.

3.2.1 The link between stock prices and oil prices

As Creti et al. (2013) and Lombardi and Ravazzollo (2016) argue, the correlation between stock returns and oil returns is not stable. Figure 1 shows a simple 1-year rolling correlation coefficient between US stock returns and oil returns during the sample period. It exhibits relatively high correlation from mid-2010 to 2012 and relatively low correlation after 2012. Different underlying factors drive such varied correlations. For example, negative correlation between stock price and oil price can be attributed to oil supply shock (i.e. positive surprise of oil production), which adversely affect oil prices and positively affect stock prices. Conversely, a positive correlation can be attributed to shocks that drive stock price and oil price in same directions.

To delve into underlying factors of comovement, we employ VAR models that allow us to identify underlying shocks that affect stock prices. In the following sections, we first examine the simple bivariate model, which comprises of stock prices and oil prices. Further, in Section 3.4, we extend our empirical exercise to the three-variable case and investigate the effect of unconventional monetary policy shock on the nexus between stock prices and oil prices.

3.3 Sign restriction VAR: bivariate model

This section disentangles nexus between oil prices and stock prices with a simple bivariate VAR model. Our empirical approach are based on sign restriction VAR model, following the approach developed by Uhlig (2005). The idea of sign restriction VAR is to identify structural shocks using some robust properties of the model, such as the sign of impulse responses discussed in the previous section, without imposing on the data the whole structure of the theoretical model, i.e., allowing for some degree of “model uncertainty." Sign restriction allows structural shocks to affect all variables simultaneously and therefore it fits our empirical exercise, whose data are all taken from the financial market and therefore have fast-moving nature. Widely employed recursive identification does not fit our empirical exercise as it limits some contemporaneous effects of structural shocks on variables.

3.3.1 A bivariate model

In this subsection, we consider a simple bivariate model as discussed in Kilian and Park (2009). Specifically, the following reduced-form VAR system is estimated:

$Y_t = c + A(L)\, Y_{t-1} + e_t$ (1)

where c is a vector of intercepts, Y_t is a vector of two endogenous variables, a nominal stock return and a nominal oil return, A(L) is a matrix of autoregressive coefficients of the lagged values of Y_t and e_t is a vector of residuals. In this model, the reduced-form error terms are related to the structural errors u_t according to:

$e_t = B^{\sim} u_t$ (2)

In the above, $B^{\sim} = BD$, where B is a Cholesky decomposition matrix of covariance matrix Σ_{et} and D is an arbitrary orthonormal matrix. In this case, $B^{\sim} B^{\sim\prime} = \Sigma_{et}$ also holds.

For parameter estimation, we employ commonly used Bayesian approach developed by Banbura (2010) and applied by many empirical papers (Alessandri and Mumutaz, 2017 and Kapetanios et al., 2012).[19] We apply the lag order of 4 weeks as suggested by Akaike Information Criteria (AIC).

For identification of structural shocks, we impose sign restrictions on responses. As displayed in Table 2, we set up two structural shocks. The first shock is demand shock, which is associated with positive economic news and boost stock prices by strengthening the expected future profitability of firms. Likewise, it also contributes to higher oil price by increasing the demand for oil. The other shock is oil supply shock. We postulate that a negative oil supply shock (i.e. negative surprise in oil production) undermines economic activities, dampening stock prices (Killian, 2008 and Kilian, 2009). In the meanwhile, we assume that this shock contributes to higher oil price through tighter supply demand balance of oil.

For N-variable VAR, the sign restriction procedure consists of following four steps.

1) Take a random draw, (A^*, Σ^*_{et}) from the posterior of the reduced form VAR parameters, and compute the N×N matrix B^* by applying lower-triangular Cholesky decomposition to $\Sigma^*_{et.}$

2) Draw N×N matrix K of normally and independent (0,1) random variables. Derive the QR decomposition of K such that $K = Q' R$, where R is an upper triangular matrix, and Q is orthonormal matrix $Q'Q = I_{n.}$

3) Let $D = Q'$. Derive impulse responses from $A^*$and $B^{\sim} \equiv B^*D$. If all implied impulse responses satisfy the sign restrictions, retain the model. Otherwise discard the model.

4) Repeat the first three steps a large number of times, recording the models that satisfy the sign

[19] Following Alessandri and Mumutaz (2017), we set the hyperparameter λ, which represents the tightness of the prior on the VAR coefficients, equals to 0.1. Likewise hyperparamerter τ, which represents the tightness of sum of coefficients prior, is set as τ=10λ. We set hyperparameter c, the tightness of the constant terms, equals to 1/1000, indicating a flat prior on constant.

restrictions (and the corresponding impulse response functions).

The loop ends if 3,000 admissible models are found. As for time horizon of restrictions, we impose sign restriction only on the first period, as we are more agnostic on dynamic responses of variables[20].

3.3.2 Empirical results: bivariate model

In this subsection, we report empirical results of the bivariate model discussed above. We first report the impulse responses produced by the sign restriction identification. Figure 2 displays median (solid line), and the 16th and the 84th percentiles (dashed lines) of the distribution of impulse responses over 11 weeks. The effects of a positive demand shock, normalized to 1 percent increase in stock, are displayed in the first column of Figure 2. The shock increases the oil price by nearly 2 percent, and most of the effects materialize contemporaneously. The effects of a positive oil supply shock, normalized to yield a 1 percent decrease in oil price, are displayed in the second column. Its impact on stock price is relatively small compared with oil price.

In addition to impulse responses, we analyze the contribution of the different structural shocks to fluctuations in stock prices and oil prices by performing a variance decomposition analysis. Table 3 reports the median of the variance decomposition at horizons up to 8 weeks[21] and the left columns report drivers of stock price fluctuations. It shows that demand shock works as the main driver of stock prices, accounting for more than 70 percent of fluctuation. The right columns show drivers of oil price fluctuations. While demand shock also explains the majority of oil price fluctuation, oil supply shock exhibits larger share compared with that observed in stock prices, accounting for one-third of total fluctuations.

3.4 Sign restriction VAR: three-variable model

In Section 3.3, we have analyzed the drivers of stock prices and oil prices with a simple bivariate model. We find that demand shocks play a larger role in both stock price and oil price fluctuations. Identification employed in Section 3.3, however, does not shed light on the source of demand shocks. In particular, it is important to investigate to what extent unconventional monetary policies taken by Federal Reserve in the sample period affect stock prices and oil prices. Given this, this section attempts to investigate the source of demand shocks. Specifically, we extend the bivariate model to a three-variable model by adding the change in 10-year US Treasury yields and identify unconventional monetary policy shocks.

[20] Unlike Kilian and Murphy (2012), we do not impose any restrictions on the size of responses as we are agnostic about that.
[21] Results for longer horizon are very similar to that of 8 weeks.

3.4.1 Shock identification

As for estimation methodologies, we follow methodologies employed in Section 3 and impose sign restriction only on the first period as done in Section 3. Table 4 displays three structural shocks identified by sign restrictions approaches: news shock; monetary policy shock; and oil supply shock. A news shock reflects the change in expected future total factor productivity as discussed in Beaudry et al. (2006). A positive news shock --- an increase in expected total factor productivity --- boosts current stock prices and oil prices as they are priced in a forward looking manner.[22] The positive news shock also increases 10-year government bond yield (Matheson and Stavrev, 2014).

The second shock is a monetary policy shock. A negative monetary policy shock raises 10-year US treasury government bond yield as the tighter stance of unconventional monetary policy widens term premium or raises expected the path of future policy rates. We postulate that stock prices and oil prices decline in response to this shock as tightening of monetary policy is expected to increase discount rates and dampen economic activities. As for oil prices, US dollar appreciation in response to the tighter monetary policy may also contribute to a decline in oil price (Zhang et al., 2008[23]). This monetary policy shock is considered to represent an unconventional monetary policy shock as this shock is identified based on 10-year US Treasury yield, which is used a gauge for unconventional monetary policy stance as previously discussed, and the policy rate is subject to zero lower bound in the sample period.

The third shock we consider is oil supply shock. We postulate that a negative oil supply shock increases oil price by tightening oil supply demand conditions. In the meanwhile, as the negative oil supply shock undermines economic activities, it dampens stock prices (Killian, 2008 and Kilian, 2009). As for US Treasury yield, we postulate that the negative oil supply shock leads to increase in interest rate, putting some inflationary pressure.

In Section 3, a demand shock, which moves the stock price and the oil price to the same direction, has been identified. However, it was not clear to what extent monetary policy contributed to the demand shock. Importantly, this three-variable model identifies two different shocks that move the stock price and the oil price to the same direction. In particular, in next subsections, we investigate the effects of a monetary policy shock on the stock prices and the oil prices.

[22] Given that crude oil is storable, it is priced not only by current supply and demand balance but also by future information.

[23] Zhang et al (2008) found that the influence of US dollar exchange rate on the international crude oil market proves quite significant in the long term. However, they also pointed out short-term influence of exchange rate on oil price is limited.

3.4.2 Impulse response and variance decomposition

We first reported the median (solid line), and the 16th and the 84th percentiles (dashed lines) of the distribution of impulse responses produced by the identification discussed previously for each variable over 10 weeks.

Since we already impose sign restrictions to all structural shocks, in this subsection, we analyze the size of effects of structural shocks comparing results obtained in Section 3. The effects of a positive news shock, normalized to 1 percent increase in stock, are displayed in the first column of Figure 3. The shock increases the oil price by 1 percent and interest rate by four basis points, and those effects materialize within first three weeks. The second column displays the effects of a positive monetary policy shock normalized to 1 percent increase in stock price. The monetary policy shock exhibits stronger impact on oil price compared with news shock, increasing oil price by 4 percent points. The effects of a positive oil supply shock, normalized to yield a 1 percent decrease in oil price, are displayed in the third column. Its impact on the stock price is relatively smaller compared with that observed in the oil price.

Comparison of those shocks with the demand shock identified in Section 3 provides an interesting observation. With the bivariate model in Section 3, we find that the demand shock exerts stronger effects on oil price. The results obtained in subsection suggest that this stronger effect of demand shock is attributed to monetary policy shock, rather than news shock.

We analyze the contribution of the different structural shocks to fluctuations in stock prices, oil prices and interest rates by performing a variance decomposition analysis. Table 5 reports the median of the variance decomposition at horizons up to 8 weeks and the first three columns report drivers of stock price fluctuations. It shows that demand shock works as the main driver of stock prices, accounting for more than 70 percent of fluctuation. The monetary shock also accounts for about 10 percent of the stock price variance, suggesting that unconventional monetary policy stance plays some role in stock price determination. The second three columns show drivers of oil supply fluctuations. In addition to oil supply shock, the monetary shocks play an important role, accounting for more than 40 percent of the oil price variance.

3.4.3. Historical Decomposition

In addition to impulse responses and a forecast error decomposition exercise, we conduct historical decomposition analysis. A historical decomposition provides a structural interpretation for those historical episodes characterized by the major fluctuation of oil price. Specifically, we focus on following two episodes: the oil price boom from 2009 to 2012; and the oil price collapse from 2013 to 2015. Figure 4 displays the historical decomposition of the stock price time series and that of the oil price from 2009 to 2012, which highlights the contribution of each structural shock to deviations of the variables from the trend. During this period, both the stock price and the oil price appreciated, and they exhibited relatively high correlation. It shows that positive news shocks largely drive stock price rally from 2009 to mid-2010. In addition to news shocks, an unconventional monetary policy largely contributed to stock price appreciation from late-2010 to 2012, following the announcement of further quantitative easing in November 2010. As for oil price, both news shock and oil supply shock supported oil price recovery from 2009 to mid-2010. From mid-2010, however, further oil price appreciation is mainly driven by unconventional monetary policy shocks while the effect of positive news shock is diminished.

Figure 5 displays the historical decompositions from 2013 to 2015. During this period, US stock price and oil price exhibited weak comovement. The left panel shows that the stock price rally in this period is supported by positive news shock and positive oil supply shock, which is partly generated by expansion of tight oil production in the US. In the meanwhile, negative monetary shock exerted downward pressure on the stock price, especially from late 2014, partly offsetting those two shock. The right panel shows corresponding historical decomposition of the oil price. The largest contribution of oil price decline is attributed to positive oil supply shocks, which exerts downward pressure on the oil price by loosening supply condition of the oil market. In addition to positive oil supply shocks, negative monetary shocks contribute to falling in oil price, and its cumulative contribution offsets that of positive news shocks.

To summarize, two important observations are found here. First, empirical exercise suggests that relatively high correlation from 2009 to 2012 is brought not only by positive news shocks but also by positive monetary shocks; in particular, positive monetary shocks, which reflect Fed's unconventional monetary policy stance, generate relatively high comovements from late-2010 to 2012. Second, weak (or even negative) comovement from 2013 to 2015 is mainly caused by positive oil supply shock. News shocks and monetary shocks, which contribute to comovement in the earlier period, offset each other and thereby weakening comovement.

3.5 Conclusion

This chapter has proposed new methodologies that disentangle the underlying shocks of stock price and oil price movement. First, by employing a bivariate sign restriction VAR, we identify demand shock and supply shock on stock prices and oil prices. Further, in Section 4, we extended our empirical model to three-variable model and examine economic news shock, oil supply shock, and monetary policy shock observed in financial markets. In particular, by applying this approach to zero lower bound period, we examine the extent to which US unconventional monetary policy affect stock prices and oil prices. Our empirical exercise shows that the unconventional monetary policy played an important role in boosting the stock price and oil price from 2009 to 2012. Further, we find that oil supply shocks drive stock price and oil price divergence from 2013 to 2015.

This chapter has an important implication from a portfolio risk management perspective. As mentioned previously, stock prices and oil prices have exhibited unstable correlation, posing difficulties to portfolio risk management. Our identification methodologies shed light to underlying shocks, which contributes to comovement (or divergence) among stock prices and oil prices.

This chapter also contributes to spillover studies. In particular, this chapter sheds light on the effect of US unconventional monetary policy on oil prices. This has an important implication for spillover of such policies to oil-exporting countries and oil-importing countries through the terms-of-trade channel.

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Figure 1: 1-year rolling correlation coefficient between US stock price and oil price

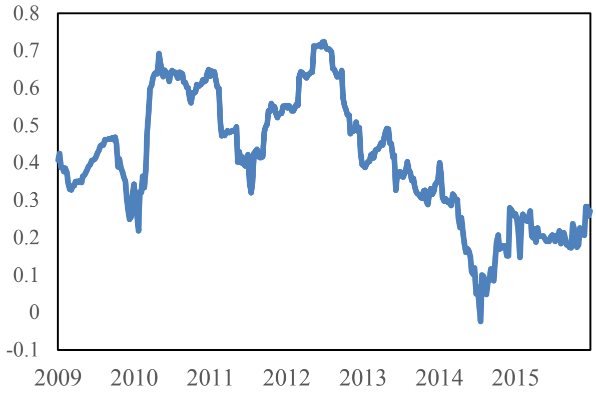
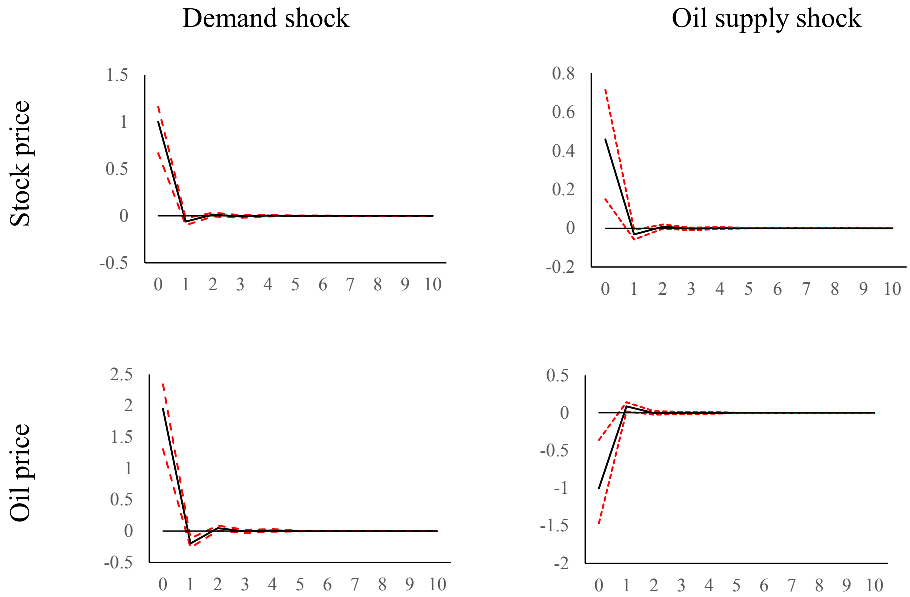
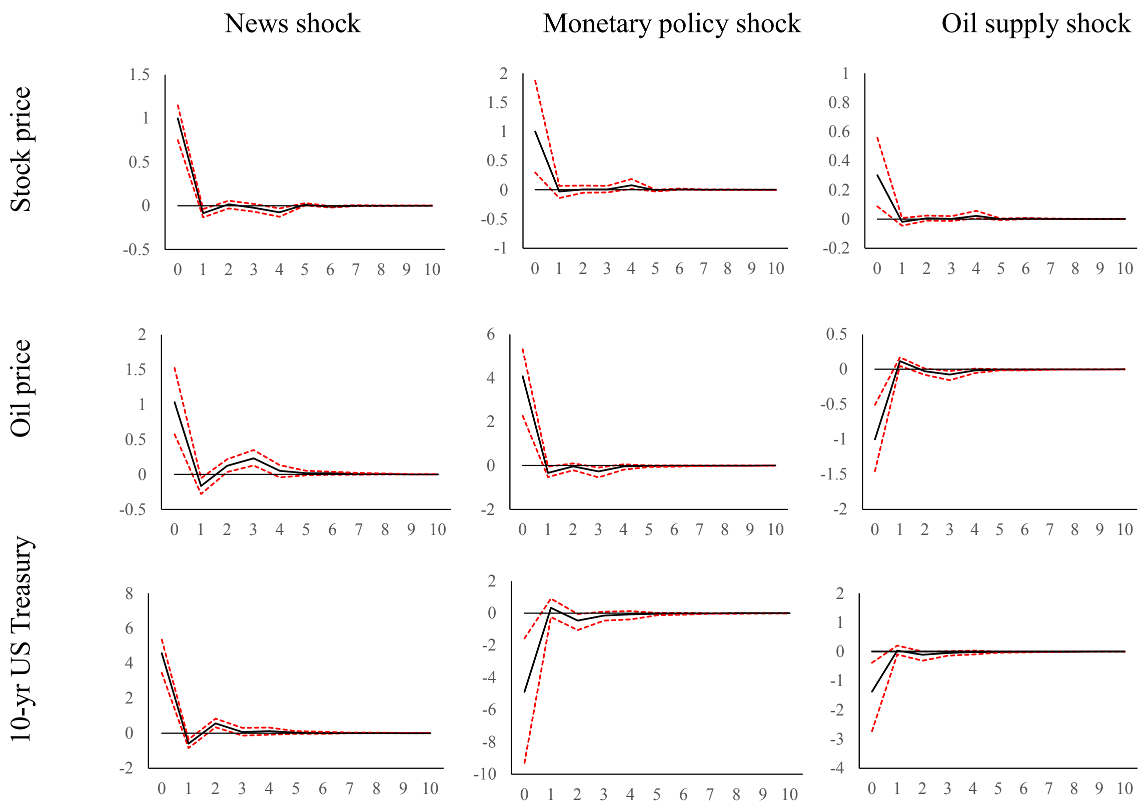


Figure 2: **Impulse response of structural shocks: bivariate model**



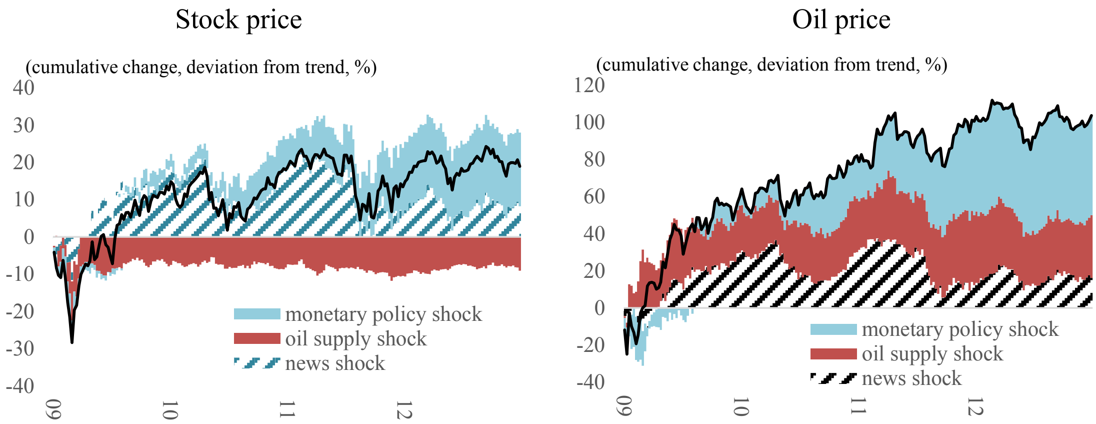
The figure shows median responses and 16th and 84th percentile responses at each time period.

Figure 3: Impulse response of structural shocks



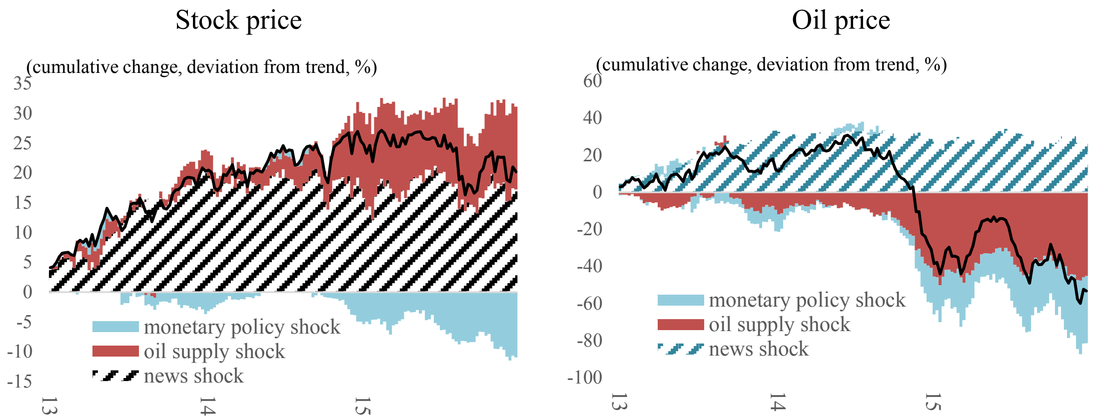
The figure shows median responses and 16th and 84th percentile responses at each time period. 10-year US Treasury yield is presented in basis points.

Figure 4: Historical decomposition from 2009 to 2012



The figure shows median values of historical decompositions observed in each period.

Figure 5: Historical decomposition from 2013 to 2015



The figure shows median values of historical decompositions observed in each period.

Table 1: Description of data

	Mean	Median	Standard Deviation	Skewness	Kurtosis	ADF test
Stock	0.07748	0.20954	2.76905	-0.9170824	7.877838	-6.4884***
Oil	-0.2273	0.1462	5.433694	-0.8671925	6.367156	-4.6657***
10-year UST yield	-0.004402	-0.015000	0.1321279	0.1550803	0.7881844	-6.9705***

Note: In the table, *** denotes 1% significant level. ADF tests are performed with 10 lags.

Table 2: Sign restriction used for identification: bivariate model

	demand shock	Oil supply shock
Stock	+	+
Oil	+	-

Table 3: Forecast error variance decomposition: bivariate model

	Stock price		Oil price	
	Demand shock	Oil supply Shock	Demand Shock	Oil supply Shock
0	0.721	0.279	0.667	0.333
4	0.721	0.279	0.669	0.331
8	0.721	0.279	0.669	0.331

Table 4: Sign restriction used for identification: three-variable model

	News shock	Monetary policy shock	Oil supply shock
Stock	+	+	+
Oil	+	+	-
10-year UST yield	+	-	-

Table 5: Forecast error variance decomposition: three-variable model

	Stock price			Oil price		
	News shock	Monetary policy Shock	Oil supply shock	News Shock	Monetary policy shock	Oil supply shock
0	0.763	0.113	0.124	0.191	0.465	0.344
4	0.763	0.113	0.124	0.202	0.458	0.340
8	0.761	0.113	0.126	0.211	0.451	0.338