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Abstract

We investigate the time-varying dynamics of global stock market volatility, commodity prices, domestic output and consumer prices. We find (i) stock market volatility and commodity price shocks impact each other and the economy in a gradual and endogenous adjustment process, (ii) impact of commodity price shock on global stock market volatility is significant during global financial crises, (iii) effects of global stock market volatility on the US output are amplified by endogenous commodity price responses, (iv) effects of global stock market volatility shocks on the economy are heterogeneous across nations and relatively larger in twelve developed countries, (v) four developing/small economies are more vulnerable to commodity price shocks.

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Global Commodity Prices and Global Stock Market Volatility Shocks: Effects across Countries

1. Introduction

Starting with Blanchard (1981) and Chiarella et al. (2009), it has been realized that financial market interaction with the real sector is the foundation of macroeconomic instability and is crucially important in influencing output and employment. Over the last twenty years, we have witnessed extraordinary shifts in global stock market volatility and in global commodity prices, particularly during the global financial crisis. Stock market volatility and commodity price shocks are expected to impact each other and to affect the macroeconomy. A growing body of literature has shown that higher global uncertainty, reflected in stock market volatility and other measures, depresses economic activity (Campbell et al., 2001; Guo, 2002; Dungey et al., 2007; Clements and Fry, 2008; Moshirian, 2011; Vu, 2015; and Choudhry et al., 2016). The literature has also established links between commodity prices and the real economy and asset markets (Kilian and Park, 2009; Sly, 2016; Bouri et al., 2017; Kang et al., 2017a, 2020; Stuermer, 2017; Choi et al., 2018; Dreschel and Tenreyro, 2018; Fernández et al., 2018; Ornelas and Mauad, 2019). Shocks to commodity prices raise global stock market volatility and result in a drop in the output and sharp increases in consumer prices. Shocks to global stock market volatility depress output as well as consumer and commodity prices. In this paper, we develop the hypothesis that the effects of global stock market volatility on the economy are amplified by the endogenous commodity price responses.

The link between stock price returns and commodity prices is well established in empirical literature. Chiarella et al. (2016) showed that stock return volatility is positively related to gold future prices and negatively related to oil price futures. Kilian and Park (2009) reported that demand and supply global oil shocks jointly account for up to 22% of the variation in the US real stock returns. Kang et al. (2016) showed that the US oil production has a positive effect on the US stock market and argue that both demand and supply oil shocks are important in explaining the US real stock returns. Lee and Ni (2002) connected oil price shocks with an increase in profits for the petroleum and chemicals industries, while there was a decrease in profit of the durable goods industries in the US. In examing the driving forces of international business cycles, Crucini et al. (2011) revealed a signficant common factor in oil prices, productivity, and the terms of trade.

In this paper, we contribute to the literature to create both global commodity price index and global stock market volatility index for 16 economies. Second, we incoporate the exogeneous shocks to global commodity prices in the structural model that is traditionally used to examine the nexus of uncertainty and stock returns in the existing literature. The time-varying parameter Structural Vector Auregression (SVAR) model allows the time variation deriving both from the regression coefficients and the elements of variance covariance matrix, which presents the advantage in investigating changes in the variance of the structural innovations in the global stock market volatility/commodity prices over time and changes in the transmission of the global volatility/price shocks to real output over time.

Our results show that shocks to global stock market volatility result in negative effects on US output, US inflation and global commodity prices. Shocks to commodity prices raise global stock market volatility and cause a drop in the output and a sharp rise in consumer prices. The cumulative effects of global stock market volatility and commodity shocks on output and consumer prices are largest during a global financial crisis. The effects of shocks to global commodity prices on US output and consumer prices are larger than the effects of shocks on global stock market volatility. Stock market volatility and commodity prices impact the economy in a gradual adjustment process and give rise to a strong, endogenous propagation mechanism that involves output and consumer prices. In the long run, shocks to commodity prices account for 11.9% and 25.1% of the variation in US industrial production and consumer prices. Shocks to global stock market volatility account for 6.6% and 11.6% of the variation in US industrial production and consumer prices. Commodity price shocks forecast there will be 32.5% variation in consumer prices at the 3-month horizon. Innovation to commodity prices predict 10.5% variation in global stock market volatility. The effect of global stock market volatility and commodity price shocks have increased over time with largest response happening during the global financial crisis.

The impact of global stock market volatility shocks are heterogeneous across economies and relatively larger in twelve developed countries over long periods of time. Four developing/small economies are comparatively more vulnerable if undergoing commodity shocks. The dates of well-known events that were followed by increases in the global stock market volatility coincide mostly with events that trigger large movements in commodity prices. During the 2008-2009 global financial crisis, the responses of output and price levels to the commodity price shocks were enhanced with the global stock market volatility found across nations. Here, we introduce a notion, which is supported by empirical evidence, that global commodity prices and the US economy interact with global stock market volatility as a measure of global uncertainty.

This paper is structured as follows. Section 2 introduces the theory and presents the hypothesis development. Section 3 describes the SVAR model and explains the estimation methodology. Section 4 presents the data and discusses the impulse response analysis of the estimated model. Section 5 concludes. The data sources and Markov chain Monte Carlo (MCMC) algorithm are presented in the Appendix A1.

2. Literature Review and Hypothesis Development

The model proposed by Blanchard (1981) extends Keynesian IS-LM analysis to emphasize the interaction between asset values and output. The share price dynamics feed back on the real output using the assumption that investment/consumption demand (I) varies with Tobin's average (Q), rather than the real rate of interest. Blanchard (1981) assumes that there are three main determinants of aggregate spending (d): the stock market value (q), income (y) and the index of fiscal policy (g); that is $d = \alpha q + \beta y + g$, where the coefficients $\alpha > 0$ and $0 \leq \beta < 1$. Define the speed of output adjustment $k_y > 0$, the output adjusts to changes in spending according to $\dot{y} = k_y(d - y)$, where $\dot{y}$ denotes the time derivative of y. The stock market adjusts to excess demand for stocks $\dot{q} = k_q(\epsilon - \bar{\epsilon}) \cdot (\epsilon - \bar{\epsilon})$, where $k_q > 0$ is the rate of stock market adjustment to excess demand for stocks, $\epsilon = (x + \alpha_0 + \alpha_1 y)/q - i$ the instantaneous differetial between returns on shares and returns on short-term bonds with the coefficient $\alpha_1 \geq 0$. Here, we define x as the instantaneous expected change in the value of the stock market and assume the existence of a long-run constant equity premium ($\bar{\epsilon}$). We assume the formation of expectations about the expected change in the value of the stock market , $\dot{x} = k_x(\dot{q} - x)$, where $k_x > 0$ denotes the rate of revisions in expectations.

One key assumption in Blanchard's (1981) model is $k_q = \infty$ and $k_x = \infty$, a definite law of motion for q and x. The dynamic law is temporarily switched off at the starting time when a shock occurs. However, Chiarella et al. (2009) argues that the reaction coefficient k_q changes as a function of market conditions.[1] A gradual adjustment of stock prices and output, instead of leaps to a more stable path, results in the endogenous propagation mechanism and fluctations in stock prices and outputs. This is based on the notion that agents become more cautious as they expect a change in the market regime and when a larger return differential occurs. The agents initially react along with the movement in the stock market, however, they react increasingly cautiously to the return differential as the economy moves futher from its steady state. In the model, the short-term interest rate (i) plays an indirect role that determines the Tobin's average (Q) on the stock market from the assumption that LM equilibrium is in the asset market; that is $i = cy - h(m - p)$, where the coefficients $c > 0$ and $h > 0$, m and p the logarithms of nominal money and prices, respectively. A summary of the dynamics of the stock market, interest rate and output is $y \to i \to q \to I \to y$ for a given price level, where I is the investment (see Chapter 2 in Chiarella et al., 2009).

In contrast, the theory of irreversible choice under uncertainty argues that uncertainty reduces the response of investment to demand shocks (e.g., Abel and Eberly, 1996; Bloom, 2009; Alfaro et al., 2018). As uncertainty heightens, so does the increased stock market volatility which in turn raises the cost of equity capital because of increased external financial frictions and potentially reduces investment, stock value and real output. It implies that the stock market volatility, as a forward-looking indicator, reflects

[1] Previous literature that argues $k_q \neq \infty$ includes Beja and Goldman (1980) and Damodaran (1993).

uncertainty for future cash flows and discount rates that drive up the compensation that shareholders demand for bearing systematic risk (see Campbell et al., 2001 and Guo, 2002).

Over recent years the literature regarding the relationships between commodity prices and stock market activity has grown quite large (see Kilian and Park (2009), Johnson and Soenen (2009), Creti et al. (2013), Chiarella et al. (2016), and Kang et al. (2017, 2020), Stuermer (2017), Choi et al. (2018), Dreschel and Tenreyro (2018), Ornelas and Mauad (2019), among others). These analyses indicate that commodity price shocks and stock market volatilities are interrelated and influence the real economic activity. Consistent with arguments made by Dungey et al. (2007) and Moshirian (2011), international equity markets are contagious in that shocks to the U.S. stock market volatility were associated with a sharp rise in the price of crude oil during the 2008-2009 global financial crisis (see Kang et al. (2016)).

Policymakers pay attention to the commodity price shocks and their potential to feed inflation pressures (Clements and Fry, 2008; Creti et al., 2013). Positive oil-market specific demand shocks may lower the real GDP and raise consumer prices (Kilian, 2009). Oil supply and demand shocks cause a rise in the policy-related economic uncertainty (Kang et al., 2017b). We build on the set of literature and examine the following hypothesis:

Hypothesis: (i) A gradual adjustment of stock prices and output, instead of leaps to stable paths, causes endogenous propagation mechanism and fluctation in stock prices and real output. (ii) The effects of stock prices on the output are amplified by the endogenous commodity price responses, and shocks to commodity prices cause an increase in the global stock market volatility and a decrease in the output.

Our hypotheses incoporate the exogeneous shocks to global commodity prices in the SVAR model that is traditionally used to examine the nexus of uncertainty and stock returns in the existing literature. We predict that the positively underlying effect of global commodity prices on the global stock market volatility gives rise to a strong endogenous propagation mechanism and causes the fluctuation in both stock prices and the output. To test the above hypothesis, we create both global commodity price index and global stock market volatility index for twelve developed countries and four developing economies.

Kang et al. (2020) found that the global stock market volatility Granger-causes the U.S. stock market volatility and has a more persistent effect on the economy. Additionally, we consider the stock market volatility measure based on findings in Campbell et al. (2001), which argues that the predictive power of the stock market volatility for the future output is stronger. The intuition is that the stock market volatility presents a forward-looking indicator, which is implicitly weighted toward the effects of different sources of uncertainty on the stock value (see Bloom et al., 2007). Furthermore, Hamilton and Lin (1996) and Campbell et al. (2001) argue that stock market volatility is related to the economic structure change. This motivated us to investigate how the stock market volatility depresses the real output in a model that utilizes time-varying parameters. Similar to Walsh (2016), we introduce the index of commodity prices to solve the price puzzle --- a funds rate shock causing increases in the price level that are the result of an absence of inflation-sensitive prices in the SVAR system.

3. The Empirical Model

Our empirical model consists of a SVAR model with time-varying parameters. Although our study is focused on different variables, the specification of the reduced-form time-varying parameter (SVAR) follows closely to those in Primiceri (2005) and Del Negro and Primiceri (2015) as follows:

$$y_t = z_t \beta_t + u_t, \tag{1}$$

where $u_t \sim iid.N(0, H_t)$. The y_t is a $m \times 1$ vector of endogenous variables, $z_t = (c_t, y_{t-1}, \dots, y_{t-p})$ and denotes a $m \times (p+1)$ matrix of p lags of the endogenous variables with a constant term c_t, and $\beta_t = (\beta_{0,t}, \beta_{1,t}, \dots, \beta_{p,t})'$ stands for the $(p+1) \times m$ matrix of the time-varying regression coefficients.

In the analysis, $y_t = (\Delta IP_t^i, \Delta CP_t^g, \Delta CPI_t^i, \Delta IR_t^i, SV_t^g)'$ includes both country-specific (i) and global (g) varibles, where IP_t denotes the log of industrial production, CP_t refers to the log of commodity price index, CPI_t stands for the log of consumer price index, IR_t represents the short-term interest rates, and SV_t is the global stock market volatility at time t. We take the lags $p = 12$ to allow for the potentially long-delayed effects of stock market volatility shocks on the economy and to mitigate the possible serial correlation issues. As reported in previous studies, the greatest effect of uncertainty on real activity is expected to occur with a delay of about one year (e.g., Hamilton (2008) and Bloom (2009)).

The time variation of specification (1) deriving both from the regression coefficients and the elements of variance covariance matrix allows us to investigate changes in the variance of the structural shocks in the global stock market volatility/commodity prices over time and in the transmission of the global volatility/price shocks to real output over time. The global stock market volatility captures the global systematic risk for securities listed in the world stock markets that is generated by a variety of sources across countries. It is expected to have potentially larger implication for the economic growth than the idiosyncratic risk in individual nations. As the literature shows, regarding the relationship between commodity prices and the stock market activity, we investigate how commodity price shocks and stock market volatilities are interrelated and influence the real economic activity based on the specification (1).

We assume that the reduced-form innovations u_t are a linear transformation of the underlying structural shocks ε_t given by[2]

$$u_t = A_t^{-1}\Sigma_t\varepsilon_t, \tag{2}$$

where $\varepsilon_t \sim iid.N(0, I_m)$ such that $H_t = A_t^{-1}\Sigma_t\Sigma_t^{-1}(A_t^{-1})'$. The A_t is a lower triangular matrix, in which the non-zero and non-one elements may be stacked by rows into a $m \times (m-1)/2$ vector as $a_t = (a'_{21,t}, a'_{31,t}, a'_{32,t}, \dots, a'_{m(m-1),t})'$. The Σ_t is a diagonal matrix, in which the non-zero elements may be stacked into a m-vector, as $ln\sigma_t = (ln\sigma_{1t}, \dots, ln\sigma_{mt})'$ in their natural logarithm form. The law of motion for the time-varying parameters, β_t, a_t and $ln\sigma_t$, evolve over-time as the random walk process

$$\mathrm{\beta_{t+1}} = \mathrm{\beta_t} + \mathrm{\mu_t}, \tag{3}$$

$$a_{t+1} = a_t + \mathrm{\nu_t}, \tag{4}$$

$$\mathrm{ln\sigma_{t+1}} = \mathrm{ln\sigma_t} + \mathrm{\eta_t}, \tag{5}$$

where $\mathrm{\mu_t}$, $\mathrm{\nu_t}$ and $\mathrm{\eta_t}$ are white noise Gaussian processes with zero mean and constant covariance matrices, Q, W and S, respectively. We assume that the error terms ϵ_t, μ_t, ν_t and η_t are independent and are mutually uncorrelated at all leads and lags. The limiting

[2] It implies that the structural form of Equation (1) is $y_t = z_t\beta_t + A_t^{-1}\Sigma_t\varepsilon_t$.

case of the system (1) - (5) is a constant coefficient VAR model by postulating Q, W and S being zeros.

The identification of the stock market volatility shock is inspired by the strategy proposed in Chiarella et al. (2009), while the ordering of endogenous variables follows Gali and Gambetti (2015). We utilize Cholesky decomposition to orthogonalize the residuals and assume that stock prices respond instantaneously to all structural shocks in the system. We assume that the stock market volatility shock does not affect industrial production, commodity prices, inflation and interest rates contemporaneously within a month. Short-term interest rates respond immediately to own shocks and shocks to industrial production, commodity prices and inflation, but only with (at minimum) a one-month delay to innovations in stock prices. Shocks to commodity prices are assumed to cause inflation within a month. While own shocks, and shocks to industrial production have simultaneous effects on the price level, the industrial production does not respond contemporaneously to innovations in the price level, given the sluggishness of real activity.

To compute the impulse response functions, we rewrite Equation (1) as

$$\tilde{y}_t = \tilde{c}_t + \tilde{\beta}_t \tilde{y}_{t-1} + \tilde{u}_t, \tag{6}$$

where $\tilde{y}_t = (y_t', y_{t-1}', \dots, y_{t-p+1}')'$, $\tilde{u}_t = (u_t', 0, \dots, 0)'$, $\tilde{c}_t = (c_{t,0}', 0, \dots, 0)'$, and the matrix of regression coefficients $\tilde{\beta}_t$. Define $B_{t,k} = (\tilde{\beta}_t^k)_{m\times m}$ the first $m \times m$ submatrix of $\tilde{\beta}_t^k$ for the forecasting horizons $k = 1,2, \dots$ and $B_{t,0} = I$. The dynamic responses of the endogenous variables in y_t to the unit structural stock market volatility shock $\varepsilon_{m,t}$ at time t are given by $\partial y_t / \partial \varepsilon_{m,t} = B_{t,k}[A_t^{-1}\Sigma_t]_m$, where $[Z]_m$ denotes the m-column of Z.

We utilize Bayesian methods to estimate the SVAR model with time-varying parameters. In the Bayesian analysis, we use the first 120 observations over 10 years to calibrate the key prior hyper-parameters at time 0: $\beta_0 \sim N(\hat{\beta}_0, m(p+1) \times \hat{V}_\beta)$, $\ln(\sigma_0) \sim N(\ln(\hat{\sigma}_0), I_m)$, and $a_0 \sim N(\hat{a}_0, m(m-1) \times \hat{V}_a)$. The calibration of $\hat{\beta}_0$ and $\hat{V}_\beta$ is obtained from the conditional maximum likelihood estimates (MLE) of the regression coefficients and the elements of their variance-covariance matrix of the time-invariant SVAR model, respectively. The specification of $\hat{\sigma}_0$, $\hat{a}_0$ and $\hat{V}_a$ is drawn from the decomposition of time-invariant error variance-covariance matrix $H = A^{-1}\Sigma\Sigma'(A^{-1})'$. We utilize Wishart distribution priors $Q^{-1} \sim W(v_Q, V_Q^{-1})$, where $v_Q = m(p+1)+1$ and $V_Q = 0.05 \times m(p+1) \times I_{m(p+1)}$, $W^{-1} \sim W(v_w, V_w^{-1})$, where $v_w = m+1$ and $V_Q = 0.0001 \times m \times I_m$, and $S^{-1} \sim W(v_s, V_s^{-1})$, where $v_s = m(m-1)+1$ and $V_s = 0.01 \times m(m-1) \times I_{m(m-1)}$, for the constant variance-covariance matrices of the innovations in the Equations (3), (4) and (5), respectively.

Our model estimation is based on the Monte Carlo simulation of the joint posterior density $p(\beta^T, \sigma^T, a^T, Q, W, S|y^T)$ obtained from the combination of the prior distribution and the likelihood function of a T-sample. To calculate the impulse response functions of the variables to a structural shock at time t, we run the MCMC algorithm executed 22,000 times with the first 20,000 draws discarded as burn-in iterates (see Appendix C for more details). This Gibbs sampling algorithm follows closely to the sampling algorithm used in Primiceri (2005) and Primiceri and Del Negro (2015), described in the Appendix.

4. Data and the Empirical Evidence

We obtain the monthly commodity price indices of energy, non-energy and precious metals from the Pink Sheet of World Bank Commodity Price Data.[3] The energy index covers coal, crude oil and natural gas prices. The non-energy commodity price index includes metals, agriculture, and fertilizer prices. The precious metal index contains gold, silver, and platinum prices. To construct the global commodity price index, we took the simple average of energy, non-energy and precious metal indices as equal weights are routinely used in the construction of commodity price index (e.g., Kilian, 2009).

This study follows Kang et al. (2020) to construct a global stock market volatility index that is given by the first principal component of stock market volatility of the largest 16 economies (data description and sources can be found in Appendix A).[4] The countries are Australia, Brazil, Canada, China, France, India, Italy, Ireland, Japan, Mexico, Netherlands, Russia, South Korea, Spain, United Kingdom (UK) and the United Sates (US).[5] The index provides a forward-looking indicator that is implicitly weighted in accordance with the impact of different sources of uncertainty across major nations on equity value. In Appendix B, the global stock market volatility index is shown, which illustrates the primary global uncertainty events.

$R_{c,t}$ is the difference of the natural log of the stock market index of country c, $R_{c,t} = \ln{(s_{ct}/s_{ct-1})}$, where s_{ct} denotes the average monthly stock price of a country c at time t, with $t = 1,2 \dots, T$. We first center on the means of $R_{c,t}$, based on the data matrix

[3] The monthly commodity price indices are available beginning in January 1960. The energy index is the weighted average of coal (4.7), crude oil (84.6) and natural gas prices (10.8). The non-energy index is the weighted average of metals (31.6), agriculture (64.9), and fertilizer prices (3.6), where the agriculture covers beverages, food, raw materials, cereals, fats & oils, and other food. The precious metal index is the weighted average of gold (77.8), silver (18.9), and the platinum prices (3.3).
[4] The largest 16 economies are measured based on the 2013 gross domestic product (based on purchase power parity). Note that this first principal component accounts for around 40% of the data variation.
[5] Because of data limitations, we exclude Indonesia, Iran, Thailand, Nigeria and Poland from the G20 economies.

with $R_{c,t}$ for the 16 largest economies and T samples; that is $V_{c,t} = (R_{c,t} - \bar{R}_c)^2$, where $V_{c,t}$ is the stock market volatility of country c at time t, and $\bar{R}_c$ is the sample average of $R_{c,t}$. The first principal component for the global stock market volatility SV_t^g is given by the linear combination of all 16 volatility indices $V_{Australia,t}, V_{Brazil,t}, \ldots, V_{US,t}$; that is $SV_t^g = a_1 V_{Australia,t} + a_2 V_{Brazil,t} + \cdots + a_{16} V_{US,t}$, where SV_t^g is calculated such that it accounts for the greatest possible variance in the data set. The weights (a_i) are the elements of an eigenvector that has a unit length and is standardized by the unity restriction of $a_1^2 + a_2^2 + \cdots + a_{16}^2 = 1$. The construction of global stock market volatility index closely follows that in Kang et al. (2020), whereas data definition, source and period availability of stock market index, industrial production, and the consumer price index for each country are reported in the Appendix.[6]

4.1. Responses of US variables to global stock market volatility shocks

In this subsection, we report the cumulative impulse response of the US variables to global stock market volatility shocks generated by our estimated SVAR models, both with constant and time-varying parameters. The cumulative responses present the dynamic effects of the differenced variables of industrial production, commodity price index and consumer price index, in terms of their levels.

4.1.1. Constant parameters

[6] Note that data on the stock market is not available for all countries from 1981. The index is constructed with data on the countries for which data are available. A shortcoming of this approach is that for the earlier period, missing data is more apparent for developing countries. Nevertheless, we argue that this is not a problem, given that in the first part of the sample (1980-1995), the relative weight of developed economies in the global economy is more important than in the more recent period (following China's unprecedented growth starting in the mid-1990s). The availability of stock market data for each country is reported in the Appendix.

We first focused on the estimated responses of industrial production, commodity price index, consumer price index, and short-term interest rate to global stock market volatility shocks and used one-standard error bands drawn from 2000 Bootstrapping samples. Results (in the last column of Figure 1) are based on the estimated SVAR, with constant coefficients for the US over the 1981:M1-2014:M12 period. An unexpected innovation to global stock market volatility caused statistically significant negative effects on US industrial production in the time between the 3rd and 13th months. Note that the terms global stock market volatility and global (stock) uncertainty are used interchangeably in this manuscript.

The responses of the commodity price index are mostly negative and statistically significant within a year. The decline in commodity prices to a shock to uncertainty is notable in the first year and then gradually declines. A shock to global stock market volatility causes the consumer price index to fall lower and this effect is statistically significant beginning in the first month. This result suggests that a one-time shock to the global volatility has a negative long-term effect on the consumer price level that is statistically significant. The response in the US short-term interest rate to an unexpected rise in global stock market volatility is statistically significant and negative in the time between the 3rd and 12th months.

The percent contributions of one-standard deviation structural shocks to the overall variability of the endogenous variables are presented in Table 1. The forecast error variance decomposition is shown at 1, 3, 12, 24 and 60-horizons. The values in parentheses represent the absolute t-statistics that are based on 2000 bootstrap samples. In the long run, shocks to global stock market volatility contribute to 6.6%, 10.5% and 11.6% of the variation in

US industrial production, commodity prices and the US consumer price index, respectively. These effects are statistically significant at the 5% level (at the 60 month horizon, reported in the last column of Table 1).

4.1.2. Time-varying parameters

We now turn to results of the SVAR model, which uses time-varying coefficients. Figure 2.1 shows the evolution of the median for cumulative responses (of variables) to the global stock market volatility shock at the 1st, 3rd, 12th and 60th month over 1981:M1-2014:M12. The response of US industrial production to a unit shock to global uncertainty, indicated by a global stock market volatility shock, is greatest during the global financial crisis, with most of the negative effects occurring after 12 months and persisting for 60 months. The effect of global stock market volatility shocks on US industrial production at the 12- and 60-month horizons increased over time until the global financial crisis. The response of US CPI to the global stock market volatility shock shows most of the negative effect occurring after 3 months and persisting for 60 months. The effect of the unit global stock market volatility shocks on US CPI at the 3-month horizon increased until the global financial crisis period. The largest effect of the global volatility on the interest rate had a delay of around 5 years. In the period of 1981:M1-2014:M12, US output, inflation and interest rate had the greatest responses (for variables) to the global stock market volatility shocks in the 2005 to 2009 period.

The response of commodity prices to the global stock market volatility shock occurs after three months and increased until the global financial crisis. The divergence between the effect of a shock to global stock market volatility and commodity prices, at the 3-month and 60-month horizons has increased over time. The implication is that in the last half of the sample, the decline in commodity prices in the first three months following a shock to global stock market volatility is greater and then erodes more in subsequent months than in the first half of the sample.

In summary, shocks to the global stock market volatility have a negative effect on US production, inflation, interest rates, and commodity prices. The responses of the variables to the global stock market volatility shock is often gradual and takes time for the responses to reach its maximum. The most dramatic effects occurred in the 2005-2009 period and were particularly acute during the global financial crisis. The negative effect on US output was relatively small until the mid-1990s, with much of the effects occurring within 12 months. The changing response of the consumer price index shows an increased negative effect from the global volatility shock from 1980s to 2000s, especially at the 3-month horizon. Much of the cumulative negative effect on the consumer price index happened within the 3-month horizon and this effect then persisted. Unexpected shocks to global stock market volatility caused a relatively larger negative effect on the interest rate during the 2000s. Shocks to global stock market volatility normally result in sharp declines in global commodity prices within 3 months, an effect that increases in magnitude over time. The effect on commodity prices is then eroded within a year.

These results provide us with supporting evidence that the stock market impacts the economy in a gradual adjustment process, which in turn gives rise to a strong endogenous propagation mechanism and causes fluctuation in both stock prices and the output (Chiarella et al, 2009). We find that the relationship between the stock market dynamics and the US macro-economy appear to be changing over time. The changing responses of production and inflation to the global stock market volatility shocks showed stronger effects during the global financial crisis.

4.2. Responses of US variables to commodity price shocks

In this subsection, we report the cumulative impulse responses to commodity price shocks generated by models with constant and time-varying parameters. Results for the constant parameter SVAR model are shown in the diagrams in Column 2 of Figure 1. An unanticipated positive innovation in commodity prices was found to associate with a negative effect on US industrial production and this association is statistically significant after 6 months. The effect is persistent and remains statistically significant through the horizon of 60 months. A positive shock to commodity prices initiates a significant increase in the consumer price index immediately and the effect continues over the 60-month forecasting horizon. The findings that a shock to commodity prices has persistent and statistically significant effect on US production and prices is striking. In contrast, an innovation in commodity prices does not have a statistically significant effect on the short-term interest.

The impacts of an unanticipated rise in commodity prices on global stock market volatility are shown in the last row and second column of Figure 1. The positive response in global stock market volatility is statistically significant beginning in the 6th month and this effect persists over the 60 months forecasting horizon. Shocks to commodity prices clearly impact and increase global stock market volatility.

The forecast error variance decomposition results in Table 1 suggest that in the long run, shocks to commodity prices account for 11.9%, 25.1% and 5.7% of the variation of industrial production, consumer price index and global stock market volatility, respectively.

Commodity price shocks forecast 32.5% of the variation consumer prices at the 3-month horizon. These effects are statistically significant in Table 1.

During the 2008-2009 global financial crisis (as shown in Figure 2.2), shocks to commodity prices caused a dramatic rise in the global stock market volatility and a sharp decline in the US industrial production at the forecasting horizons of 12 and 60 months. The near-proximity of the cumulative responses during the 12th and 60th months for industrial production and for global stock market volatility confirms the persistent effects on output and global stock market volatility from commodity price shocks that occur after the first few months. The impact of a commodity price shock on global stock market volatility was far greater during the global financial crisis than at other times (at the forecasting horizons of 12 and 60 months). These results suggest that the effects of global stock market volatility on the US output are amplified by the endogenous commodity price responses.

The effect of a commodity price shock on consumer prices at the 60-month horizon was largest in the late 1990s, however, at the 1 and 3-month horizons, the effect was largest in the mid-2000s. Prior to the year 2000, a positive shock to commodity prices had positive effects on consumer prices that accumulated over time. Between 2006-2009, a period of maximum impact at the 1 and 3-month horizons, the near full extent of the effect of commodity price shocks on consumer prices was achieved in the first month.

Figure 2.2 shows that the estimated dynamic responses of industrial production, interest rate and the global stock market volatility are unstable and gradually increase over time and the impulse responses of consumer prices are relatively stable over time. The changing responses of US variables to commodity price shocks show a different pattern from the responses to the global stock market volatility shocks.

4.3. Heterogeneous impact of global stock market volatility/commodity price shocks on the economy across countries

In this subsection, we investigate the heterogeneous impact of the global stock market volatility/commodity price shocks on the output and price level of major countries that include four developing (Brazil, China, India, Russia) and twelve developed countries (Australia, Canada, France, Germany, Ireland, Italy, Japan, Korea, Netherland, Spain, UK, US).

Table 2 reports the percent contributions of structural shocks to commodity prices/global stock market volatility and to the output and price levels across countries. These data are based on the SVAR model with constant coefficients and 2000 bootstrap samples.[7] Over time, the forecast error variance decomposition indicates that shocks to commodity prices account for a statistically significant variation in industrial production (at the 5% level) in 9 countries: Australia, Brazil, France, India, Italy, Japan, Korea, Russia and the UK. This shock also explains a statistically significant variation in the consumer price index in 10 countries: Canada, France, Germany, India, Ireland, Italy, Korea, Netherland, Spain, and the UK.[8] Shocks to global stock market volatility account for a statistically significant variation in industrial production (at the 5% level) in 4 countries: Brazil, Italy, Korea, and Russia. This shock explains the variation in the consumer price index measured in France, India, Ireland that was significant over time.

[7] The forecast at the 1st month is around zero across countries and is omitted for the exposition purpose.
[8] It is acknowledged that the significance is marginal for India.

In terms of magnitude, shocks to commodity prices account for 13.5% of the variation in industrial production in India and 14.1% of the variation in the consumer price index in France, respectively. The cumulative response of output and price levels to the commodity price shocks in India and France (at the 12th month) in Figure 3 reveal a drop during the 2008-2009 global financial crisis. A unit shock to commodity prices causes 25% decreases in the industrial production in India in 12 months, around October 2008 for example.[9]

Shocks to global stock market volatility account for 16% of the variation in industrial production in Brazil and 15.5% of the variation in consumer price index in Ireland in the long run, respectively. During the 2008-2009 global financial crisis, the negative response of output and price levels to the commodity price shocks in Brazil and Ireland at the 12th month (in Figure 3) decreases. A unit shock to global stock market volatility results in 10% reduction in the consumer price index for Ireland in 12 months, around October 2008 in particular.[10]

In summary, both shocks to global commodity prices and stock market volatility show heterogeneous effects on the output and price level in general. Commodity price shocks present broader effects on the economy across countries than do shocks to the global stock market volatility. A significant global stock market volatility shock is always associated with a significant commodity shock on the output/price level. Developing/small economies such as Brazil, India and Russia are more vulnerable to commodity shocks. In

[9] During the 2008-2009 global financial crisis, the responses of output and price levels to the commodity price shocks also decrease across other countries as shown in Figure 3.

[10] The responses of output and price levels to the global stock market volatility shocks also show a drop across other countries during the 2008-2009 global financial crisis, as shown in Figure 3.

the long run, the effects of global stock market volatility shocks on the economy are larger in developed countries such as Italy, Korea and the US. During the 2008-2009 global financial crisis, the responses to output and price levels to the commodity price shocks are enhanced with the global stock market volatility across countries.

5. A Robustness Check and Brief Literature Reconciliation

We conduct the robustness check to show that we obtain similar results of impulse response functions when we perform some variations on the analysis with respect to the lag length and the ordering of the SVAR model with time-varying parameters. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) show that the optimal lags are 3 and 1 in Model (1) respectively. In Figure 4, we present the cumulative responses of industrial production (IP), consumer price index (CPI), and short-term interest rate (IR) to the structural shocks in the US at the 12th month when we choose 3 lags in the model. The result in Figure 4 is qualitatively similar to that in Figure 2, in the sense that the responses of IP, CPI and IR are negative to the global uncertainty shock, whereas the responses of CPI are positive to the global commodity price innovations for example. When the global stock market volatility variable is ordered first in the Model, we obtain very similar results as shown in Figure 2. Given the standard nature of the AIC and BIC tests, we use the long lag of 12 as do in the prior literature in our main analysis, because even some variables that do not show inertia do not necessarily show absence of long lags in regressions on other variables (see Hamilton, 2008; Bloom, 2009; Kilian, 2009).

Existing literature documents that greater uncertainty reflected in the stock volatility depresses economic activity (e.g., Bloom, 2009), higher commodity prices reduce the real economy and dive the inflation up (see Kilian and Park, 2009), and bigger news innovations produce the price continuation longer in the stock market (e.g., Kothari et al., 2006). Asset pricing model argues that stock prices react immediately to news shocks, and the reaction would be temporarily switched off at the starting time when a shock occurs in an efficient market (for example, Blanchard, 1981; Campbell, 1991). In line with Chiarella et al. (2009), we present that the reaction of stock market prices changes as a function of market conditions driven by the exogenous global commodity price innovations.

6. Conclusion

Building on the insightful empirical work of Chiarella et al. (2009) and the theoretical framework of Blanchard (1981), this paper investigates the time-varying dynamics of global stock market volatility, commodity prices, and domestic output and consumer prices across 16 countries. Our results indicate that shocks to global stock market volatility have negative effects on commodity prices that are statistically significant in the first year. Shocks to global commodity prices have positive effects on global stock market volatility that are statistically significant and persistent. During the global financial crisis, shocks to commodity prices caused a dramatic rise in the global stock market volatility and a sharp decline in the US industrial production. Prior to 2000, a positive shock to commodity price had positive effects on consumer prices that accumulated over time. The effects of global stock market volatility on the US output are amplified by the endogenous commodity price responses. Shocks to commodity prices cause large fluctuations in both output and the interest rates over time. While four developing/small economies in our sample are relatively more vulnerable to commodity shocks, the effects of global stock market volatility shocks on the economy, over time, are heterogeneous across nations and relatively larger in twelve developed countries.

These results provide us with supporting evidence on the hypothesis that the stock market impacts the economy in a gradual adjustment process, while the positive effect of global commodity prices on the global stock market volatility in turn gives rise to a strong endogenous propagation mechanism and causes the fluctuation in both stock prices and the output. Our findings are in line with many studies for investors (e.g., Kothari et al., 2006), which show that returns are predictable after news innovations in the sense that stock market prices/output react immediately to global commodity price shocks and would continue to drift in the same direction for months due to the endogenous propagation mechanism. As policymakers are typically interested in responding to global uncertainty shocks, our findings highlight the importance of distinguishing the heterogeneous impact effects of global stock market volatility/commodity price shocks on the economy between developed and developing economies.

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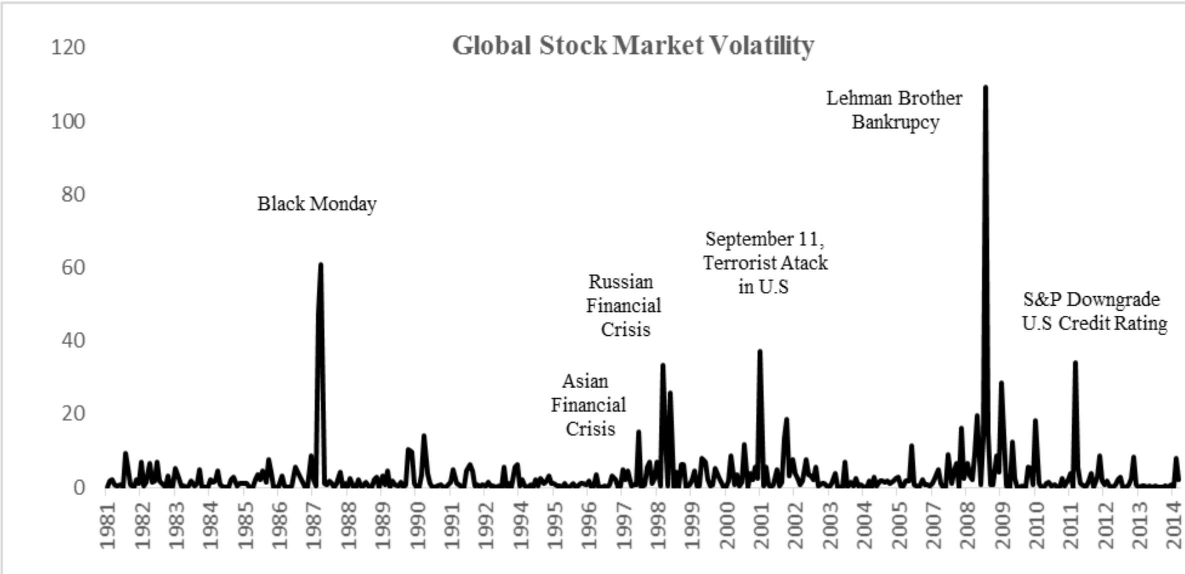
Appendix A: Data Source

Panel A. Stock market indices	*Period*
Australia: Standard & Poor's/ASX 200 Index	Jan 1981- Dec 2014
Brazil: BM&F BOVESPA Index	Jan 1991- Dec 2014
Canada: Toronto Stock Exchange index	Jan 1981- Dec 2014
China: Shanghai Stock Exchange Composite Index	Dec 1990- Dec 2014
France: France CAC 40 Stock Market Index	Jan 1987- Dec 2014
Germany: Deutsche Boerse AG German Stock Index	Jan 1993- Dec 2014
India: NSE CNX 100 Index	Jan 2003- Dec 2014
Ireland: ISEQ Equity Index	Jan 1984- Dec 2014
Italy: FTSE MIB Index	Mar 2003- Dec 2014
Japan: NIKKEI 225 Stock Market Index	Jul 1988- Dec 2014
Mexico: Mexican Bolsa IPC Index	Dec 1991-Dec 2014
Netherland: AEX Index	Jan 1986- Dec 2014
Russia: Russia MICEX Stock Market Index	Jan 1994- Dec 2014
South Korea: Korea Stock Exchange KOSPI Index	Jan 1990- Dec 2014
US: Standard & Poor's 500 index	Jan 1981- Dec 2014
UK: UK FTSE 100 Stock Market Index	Jan 1981- Dec 2014
Panel B. Industrial production, CPI and interest rate	*Period*
IP for the US: is the total industrial production excluding construction for the US economy	Jan 1981- Dec 2014
IP for economies excluding the US: is the total industrial production excluding construction for an advanced/developing economy	Jan 1981- Dec 2014
CPI for the US: is the headline consumer price index for the US	Jan 1981- Dec 2014
CPI for economies excluding the US: is the headline consumer price index for an advanced/developing economy	Jan 1981- Dec 2014
Interest rate for the US: Federal funds target rate	Jan 1981- Dec 2014
Interest rate for economies excluding the US: Short-term official policy rate (maturity 3 months or less) for an advanced/developing economy	July 1981- Dec 2014

Notes: Stock market data are drawn from Datastream 5.1.

Appendix B: Plot of Global Stock Market Volatility



Notes: Dates of events are Black Monday (October 19, 1987), Asian Financial Crisis (July, 1997), Russian Financial Crisis (August 17, 1998), U.S Terrorist Attack (September 11, 2001), Gulf War II, Lehman Brother Bankruptcy (September 15, 2008), S&P Downgrade U.S Government Debt Credit Rating (August 5, 2011).

Appendix C: Markov chain Monte Carlo (MCMC) Algorithm

The appendix describes the Markov chain Monte Carlo (MCMC) Algorithm for the estimation of the time-varying coefficients VAR model. Following Primiceri (2005) and Primiceri and Del Negro (2015) closely, we simulate the joint posterior density $p(\beta^T, a^T, \sigma^T, Q, W, S \mid y^T)$ from full conditionals as follows:

Step 1. Drawing reduced-form VAR parameters β^T

Utilizing the initial values β_0, a_0, σ_0, Q, W, and S based on their prior distribution and the data y^T, we caculate $\beta_{T|T}$ and $P_{T|T}$ from the state-space model (1) and (3) by the last recursion of forward Kalman filter, where

$\beta_t \mid \beta_{t+1}, a^T, \sigma^T, Q, y^t \sim N(\beta_t \mid \beta_{t|t+1}, P_{t|t+1})$,

$\beta_{t|t+1} = E(\beta_t \mid \beta_{t+1}, y^t, a^T, \sigma^T, Q)$,

$P_{t|t+1} = Var(\beta_t \mid \beta_{t+1}, y^t, a^T, \sigma^T, Q)$.

We are then able to simulate the smoothed estimates of $\beta_t, t = 1, 2, ..., T-1$, by backward recursions from $\beta_{T|T}$ and $P_{T|T}$, a Gibbs sampling developed in Carter and Kohn (1994).

Step 2. Drawing the hyperparameter Q

Note that the prior of Q is the inverse-Wishard distribution $Q^{-1} \sim W(\underline{v}_Q, \underline{V}_Q^{-1})$, the posterior of Q is an inverse-Wishard distribution $Q^{-1} \sim W(\bar{v}_Q, \bar{V}_Q)$, where $\bar{v}_Q = T + \underline{v}_Q$ and $\bar{V}_Q^{-1} = (\underline{V}_Q + \sum_{t=1}^{T} (\alpha_{t+1} - \alpha_t)(\alpha_{t+1} - \alpha_t)^{'})^{-1}$.

Step 3. Drawing the covariance elements a^T

The reduced-form VAR model (1) can be written as $\hat{y}_t = D_t a_t + \Sigma_t u_t$, where the estimate $\hat{y}_t = y_t - z_t \alpha_t$ and the matrix

$$D_t = \begin{pmatrix} 0 & 0 & \cdots & 0 \\ -\hat{y}_{1,t} & 0 & \cdots & 0 \\ 0 & -\hat{y}_{(1,2),t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & -\hat{y}_{(1,\ldots,n-1),t} \end{pmatrix},$$

where $-\hat{y}_{(1,\ldots,n-1),t}$ denotes the row vector $(\hat{y}_{1,t}, \hat{y}_{2,t}, ..., \hat{y}_{n-1,t})$. Therefore, a_t can be obtained from the state-space system of equations $\hat{y}_t = D_t a_t + \Sigma_t u_t$ and (4) by the Kalman filter and the backward recursion Gibbs sampling in the following form

$a_{i,t} \mid a_{i,t+1}, \beta^T, \sigma^T, W, y^t \sim N(a_{i,t} \mid a_{i,t|t+1}, \Lambda_{i,t|t+1})$,

$a_{i,t|t+1} = E(a_{i,t} \mid a_{i,t+1}, y^t, \beta^T, \sigma^T, W)$,

$\Lambda_{i,t|t+1} = Var(a_{i,t} \mid a_{i,t+1}, y^t, \beta^T, \sigma^T, W)$,

where $a_{i,t|t+1}$ is the i-th block of a_t that is corresponding to the coefficients of the i-th equation $\hat{y}_t = D_t a_t + \Sigma_t u_t$.

Step 4. Drawing the hyperparameter W

Note that the prior of W is the inverse-Wishard distribution $W^{-1} \sim W(\bar{v}_W, \bar{V}_W)$, the posterior of W is an inverse-Wishard distribution, where $\bar{v}_W = T + \underline{v}_W$ and $\bar{V}_W^{-1} = (\underline{V}_W + \sum_{t=1}^{T}(a_{t+1} - a_t)(a_{t+1} - a_t)')^{-1}$.

Step 5. Drawing the variance elements σ^T

The reduced-form VAR model (1) can be written as $y_t^{**} = 2\ln\sigma_t + e_t$, where $e_{i,t} = \ln \varepsilon_{i,t}^2$, $y_{i,t}^{**} = \ln((y_{i,t}^*)^2 + c)$, $y_t^* = A_t(y_t - z_t\beta_t)$, and a constant c set to 0.001. This transformation makes $e_{i,t}$ is independent of $e_{j,t}$ for $i \neq j$ that allows one to use the same independent mixture of normals approximation for any element of e_t. As in Kim et al. (1998), we define $s^T = (s_1, ..., s_T)'$ as the state-indicator matrix showing in each point of time which member of the mixture of normals is used for each element of e_t. The s^T can be updated by independently sampling each $s_{i,t}$ from the discrete density

$\Pr(s_{i,t} = j \mid y_{i,t}^{**}, \ln\sigma_{i,t}) \propto q_j f_N(y_{i,t}^{**} \mid 2\ln\sigma_{i,t} + m_j - 1.2704, v_j^2)$, $j = 1, ..., 7$, $i = 1, ..., n$,

where $f_N(\cdot)$ denotes the normal density for j with probability q_j, mean $m_j - 1.2704$ and variance v_j^2 chosen as constants as in Kim et al. (1998) to match a number of moments of the $\log\chi^2(1)$ distribution. Therefore, σ_t can be obtained from the state-space system of equations $y_t^{**} = 2\ln\sigma_t + e_t$ and (5) by the Kalman filter and the backward recursion Gibbs sampling in the following form

$\ln\sigma_t \mid \ln\sigma_{t+1}, \beta^T, a^T, S, y^t, s^T \sim N(\ln\sigma_t \mid \ln\sigma_{t|t+1}, H_{t|t+1})$,

$\ln\sigma_{t|t+1} = E(\ln\sigma_t \mid \ln\sigma_{t+1}, y^t, \beta^T, a^T, S, s^T)$,

$H_{t|t+1} = Var(\ln\sigma_t \mid \ln\sigma_{t+1}, y^t, \beta^T, a^T, S, s^T)$,

where the smoothed estimate of σ_t can be recovered by the transformation $\sigma_t = \exp(\ln\sigma_t / 2)$.

Step 6. Drawing the hyperparameter S

Note that the prior of S is the inverse-Wishard distribution $S^{-1} \sim W(\bar{v}_S, \bar{V}_S)$, the posterior of S is an inverse-Wishard distribution, where $\bar{v}_S = T + \underline{v}_S$ and $\bar{V}_S^{-1} = (\underline{V}_S + \sum_{t=1}^{T}(\sigma_{t+1} - \sigma_t)(\sigma_{t+1} - \sigma_t)')^{-1}$.

Finally, we run the MCMC algorithm from Step 1 to Step 6 executed 22,000 times, with the first 20,000 draws discarded as burn-in iterates.

Table 1. Percent contribution of one-standard deviation structural shocks to the overall variability of the endogenous variables in U.S.

Panel A. Industrial Production

Horizon	Productivity Shock	Commodity Price Shock	Price Level Shock	Interest Rate Shock	Global Uncertainty Shocks
1	1.000---	0.000---	0.000---	0.000---	0.000---
3	0.951(36.88)	0.018(1.10)	0.007(0.67)	0.014(0.98)	0.011(0.91)
12	0.797(16.55)	0.082(2.36)	0.039(1.71)	0.021(1.20)	0.062(2.05)
24	0.749(13.76)	0.119(2.72)	0.044(2.00)	0.023(1.25)	0.065(2.11)
60	0.746(13.46)	0.119(2.73)	0.045(2.01)	0.024(1.19)	0.066(2.12)

Panel B. Commodity Price Index

Horizon	Productivity Shock	Commodity Price Shock	Price Level Shock	Interest Rate Shock	Global Uncertainty Shocks
1	0.015(0.85)	0.985(56.96)	0.000---	0.000---	0.000---
3	0.035(1.29)	0.879(16.80)	0.027(1.40)	0.003(0.43)	0.056(1.61)
12	0.049(1.89)	0.743(13.08)	0.094(2.95)	0.017(1.02)	0.098(2.34)
24	0.055(2.12)	0.726(12.64)	0.096(3.07)	0.018(1.03)	0.104(2.50)
60	0.056(2.15)	0.722(12.48)	0.098(3.07)	0.019(1.06)	0.105(2.51)

Panel C. Consumer Price Index

Horizon	Productivity Shock	Commodity Price Shock	Price Level Shock	Interest Rate Shock	Global Uncertainty Shocks
1	0.002(0.16)	0.184(3.39)	0.814(14.90)	0.000---	0.000---
3	0.008(0.47)	0.325(5.31)	0.568(9.40)	0.005(0.62)	0.095(1.95)
12	0.050(1.84)	0.275(5.09)	0.540(9.69)	0.017(1.14)	0.119(2.38)

24	0.054(2.01)	0.259(4.95)	0.541(9.81)	0.029(1.53)	0.117(2.46)
60	0.058(2.11)	0.251(4.77)	0.541(9.57)	0.035(1.61)	0.116(2.44)

Panel D. Interest Rate

Horizon	Productivity Shock	Commodity Price Shock	Price Level Shock	Interest Rate Shock	Global Uncertainty Shocks
1	0.038(1.21)	0.006(0.53)	0.003(0.31)	0.953(28.25)	0.000---
3	0.064(1.45)	0.004(0.33)	0.001(0.12)	0.912(18.37)	0.019(1.29)
12	0.271(2.61)	0.001(0.06)	0.002(0.11)	0.707(6.54)	0.019(0.71)
24	0.379(2.87)	0.011(0.27)	0.003(0.07)	0.598(4.35)	0.009(0.34)
60	0.414(2.92)	0.023(0.36)	0.002(0.05)	0.551(3.60)	0.010(0.26)

Panel E. Global Stock Market Volatility

Horizon	Productivity Shock	Commodity Price Shock	Price Level Shock	Interest Rate Shock	Global Uncertainty Shocks
1	0.010(0.35)	0.000(0.01)	0.007(0.51)	0.000(0.06)	0.983(24.51)
3	0.022(0.71)	0.007(0.27)	0.008(0.56)	0.004(0.37)	0.960(19.32)
12	0.040(1.40)	0.045(1.42)	0.031(1.46)	0.021(0.81)	0.864(15.44)
24	0.044(1.55)	0.057(1.66)	0.040(1.71)	0.023(0.87)	0.837(14.03)
60	0.045(1.59)	0.057(1.67)	0.041(1.74)	0.023(0.87)	0.834(13.79)

Notes: Percent contributions of one-standard deviation structural shocks to the overall variability of the endogenous variables. The forecast error variance decomposition is based on the structural VAR model described in the text. The values in parentheses represent the absolute t-statistics based on 2000 bootstrap samples.

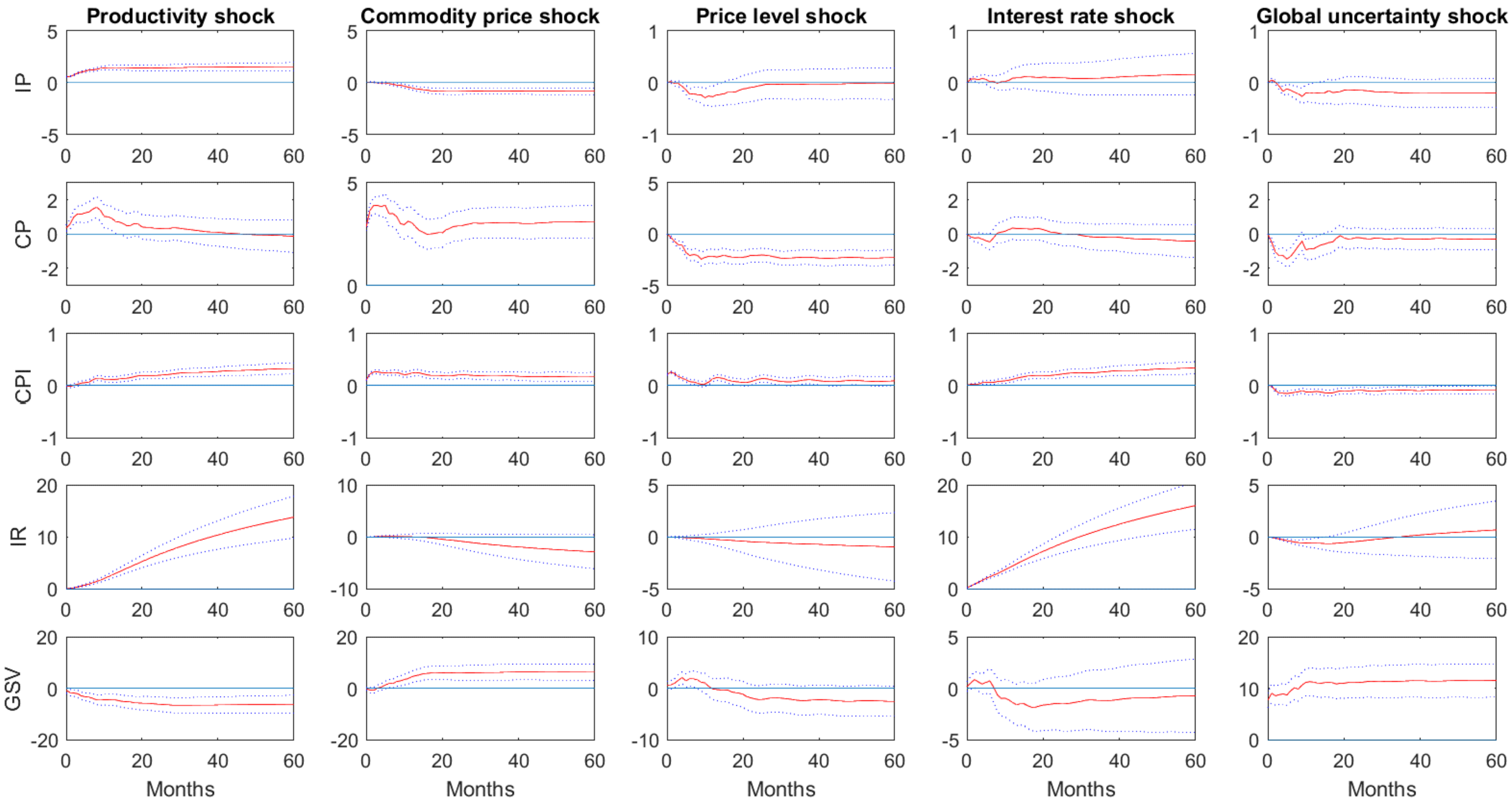
Table 2. Percent contribution of commodity price/global stock market volatility shocks to the overall variability of output and price level across countries

Horizon	Commodity Price Shock: Industrial Production		Commodity Price Shock: Consumer Price Index		Global Uncertainty Shock: Industrial Production		Global Uncertainty Shock: Consumer Price Index	
Australia								
3	0.020	(1.41)	0.058	(1.83)	0.010	(0.90)	0.014	(0.94)
12	0.051	(2.06)	0.062	(2.12)	0.030	(1.43)	0.020	(1.09)
60	0.053	(2.16)	0.047	(1.57)	0.032	(1.46)	0.025	(0.87)
Brazil								
3	0.020	(0.85)	0.020	(0.69)	0.078	(1.68)	0.000	(0.02)
12	0.091	(1.83)	0.043	(1.05)	0.152	(2.60)	0.026	(0.85)
60	0.109	(2.25)	0.050	(1.21)	0.160	(2.86)	0.055	(1.38)
Canada								
3	0.006	(0.59)	0.078	(2.29)	0.001	(0.13)	0.009	(0.73)
12	0.035	(1.68)	0.094	(2.84)	0.058	(1.75)	0.044	(1.72)
60	0.044	(1.84)	0.086	(2.88)	0.059	(1.81)	0.043	(1.75)
China								
3	0.035	(0.80)	0.034	(0.97)	0.004	(0.27)	0.030	(1.04)
12	0.070	(1.28)	0.067	(1.70)	0.012	(0.51)	0.057	(1.62)
60	0.081	(1.55)	0.061	(1.67)	0.040	(1.16)	0.064	(1.77)
France								
3	0.032	(1.68)	0.147	(2.99)	0.009	(0.88)	0.040	(1.60)
12	0.084	(2.75)	0.166	(3.71)	0.025	(1.26)	0.082	(2.27)
60	0.088	(2.88)	0.141	(3.67)	0.034	(1.54)	0.080	(2.28)
Germany								
3	0.003	(0.45)	0.077	(2.27)	0.016	(0.91)	0.023	(1.39)
12	0.038	(1.62)	0.105	(2.99)	0.039	(1.57)	0.040	(1.85)
60	0.043	(1.75)	0.089	(2.88)	0.042	(1.65)	0.035	(1.76)
India								
3	0.002	(0.06)	0.036	(0.60)	0.036	(0.76)	0.009	(0.28)
12	0.132	(1.96)	0.132	(2.10)	0.052	(1.26)	0.109	(2.22)
60	0.135	(2.12)	0.133	(1.93)	0.059	(1.35)	0.118	(2.38)
Ireland								
3	0.002	(0.28)	0.053	(1.92)	0.001	(0.16)	0.026	(1.12)
12	0.016	(0.93)	0.100	(2.30)	0.015	(0.83)	0.165	(2.33)
60	0.018	(0.99)	0.075	(2.27)	0.023	(1.01)	0.155	(2.36)

Italy								
3	0.006	(0.55)	0.082	(1.98)	0.0265	(1.10)	0.032	(1.37)
12	0.047	(1.84)	0.120	(2.68)	0.0759	(1.94)	0.058	(1.99)
60	0.069	(2.34)	0.099	(2.30)	0.0852	(2.11)	0.049	(1.53)
Japan								
3	0.027	(1.44)	0.017	(1.17)	0.008	(0.53)	0.003	(0.46)
12	0.081	(2.38)	0.024	(1.46)	0.066	(1.43)	0.023	(1.49)
60	0.088	(2.45)	0.019	(1.17)	0.072	(1.54)	0.021	(1.38)
Korea								
3	0.046	(1.78)	0.066	(1.49)	0.076	(1.57)	0.000	(0.05)
12	0.103	(2.49)	0.074	(1.92)	0.145	(2.50)	0.011	(0.67)
60	0.108	(2.76)	0.106	(2.25)	0.154	(2.72)	0.016	(0.84)
Netherland								
3	0.004	(0.45)	0.030	(1.15)	0.007	(0.79)	0.013	(0.99)
12	0.029	(1.57)	0.076	(2.46)	0.060	(1.50)	0.037	(1.45)
60	0.032	(1.71)	0.067	(2.05)	0.065	(1.64)	0.039	(1.49)
Russia								
3	0.044	(1.13)	0.005	(0.15)	0.095	(1.74)	0.002	(0.11)
12	0.098	(2.17)	0.028	(0.71)	0.087	(1.94)	0.073	(1.53)
60	0.107	(2.54)	0.058	(1.14)	0.099	(2.22)	0.089	(1.68)
Spain								
3	0.026	(1.40)	0.071	(2.28)	0.001	(0.18)	0.012	(1.10)
12	0.047	(1.53)	0.098	(3.15)	0.013	(0.75)	0.038	(1.79)
60	0.050	(1.61)	0.081	(2.61)	0.014	(0.78)	0.027	(1.39)
UK								
3	0.006	(0.71)	0.068	(2.16)	0.006	(0.63)	0.010	(0.84)
12	0.031	(1.77)	0.117	(3.17)	0.020	(1.06)	0.033	(1.67)
60	0.040	(2.10)	0.095	(2.85)	0.026	(1.27)	0.027	(1.53)

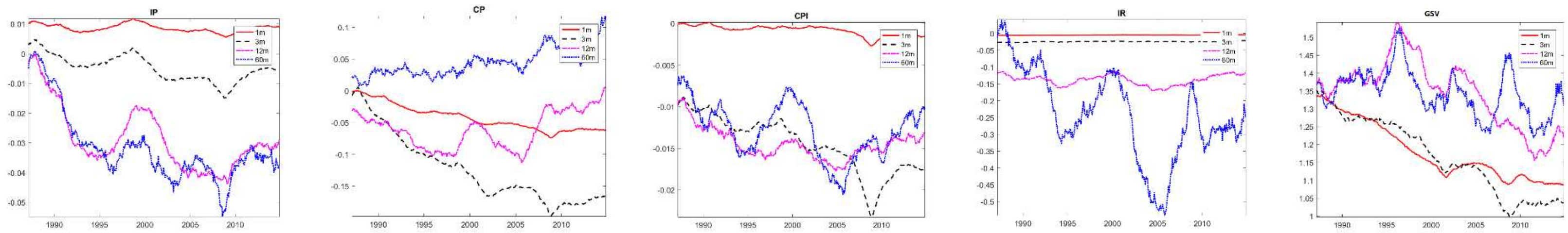
Notes: Percent contributions of one-standard deviation structural shocks of commodity prices to the overall variability of the endogenous variables. The forecast error variance decomposition is based on the structural VAR model described in the text. The values in parentheses represent the absolute t-statistics based on 2000 bootstrap samples. The forecast at the first month is around zero and is omitted for the exposition purpose.

Figure 1. Cumulative Responses to One-Standard Deviation Structural Shocks: VAR with Constant Coefficients in US, 1981:M1-2014:M12



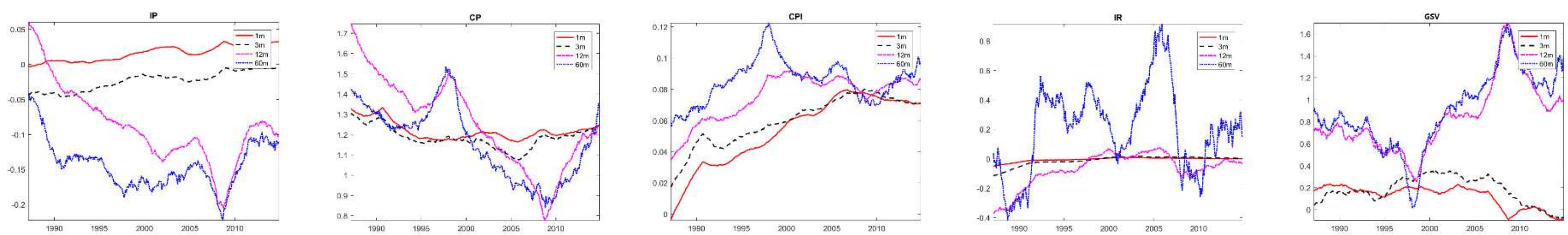
Notes: The figure shows the cumulative response of industrial production (IP), commodity price index (CP), consumer price index (CPI), short-term interest rate (IR) and the global stock market volatility (GSV) to one-standard deviation structural shocks with one-standard error bands based on 2000 Bootstrapping samples.

Figure 2.1. Cumulative Responses to Global Uncertainty Shocks: VAR with Time-Varying Coefficients in US at the 1st, 3rd, 12th, and 60th Month, 1981:M1-2014:M12



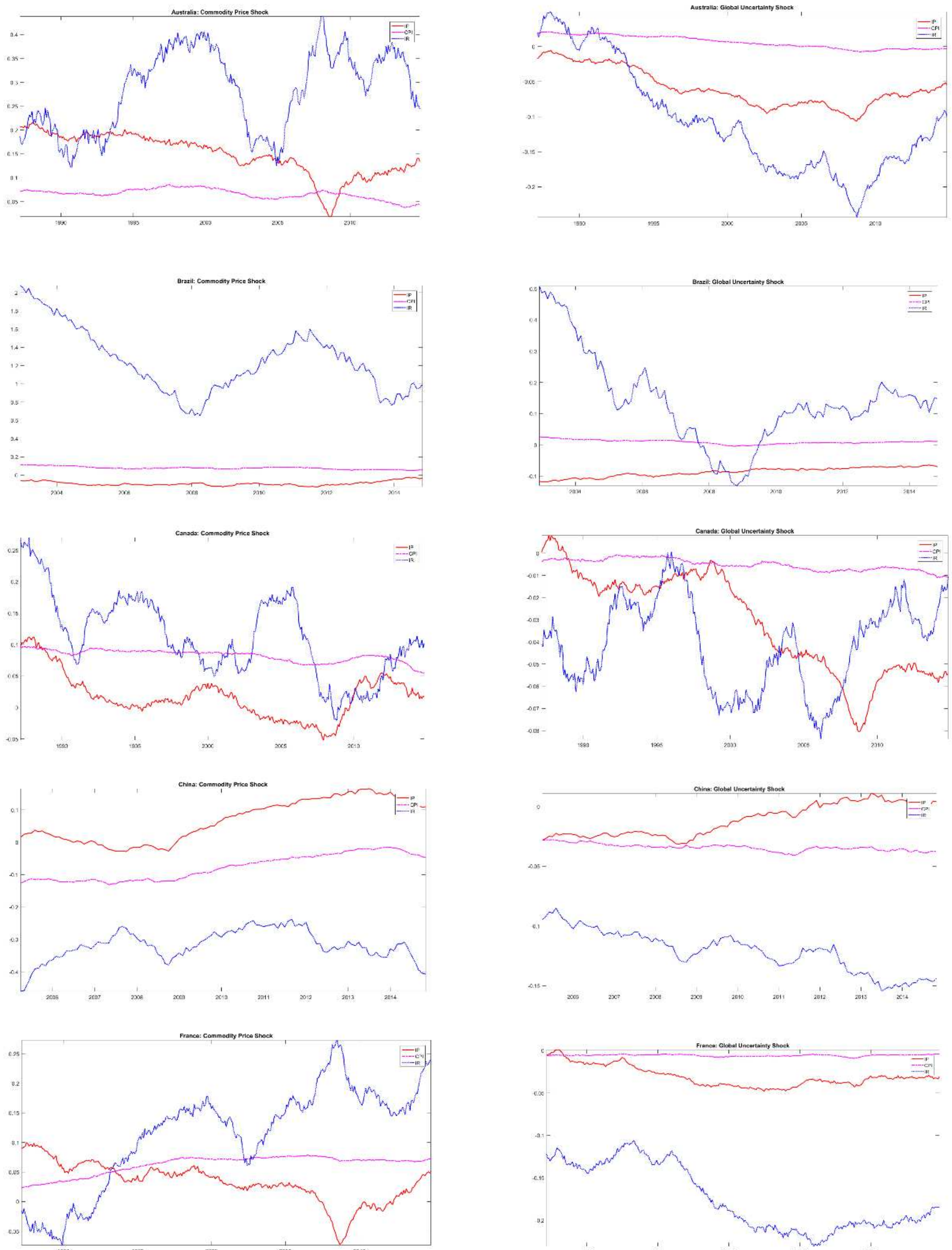
Notes: The figure shows the cumulative response of industrial production (IP), commodity price index (CP), consumer price index (CPI), short-term interest rate (IR) and the global stock market volatility (GSV) to the global stock market volatility shocks at the 1st, 3rd, 12th, and 60th month. The Y-axis shows the cumulative responses, and the X-axis the timing from 1981M1 to 2014M12.

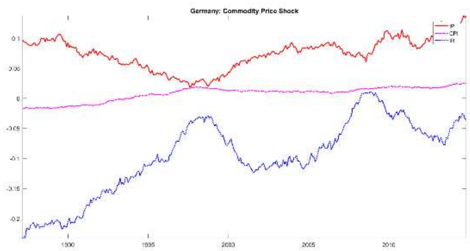
Figure 2.2. Cumulative Responses to Commodity Price Shocks: VAR with Time-Varying Coefficients in US at the 1st, 3rd, 12th, and 60th Month, 1981:M1-2014:M12

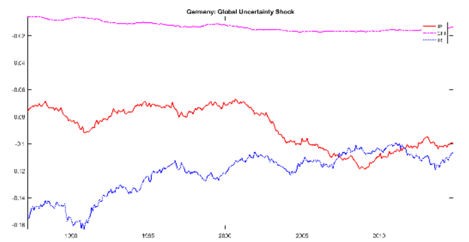


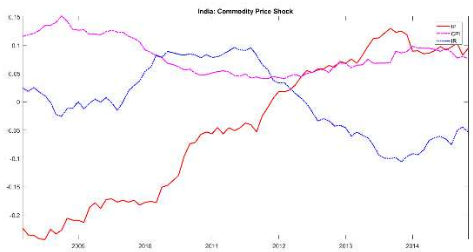
Notes: The figure shows the cumulative response of industrial production (IP), commodity price index (CP), consumer price index (CPI), short-term interest rate (IR) and the global stock market volatility (GSV) to the commodity price shocks at the 1st, 3rd, 12th, and 60th month. The Y-axis shows the cumulative responses, and the X-axis the timing from 1981M1 to 2014M12.

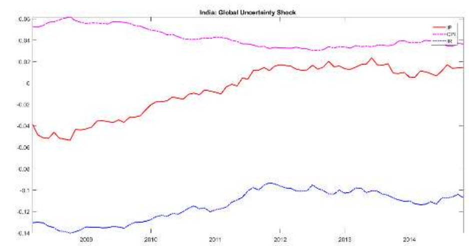
Figure 3. Cumulative Responses to Commodity Price/Global Uncertainty Shocks: VAR with Time-Varying Coefficients across Countries at the 12th Month, 1981:M1-2014:M12

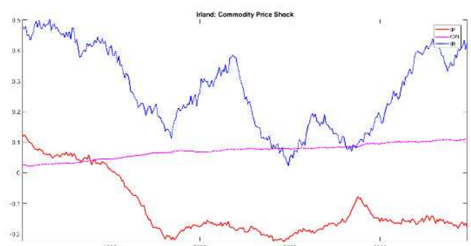


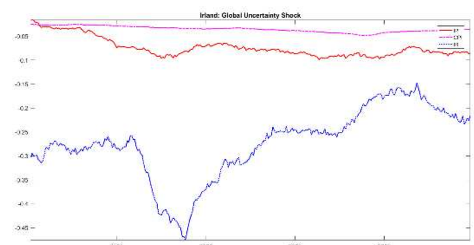

Germany: Commodity Price Shock
IP
CPI
IR

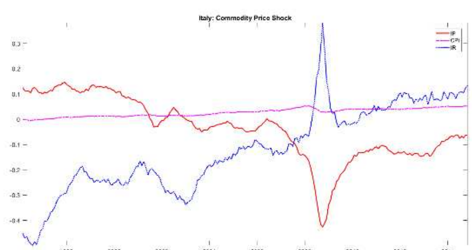

Germany: Global Uncertainty Shock
IP

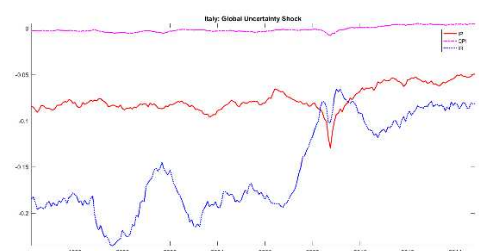

India: Commodity Price Shock
IP
CPI
IR

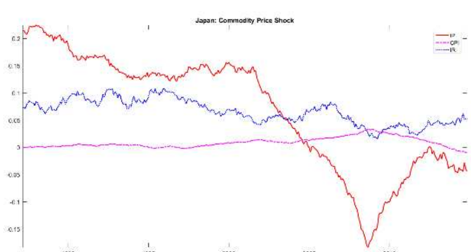

India: Global Uncertainty Shock
IP
CPI
IR

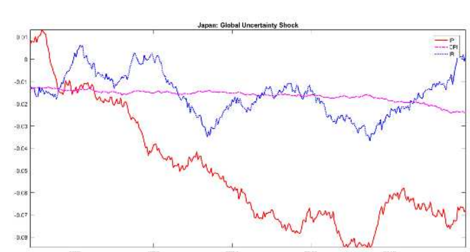

Irland: Commodity Price Shock
IP
CPI
IR

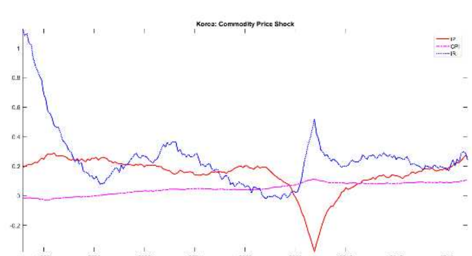

Irland: Global Uncertainty Shock
IP
CPI
IR

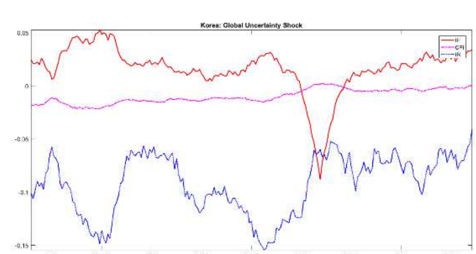

Italy: Commodity Price Shock
IP
CPI
IR

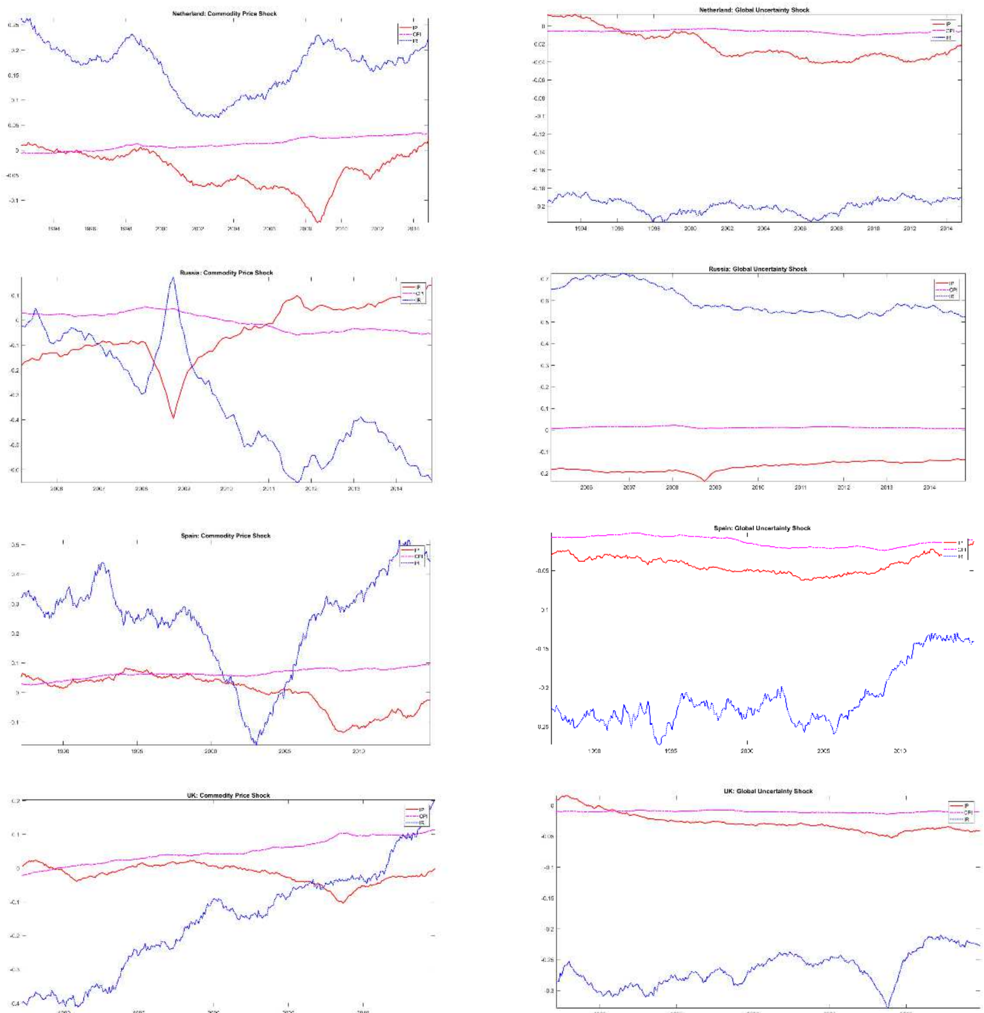

Italy: Global Uncertainty Shock
IP
CPI
IR


Japan: Commodity Price Shock
IP
CPI
IR


Japan: Global Uncertainty Shock
IP
CPI
IR

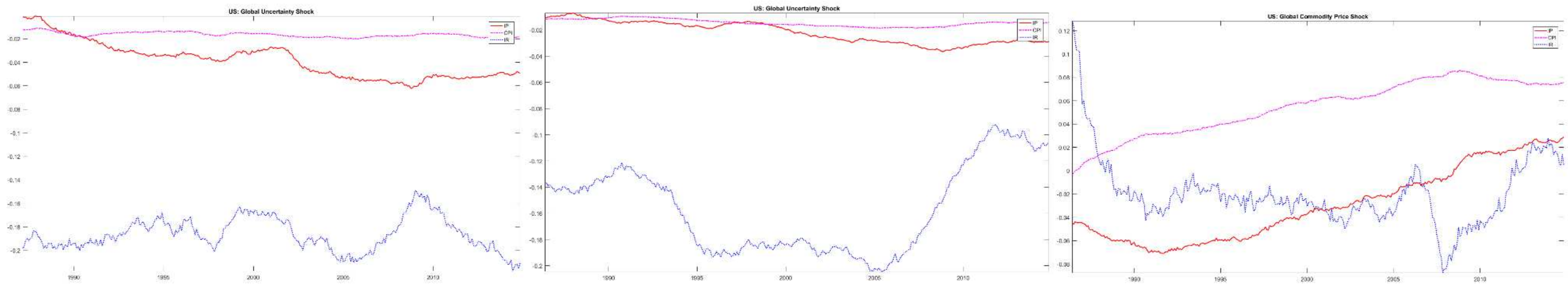

Korea: Commodity Price Shock
IP
CPI
IR


Korea: Global Uncertainty Shock
IP
CPI
IR



Notes: The figure shows the cumulative responses of the industrial production (IP), consumer price index (CPI) and short-term interest rate (IR) to global commodity price innovations in the left column and to global uncertainty shocks in the right column in 12 months across 15 economies in the order: Australia, Brazil, Canada China, France, Germany, India, Ireland, Italy, Japan, Korea, Netherland, Russia, Spain, and UK. The Y-axis shows the cumulative responses, and the X-axis the timing from 1981M1 to 2014M12.

Figure 4. Cumulative Responses to Structural Shocks: VAR with Time-Varying Coefficients in US at the 12th Month, 1981:M1-2014:M12



Notes: The figure shows the cumulative responses of industrial production (IP), consumer price index (CPI), and short-term interest rate (IR) to the structural shocks in US at the 12th month. The left figure presents the three responses to global uncertainty shocks when the global stock market volatility is ordered first in the VAR model, the middle figure illustrates the three responses to global uncertainty shocks when lags=3 in the VAR model (1), and the right figure shows the three responses to global commodity price shocks when lags=3 in the VAR model (1). The Y-axis shows the cumulative responses, and the X-axis the timing from 1981M1 to 2014M12.