Commodity Price Co-movement: Heterogeneity and the Time Varying Impact of Fundamentals

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Abstract

This paper extends the topical literature on the co-movement and determinants of primary commodity prices, by considering heterogeneity in commodities and time variation in the impact of fundamentals. We account for heterogeneity by employing a dynamic hierarchical factor model, which decomposes commodities into global and sectoral factors. Using a time varying parameter factor augmented VAR model, we shock global and sector-specific factors over time. We present plausible impulse responses to demand shocks, real interest rate shocks, and to elevated risks during the global financial crisis. We also identify that materials, food and metals respond heterogeneously to these shocks.

Keywords: Commodity Prices; Co-movement; Dynamic Hierarchical Factor Models; Time Varying Parameter Factor Augmented VAR.

JEL Classification Numbers: E3, F3, F4, G1.

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1. Introduction

Synchronized surges and declines in primary commodity prices has been the catalyst for a lively recent debate about their commonalities and determinants. These studies document a significant degree of co-movement in commodity prices, which can be modelled by a common factor. See recent commodity prices research by Cuddington and Jerrett (2008), Vanstenkiste (2009), Byrne *et al.* (2013), Alquist and Coibion (2014), West and Wong (2014), Daskalaki *et al.* (2014), Yin and Han (2015), Antonakakis and Kizys (2015) and Alam and Gilbert (2017). A potential criticism of factor models with a single common element however is that they can forsake useful information. If commodity prices display important heterogeneity and/or are impacted by different fundamentals, then a single factor extracted from all commodities may not fully reflect price dynamics (Moench *et al.*, 2013). We contribute therefore to the commodities literature by decomposing commodity prices into common and group factors using a hierarchical factor model, and examine commodities' relationships with fundamentals.

To the extent that commodity prices share common determinants, the literature is ambiguous as to what drives recent movements, possibly because heterogeneity is unaccounted for, or the relative importance of determinants change over time. Among possible determinants, Wolf (2008), Svensson (2008), Frankel (2014) and Ratti and Vespignani (2015) have underlined that shifts in global demand matter for commodity prices. Interest rates have been emphasised by Frankel (2008, 2014) and Svensson (2008). Also, Beck (1993, 2001) indicated that uncertainty is an important determinant of primary commodity prices. A limited number of empirical studies have so far tested these different hypotheses and they rely upon a time-invariant methodology (e.g., Byrne *et al.*, 2013; Poncela *et al.*, 2014; Ratti and Vespignani, 2015). Previous work on the determinants of commodity prices implicitly assumed that the impact of shocks does not vary over time and we investigate this assumption.

There are reasons to believe that the relationship between primary commodity prices and macro fundamentals may be unstable (Alvarez-Ramirez *et al.*, 2012). For example, China has significantly increased its market shares of global commodities following its rapid development and this may impact demand effects (e.g., Kilian, 2009; Roache, 2012). Financial investors' risk-bearing appetite and risk premium may vary over time (Cheng and Xiong, 2014). Another potential cause of time varying commodity effects is due to variation in commodity market participants. Since 2000s there has been a large inflow of investment capital from speculators, which has added to commodity market activity from commercial hedgers (e.g., farmers, producers and consumers) and non-commercial traders such as financial institutions (e.g., Cheng and Xiong, 2014).

This paper therefore empirically examines the relationship between commodity common factors and fundamentals, while accounting for heterogeneity and potential instability. Our analysis incorporates important innovations relative to previous studies. Firstly, we fully account for the determinants of commodity prices while allowing for price heterogeneity using a dynamic hierarchical factor model (DHFM). The existing literature typically explored the impact of macro fundamentals on a single aggregate common factor. But each sector may have a heterogeneous market structure, level of competition and concentration, and a differing elasticity of demand (e.g., Yin and Han, 2015). The DHFM allows us to assess whether agricultural raw material, food and metal sectors respond differently to macro shocks. To our knowledge commodity heterogeneity has not been widely considered in the literature within a unified framework. Our second contribution is to use a time varying parameter factor augmented vector autoregression (TVP-FAVAR) model with stochastic volatility to flexibly delineate the impact of fundamentals. This approach allows all parameters to evolve continuously, informing us when, and to what extent, changes have occurred over time; rather than imposing an arbitrary sample split to account for changing dynamics. Our model also allows for time varying heteroskedasticity in the VAR innovations to account for changes in the magnitude of shocks. This feature is especially important given intense commodity price and macroeconomic volatility between the Great Moderation and Global Financial Crisis (Primiceri, 2005; Baumeister and Peersman, 2013).

Our findings can be summarized as follows. We find an important degree of commodity price co-movement due to common and sectoral factors, highlighting the importance of commodity heterogeneity. Commodities can be modelled therefore by a single common factor, but there are notable differences between commodities, especially during episodes of extreme price volatility. Next, we report and discuss the estimation results from time-invariant and time-varying FAVAR models. Under both approaches, we provide empirical evidence that macro fundamentals affect the returns of a large number of commodities. The impulse responses indicate qualitative and quantitative changes over time in commodity prices to demand, real interest rate and uncertainty shocks. We provide additional evidence that fundamental shocks relate differently to the material, food and metal sectors. For example, demand shocks have a more powerful impact upon the metals' sector than others, while materials are more sensitive to uncertainty. Intuitively, and supporting the use of a time-varying methodology, we also find Chinese demand shocks have had an increasingly positive impact upon commodity prices. The rest of the paper is organized as follows. Section 2 reviews the related literature. Section 3 formally presents our econometric methodology. Section 4 discusses the data. Section 5 reports the empirical results and robustness checks. Section 6 offers some concluding remarks.

2. Brief Literature Review

Changes in commodity prices can be rapid, and large price swings severely impact commodity importers, exporters and speculators.[1,2] Thus, a better understanding of the nature of commodity prices and their determinants may lead to better decision making in areas such as macroeconomic policy, risk and portfolio management. A long-standing literature focused upon commodity prices' time series properties (e.g., Cuddington, 1992; Deaton, 1999; Cashin *et al.*, 2000). This is related to trends in primary commodity prices relative to the price of manufactured goods, within the context of the Prebisch (1950) and Singer (1950) hypothesis.[3] The literature has also considered commonalities in commodity prices. The seminal work by Pindyck and Rotemberg (1990), for example, was the first paper to confirm that prices of seemingly unrelated commodities tend to co-move. Deaton (1999) stressed that it is important to consider the time series properties of individual commodities and their co-movement, in order to assess the different impact of commodity prices on developing and industrial countries, and therefore the need for stabilization policies. Cashin *et al.* (2002) also found evidence of price synchronization of related commodities.

The co-movement of commodity prices since the turn of the twenty-first century has promoted a renewed interest in commonalities and sought to explain why prices co-move. Alquist and Coibion (2014) employed a general equilibrium model to decompose the sources of commodity price co-movement. They evidenced indirect shocks that impact on commodity prices through the change in aggregate output are main sources for commodity price commonalities. This empirical literature has, for example, employed factor models to extract

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[1] For example, higher commodity prices may lead to lower aggregate demand and production outputs, induce inflationary tendencies and higher interest rates for importing countries; whereas a sustained decline in commodity prices supports the so-called "resource curse" hypothesis for commodity abundant emerging economies. See among the others, Frankel (2008, 2014), Neftci and Lu (2008) and Ghoshray *et al.* (2014).

[2] Commodity markets facilitate risk sharing among a broad set of agents, and institutional investors have recently increased their portfolio allocations to commodities (Daskalaki *et al.*, 2014).

[3] The Prebisch-Singer hypothesis examines whether the terms of trade of commodity exporters are trending, such that living standards would be further impoverished by specialising in commodity extraction with a secular decline in commodity prices. The hypothesis was revisited recently by Harvey *et al.* (2010).

commonalities. Cuddington and Jerrett (2008) used principal component analysis to investigate the degree of concordance between metal commodity prices. Panel time series methods were utilised by Byrne *et al.* (2013) and they found evidence of co-movement of a large number of commodities, due to one common factor. Chen *et al.* (2014) showed that the movements of 51 tradeable commodities were mostly due to the first common component. Poncela *et al.* (2014) extracted a principal component from 44 non-fuel commodity prices from 1992 to 2012. Evidence has also been found that commodity prices consistently display a tendency to revert towards one factor, see West and Wong (2014). The main drawback with extracting a single common component from commodities is that the estimated factor can be difficult to interpret and may not fully account for heterogeneity. Recent research has sought to decompose the sources of commodity price co-movement using more granular methods. For example, Yin and Han (2015) used a multilevel factor model to decompose 24 commodity returns into global, sectoral and idiosyncratic components. They highlighted the heterogeneous impacts of sectoral factors at different points in time.

Monetary policy plays an important role for commodity prices. For instance, Barsky and Kilian (2004) pointed out that high prices for oil and other commodities in the 1970s was because of an expansionary monetary policy. Frankel (2008, 2014) argued that a substantial increase in US real interest rates drove commodity prices down in the early 1980s. According to asset pricing models, commodity prices are determined by the expected discount rate and expected future returns.[4] Therefore, an increase in real interest rates will raise the discount factor, so the present value of future returns will fall, and subsequently lead to lower commodity prices. Higher rates of return on fixed income assets will also offer substitution opportunities and reduce speculative demand for commodities. In addition, high interest rates increase the supply for storable commodities by increasing extraction incentives today, and/or by decreasing firms' desire to carry inventories. Gruber and Vigfusson (2012) showed that lower interest rates can reduce commodity prices' volatilities and interest rates can impact commodities heterogeneously.

A parallel and lively debate also spurred by the recent price boom-bust cycle, has focused upon the determinants of commodity prices. First, it is frequently argued that commodity prices are primarily driven by global economic activity (e.g., Svensson, 2008; Wolf, 2008; Kilian, 2009; Abhyankar *et al.*, 2013). This argument stems from increases in demand due to the unexpectedly strong economic growth in emerging economies after 2000

[4] If we assume commodity prices are determined like other assets, see Svensson (2008).

and their rapid recovery from the global financial crisis (Singleton, 2012; Frankel, 2014). The impact upon commodity prices of rapid Chinese economic growth can similarly be understood as a demand shock. This has been highlighted in work by Dwyer *et al.* (2012), Roache (2012) and Frankel (2014) and is especially topical since recent commodity price collapses are related to fears about China's growth slowdown.

Uncertainty may also be important for commodity prices. According to standard option theory, investment in primary commodities may be irreversible; hence, an increase in the variance of the distribution of investment returns would increase the option value of waiting, causing delays in such investment and possible price effects (Dixit and Pindyck, 1994). Therefore, there is a negative role for uncertainty as a determinant of commodity prices. Beck (2001), for example, found some evidence on the relationship between risk and agricultural commodities. The recent literature on compound option theory may suggest a U-shaped relationship between uncertainty and investment. To be more specific, the option to delay investment encourages investors to wait for new information, but delaying the investment can allow competitors to seize the opportunity to grow. Therefore, rising uncertainty increases the value of waiting and discourages investment, but only up to the point that the option value of taking exceeds the option value of waiting (Kulatilaka and Perotti, 1998). It becomes an empirical question as to which effect dominates.

In reviewing the literature, we have identified a number of empirical studies on investigating the determinants of commodity price fluctuations. For example, Vansteenkiste (2009) showed that the common factor was affected by oil price, global demand, the US dollar effective exchange rate and the real interest rate. Using a FAVAR approach, Byrne *et al.* (2013) related the common factor in commodity prices to their macroeconomic fundamentals. They found real interest rate and uncertainty were both negatively related to the common factor. Poncela *et al.* (2014) also applied a FAVAR to assess the impact of real interest rates, US real effective exchange rate, VIX, world industrial production, and an energy index. They found uncertainty after 2003 has played a more important role in explaining price fluctuations than real fundamentals such as the real exchange and the real interest rate. West and Wong (2014) computed the first principal component's correlation with fundamentals, and found that commodities were positively related to industrial production and negatively related to the exchange rate. A common feature of all these empirical studies is that they rely on time-invariant regressions. Therefore, the impact of demand shocks on the commodity prices is assumed to be time invariant.

To summarize, our study extends the literature on the co-movement and determinants of primary commodity prices for the following reasons. While previous studies focused on a single common factor in a wide range of commodities, we account for heterogeneity by employing a dynamic hierarchical factor model to decompose commodities into global, sectoral and idiosyncratic components. Next, using a time varying parameter factor augmented vector autoregressive model with stochastic volatility, we examine determinants of commonalities over time and across sectors. We now turn to formally laying out our econometric methodology.

3. Methodology

3.1. Dynamic Hierarchical Factor Model

We adopt a four-level dynamic hierarchical factor model (DHFM) following Moench *et al.* (2013). For each commodity price series $(n = 1, .., N)$, at each period $t = 1, \dots, T$, in a given sub-sector s $(s = 1, .., j)$ of sector b $(b = 1, .., i)$ has four sources of variations $(X_{b,s,n,t})$: commodity-specific, sub-sector $(H_{b,s,t})$, sector $(G_{b,t})$, and common (F_t). Our dynamic factor model is set out as follows:

$$X_{b,s,n,t} = \lambda_H(L)H_{b,s,t} + e_{X,t} \tag{1}$$

$$H_{b,s,t} = \lambda_G(L)G_{b,t} + e_{H,t} \tag{2}$$

$$G_{b,t} = \lambda_F(L)F_t + e_{G.t} \tag{3}$$

where λ_H, λ_G, and λ_F denote parameters for sub-sector factors, sector-factors, and common factor, respectively. Error terms $e_{X,t}$, $e_{H,t}$, and $e_{G,t}$ denote commodity-specific, sub-sector and sector-level residual variations, respectively. Note that $e_{X,t}$, $e_{H,t}$, $e_{G,t}$, and F_t are assumed to be stationary, normally distributed autoregressive processes of order one, AR(1), and evolve as follows:

$$e_{X,t} = \psi_X e_{X,t-1} + \varepsilon_{X,t} \tag{4}$$

$$e_{H,t} = \psi_H e_{H,t-1} + \varepsilon_{H,t} \tag{5}$$

$$e_{G,t} = \psi_G e_{G,t-1} + \varepsilon_{G,t} \tag{6}$$

$$F_t = \psi_F F_{t-1} + \varepsilon_{F,t} \tag{7}$$

where ψ_X, ψ_H, ψ_G, and ψ_F denote the coefficient of the AR(1) dynamics. $\varepsilon_{X,t}$, $\varepsilon_{H,t}$, $\varepsilon_{G,t}$, and $\varepsilon_{F,t}$ follow $N(0,\sigma_j^2)$, *j=X, H, G* and *F,* which are uncorrelated across time and sectors. We assume that the factor loading matrix is constant and estimate one common factor per sector, and one factor per sub-sector. A standard method to estimate latent factors from a large number of data series is principal components. However, principal components would not account for potential relations between common and sector factors, nor the AR(1) time series structure described in equations (4) to (7). Moench *et al.* (2013) propose a Markov Chain Monte Carlo (MCMC) method to overcome these problems. Following Moench *et al.* (2013), we first employ principal components to obtain the initial values of factors, then run the MCMC method and discard the first 20,000 draws as burn-in, and save every 100th of the remaining 50,000 draws.

3.2 Factor Augmented Vector Auto Regression (FAVAR) models

Now we set out the basic Bayesian Factor Augmented VAR model to examine the determinants of commodity commonalities and explain how it can be extended to a time varying parameter (TVP) model. The TVP-FAVAR model with stochastic volatility allows us to understand how changes in macroeconomic fundamentals affect real commodity prices over time.

3.2.1 *Bayesian FAVAR model*

The basic Bayesian FAVAR model can be written as follows:

$$AY_t = \sum_{i=1}^{p} \Gamma_i Y_{t-i} + u_t, \quad t = p+1, \dots, T \tag{8}$$

where Y_t is a $K \times 1$ vector of endogenous variables and divided into two blocks: the first block includes the growth rate of real US industrial production $(Demand_t)$, the real interest rate (R_t), and an uncertainty term $(Risk_t)$; the second block includes the common factors in commodity prices (F_t);[5] Γ_i is a $K \times K$ matrix of coefficients, A is a $K \times K$ matrix of contemporaneous coefficient of Y_t, and u_t captures the structural shocks in the commodity market and macroeconomic conditions. We assume u_t to be $i.i.d.N(0,\ \Sigma\Sigma)$. The lag length is two (i.e. $p = 2$),[6] where Σ is the diagonal matrix:

[5] When accounting for commodity heterogeneity we replace the common factor F_t with sectoral factors $G_{b,t}$.

[6] Most lag length specification tests (e.g., Final Prediction Error; Akaike Information Criterion; and Hannan-Quinn Information Criterion) suggest that two lags should be included for our model with quarterly data.

$$\Sigma = \begin{pmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_k \end{pmatrix}$$

To specify the simultaneous relations of the structural shock, we employ its reduced-form representation by multiplying both sides by A^{-1}, resulting in:

$$Y_t = \sum_{i=1}^{p} B_i Y_{t-i} + A^{-1}\Sigma\varepsilon_t,\ \ \varepsilon_t \sim N(0, I_k) \tag{9}$$

where $B_i = A^{-1}\Gamma_i$ for $i = 1, \ldots, p$. We can stack all the VAR coefficients (B_i) into a $K^2p \times 1$ vector to form B and define $X_t = I_k \otimes \left(Y'_{t-1}, \ldots, Y'_{t-p}\right)$, where $\otimes$ denotes the Kronecker product. We rewrite equation (9) as:

$$Y_t = X_t B + A^{-1}\Sigma\varepsilon_t \tag{10}$$

Note that the reduced-form residuals ε_t are correlated between each equation and can be viewed as a weighted average of the structural shocks u_t in equation (8). In order to orthogonalize the shocks, we impose a recursive structure on the contemporaneous terms and assuming that *A* is lower-triangular,

$$A = \begin{pmatrix} 1 & \cdots & \cdots & 0 \\ a_{21} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{k1} & \cdots & a_{k,k-1} & 1 \end{pmatrix}$$

The ordering of the variables is as follows: $Y_t = [\,Demand_t, R_t, Risk_t, F_t]$. The structural shocks u_t are identified by decomposing the reduced-form errors ε_t as follows:

$$\varepsilon_t = \begin{pmatrix} \varepsilon_t^{Demand} \\ \varepsilon_t^{R} \\ \varepsilon_t^{Risk} \\ \varepsilon_t^{F} \end{pmatrix} \begin{bmatrix} 1 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 \\ a_{41} & a_{42} & a_{43} & 1 \end{bmatrix} \begin{pmatrix} u_t^{Demand} \\ u_t^{R} \\ u_t^{Risk} \\ u_t^{F} \end{pmatrix}$$

In the global macroeconomic block, u_t^{Demand} denotes the *aggregate demand shock* that captures the shift in the demand for all commodities driven by the global business cycle. Next, u_t^R is the *real interest rate shock* which reflects deviations from the expected or average monetary policy, whether via changes in the nominal interest rate, expected inflation, or both (e.g., Frankel, 2008; Kilian, 2013). Finally, u_t^{Risk} denotes the *uncertainty shock* that captures innovations to agents' expectations about future economic and financial conditions. Intuitively, this can also be thought of as precautionary trading arising from revisions to commodity market expectations. These expectations may arise from elevated risks in financial markets, as in the global financial crisis. In the commodity market block, u_t^F is the shock to the common factor in commodity prices.

The restrictions on A^{-1} are based on the following assumptions and economic intuition. The first assumption is that global real economic activity does not respond immediately to real interest rate shocks, uncertainty shocks and commodity markets, but does so with a delay of at least a quarter. Our second exclusion restriction imposed in the VAR is that increases in uncertainty regarding the economic and financial outlook will not affect real interest rates immediately. Our third assumption is that innovations to risk respond to demand and policy shocks without a delay. These assumptions are based upon Bernanke *et al.* (2005) and Stock and Watson (2005), who have classified the series into slow-moving variables, such as real output and income, wages and spending; and fast-moving variables such as stock prices, money and credit. Global real economic activity is considered slow-moving: it is plausible that consumers and firms slowly revise their spending plans after a monetary policy or financial market shocks. In contrast, commodity price volatility is considered as a fast-moving variable, responding contemporaneously to slow-moving variables and policy shocks. For the commodity market block, we assume that u_t^F does not affect global real activity, the real interest rates and uncertainty within a given quarter, but instead with a delay of at least one quarter. This is imposed through the exclusion restrictions in the last column of A^{-1}. This assumption is implied by the standard approach of treating innovations to the price of commodities as predetermined with respect to the economy (e.g., Kilian and Park, 2009).

We estimate the FAVAR model in the context of Bayesian inference and adopt the independent Normal-Wishart prior, which is more flexible than the natural conjugate prior. The *prior* distributions are described as:

$$B \sim N\left(\underline{B}, \underline{V_B}\right)$$

$$\Sigma^{-1} \sim W\left(\underline{S}^{-1}, \underline{v}\right)$$

Where $\underline{B} = 0, \underline{V_B} = 10 I_4$, $\underline{S} = I_4$, and $\underline{v} = 5$ as in Koop and Korobilis (2010). The conditional posterior distributions $p(B|Y, \Sigma^{-1})$ and $p(\Sigma^{-1}|Y, B)$ are computed by the MCMC method. Following Primiceri (2005), we use a training sample prior to obtain the initial Σ^{-1}. The training sample is the first 40 observations (1974:Q1 to 1982:Q4). Using the MCMC method, 20,000 samples are obtained after the initial 10,000 samples are used as burn-in and discarded.

3.2.2 *Time Varying Parameter FAVAR with Stochastic Volatility*

Note that all parameters in equation (10) are time-invariant. Next, we adjust the model by allowing these parameters to vary over time:

$$Y_t = X_t B_t + A_t^{-1} \Sigma_t \varepsilon_t \tag{11}$$

where the coefficients B_t, and the parameters A_t, and Σ_t are all time varying. Time varying parameters allow the relationship between fundamentals and commodities to evolve over time. Stochastic volatility allows for varying shock intensity and improves estimation precision (see Nakajima *et al.*, 2011). We follow Primiceri (2005) and let $a_t = (a_{21}, a_{31}, a_{32}, a_{41}, a_{42}, a_{43})'$ be a stacked vector of the lower-triangular elements in A_t and $h_t = (h_{1,t}, \dots, h_{k,t})'$ with $h_{j,t} = log\sigma_{j,t}^2$, for $j = 1, \dots, k$ and σ_{jt} is the diagonal element of Σ_t. We assume that the parameters in (11) follow a driftless random walk process, thus allowing both temporary and permanent shift in the parameters:

$$\begin{aligned} B_t &= B_{t-1} + u_{B,t}\,, \\ a_t &= a_{t-1} + u_{a,t}\,, \\ h_t &= h_{t-1} + u_{h,t}\,, \end{aligned} \qquad \begin{pmatrix} \varepsilon_t \\ u_{B,t} \\ u_{a,t} \\ u_{h,t} \end{pmatrix} \sim N\left(0, \begin{pmatrix} I_K & 0 & 0 & 0 \\ 0 & \Sigma_B & 0 & 0 \\ 0 & 0 & \Sigma_a & 0 \\ 0 & 0 & 0 & \Sigma_h \end{pmatrix}\right), \; t = 1, \dots, T$$

The shocks to the innovations of the time varying parameters are assumed uncorrelated among the parameters B_t , a_t and h_t. We further assume for simplicity that Σ_B, $\Sigma_a$and Σ_h are all diagonal matrices. Our dynamic specification permits the parameters to vary and the shock log variance follows a random walk process to capture possible gradual or sudden structural changes, as discussed by Primiceri (2005).

For estimation, we employ a training sample prior, as shown in Section 3.2.1 and the prior distributions are set as follows:

$$B_0 \sim N\big(B_{OLS}, 4 \cdot \mathrm{V}(B_{OLS})\big)$$

$$A_0 \sim N\big(A_{OLS}, 4 \cdot \mathrm{V}(A_{OLS})\big)$$

$$h_0 \sim N(h_{OLS}, 4 \cdot I_k)$$

where B_{OLS}, A_{OLS}, and h_{OLS} denote the OLS point estimates and $\mathrm{V}(\cdot)$ denotes the variance. We also need to set the hyper-parameters Σ_B, Σ_a, and Σ_h and we postulate the following inverse-Wishart prior distributions:

$$
\begin{aligned}
\Sigma_B &\sim IW(k_B^2 \cdot 40 \cdot \mathrm{V}(B_{OLS}), 40) \\
\Sigma_a &\sim IW(k_a^2, 2) \\
\Sigma_{1,h} &\sim IW\left(k_h^2 \cdot 2 \cdot V\left(A_{1,OLS}\right), 2\right) \\
\Sigma_{2,h} &\sim IW\left(k_h^2 \cdot 3 \cdot V\left(A_{2,OLS}\right), 3\right) \\
\Sigma_{3,h} &\sim IW\left(k_h^2 \cdot 4 \cdot V\left(A_{3,OLS}\right), 4\right)
\end{aligned}
$$

where $k_B = 0.01$, $k_\alpha = 0.1$, and $k_h = 1$. $\Sigma_{1,h}$, $\Sigma_{2,h}$, and $\Sigma_{3,h}$ denote the three blocks of Σ_h and $A_{j,OLS}$ for $j = 1, \cdots, 3$, denotes the three corresponding blocks of A_{OLS}. The estimation procedure is the MCMC method and the first 10,000 samples are discarded and 20,000 samples are obtained for the inference. The details of the MCMC procedure for TVP-VAR are explained by Primiceri (2005), Koop and Korobilis (2010) and Nakajima *et al.* (2011).

4. Data

To carry out our investigation, we use quarterly primary commodity prices and fundamentals data from 1974Q1 to 2014Q3. For the dynamic hierarchical factor model, we collect a panel of 38 commodity prices from the International Monetary Fund (IMF) *International Financial Statistics* and World Bank commodity price data. Following the structure of the IMF non-fuel commodity index, we arrange the commodity data into three sectors: (a) *agricultural raw materials*, (b) *food* and (c) *metals*. First, the materials sector includes eight commodities: cotton, hides, plywood, rubber, hardwood logs, hardwood sawn wood, coarse wool, and fine wool. Second, our dataset includes 23 food commodities, and we further decomposed them into four sub-sectors; namely, cereals (i.e. barley, maize, rice, sorghum and wheat); meat (i.e. beef, lamb and chicken), vegetable oil and protein meals (i.e. coconut oil, copra, groundnuts, groundnut oil, linseed oil, palm oil, soybeans, soybeans meal, and soybeans oil), and others (i.e. cocoa beans, coffee, tea, banana, fishmeal, sugar). Finally, we include seven metal commodities: aluminium, copper, gold, lead, silver, tin and zinc. Table 1 summarizes our data and model structure of commodity prices. Quarterly data is preferred when estimating our time-varying parameter model: TVP-VAR estimation at a monthly frequency would require many lags to capture data dynamics, and hence would be computationally intensive (Nakajima *et al.*, 2011). Before the factor analysis, we deflate the nominal commodity prices using US CPI. As real commodity prices are non-stationary, and our factor model requires stationary data (Stock and Watson, 2009; Moench *et al.*, 2013), we first difference the logarithm of real commodity prices. A detailed description of the commodity price series is presented in Appendix A, Table A1.

[INSERT Table 1 Here]

Next, we collected fundamentals data from the Federal Reserve Bank of St. Louis and DataStream, and consider their impact within our FAVAR models. We firstly use US industrial production as our proxy for global economic activity. The rationale for using this proxy is that the growth of industrial production will reflect changes in the demand for industrial commodities (e.g., copper, lumber) and it will also impact demand for non-industrial commodities (e.g., cocoa, wheat) as income changes, see Pindyck and Rotemberg (1990). Given the potentially increasing importance of the Chinese economy for commodities, we also proxy demand using the growth rate of Chinese industrial production.[7] Secondly, we consider the role of the real short-term interest rate based upon the three-month US Treasury Bill as a proxy for monetary policy shocks (e.g., Primiceri, 2005). The real rate is obtained by subtracting US CPI inflation from the nominal interest rate, based upon the Fisher equation. Note that we also test the robustness of our approach by using the federal fund rate as an alternative interest rate proxy (e.g., Bernanke *et al.*, 2005; Frankel, 2014).

In order to examine the uncertainty effects on commodity prices' growth, we model uncertainty that arise from agents' perspectives on future outcomes. To that end, we fit a GARCH model of the log difference of the daily S&P GSCI (Goldman Sachs Commodity Index) to cover the period from January 1970 to December 2014.[8] We should note that prior to estimating this model, we confirmed the presence of ARCH effects in the GSCI using the Lagrange Multiplier (LM) test. We also check whether the standardized residuals exhibit higher order autocorrelation and ARCH effects. Ascertaining that the selected model is well specified, we take the within quarter average of the estimated conditional variances to match the frequency of the commodity data. This series is then used as a measure of uncertainty in the market. Here, higher levels of conditional variance imply higher perceived uncertainty. In such an environment, decision makers (e.g., fund managers, commodity producers) will not be able to predict the viability and returns of projects. Thus, one may behave more

[7] For robustness we also consider Kilian's (2009) global economic activity index as an alternative proxy for demand. This is a measure from an equal-weighted index of the percent growth rates of a panel of single dry cargo ocean shipping freight rates in dollars per metric ton. Given the supply of ocean-going vessels is likely to be inelastic in the short-run, shipping rates shall reflect global demand for commodities.

[8] For standard references to GARCH estimation see Engle (1982) and Bollerslev (1986).

conservatively, and opt to postpone the investment to avoid potentially large losses when the project outcome is unfavourable. To check for the robustness of our investigation, we also proxy uncertainty using the within quarter standard deviation of the GSCI non-energy spot index and a GARCH model fitted to the stock market. We next proceed to estimate our empirical models.

5. Empirical Results

This section presents our core results on the nature and determinants of commodity prices. We first report the empirical findings on commodity price co-movement using the dynamic hierarchical factor model of Moench *et al.* (2013). Next, we discuss the results from a constant parameter FAVAR model and those from a time varying parameter FAVAR model with stochastic volatility.

5.1 Commodity Price Co-movement

The four-level dynamic hierarchical factor model allows us to capture the aggregate common dynamics, as well as to track the developments in different commodity sectors. Figure 1 plots the estimated global common factor, $\hat{F}$, plus material, food and metal sectoral factors, $\hat{G}$. Similarities between the sectors include, for instance, the commodity price peaks in mid-2008, fall thereafter and peak again in 2011. There are however some important differences between the common and sectoral factors, especially during episodes of extreme price volatility. For example, agricultural raw material and metal sectors react more strongly than the common factor during the striking collapse of commodity prices in the global financial crisis. The growth of materials and metals also exceed the common factor before the crisis. This may imply that agricultural raw materials and metals are more sensitive to the global business cycle, compared to food commodities.

[INSERT Figure 1 Here]

We now turn to the important question of evaluating how much of the variation in real commodity prices can be attributed to the aggregate common ($Share_F$), sector ($Share_G$), and sub-sector ($Share_H$) components and to idiosyncratic noise ($Share_Z$). Table 2 reports the average posterior means (μ) and standard deviations (σ) of the estimated variance shares for the four level decomposition of our data set, including all sectors and sub-sectors. Our first evidence of heterogeneity in commodities is that the aggregate common factor is most important for metals in which a third of commodity price variation is explained by the global commonalities in commodities, while less than 1% is explained for food-meats. Mirroring the latter result, idiosyncratic variations play an important role for food-meats as it accounts for most of the variation in this sub-sector (i.e. μ=0.742). On the other hand, cereals, non-fuel oils, agriculture raw materials, and metals are explained to a lesser extent by idiosyncratic variation. As mentioned above, our hierarchical model goes beyond principal components since it accommodates sector and sub-sector level shocks. In sum, our result suggests that co-movement in commodity prices co-exist with heterogeneous variations between sectors and highlight the importance of modelling common variations at different levels (Moench *et al.*, 2013; Yin and Han, 2015). Given these results, sectoral heterogeneity is the focus of our later analysis.

[INSERT Table 2 Here]

5.2 Commonalities, Fundamentals and Heterogeneity

In this section, we model commodity prices by examining the relationship between their common factors and key macro fundamentals highlighted in the literature. We first present impulse response functions to the shocks, based upon a Bayesian FAVAR model with common ($\hat{F}$). Thereafter, we investigate whether FAVAR models are robust to time variation and commodity heterogeneity, based upon findings from our TVP-FAVAR model for the common factor ($\hat{F}$) and groups of commodities ($\hat{G}$). As we noted above, such an approach has not been extensively researched in the literature.

5.2.1 *Impulse responses from a FAVAR model*

Using our Bayesian FAVAR model, Figure 2 depicts impulse responses of the common factor of commodity returns over three sample periods and to three macro shocks. For this we use demand, real interest rate and risk shocks and the non-informative prior. We present results for a ten quarter response horizon. Our responses include the posterior median as the solid line, while the dotted lines are the 16th and 84th percentiles of the posterior distribution.[9]

[INSERT Figure 2 Here]

We start by reporting the full sample period results in first column of Figure 2. We find that demand shocks, as measured by US industrial production growth, lead to an immediate increase in the real price of commodities, but the effect declines sharply after four quarters. From the top left window in Figure 2, we also see that commodities' response to demand is important for the first four quarters, since the zero axis is not within the error

[9] Under normality, the 16th and 86th percentiles correspond to the bounds of one-standard-deviation (Primiceri, 2005).

bands. This response can be interpreted as statistically significant within a frequentist methodology. This finding is consistent with Boughton and Branson (1991), Vansteenkiste (2009), Byrne *et al.* (2013) and West and Wong (2014), who also find that positive innovations to measures of the global business cycle positively impact the price of commodities. Secondly, we find for the full sample period that a real interest rate shock leads to an immediate and sizable decrease in commodity prices for the first quarter as shown in the middle left window of Figure 2. Furthermore, an uncertainty shock causes an immediate drop in commodity prices and then dies out five quarters after the shock. See the bottom left response in Figure 2. Therefore, our findings not only confirm the view of Frankel (2008), and Byrne *et al.* (2013) that interest rates have an adverse impact on commodity prices, but also are consistent with the idea of Beck (1993), Dixit and Pindyck (1994), and Kulatilaka and Perotti (1998) that risk is strongly associated with movements in commodity prices.

Next, we consider whether the impact of fundamental shocks is broadly time-varying, by splitting the sample into two sub-periods. The second and third column of Figure 2 displays the median impulse responses of the common factor to macro shocks over the subsamples 1974Q1–1993Q4 and 1994Q1–2014Q3. We identify an evolving relationship between primary commodity prices and macro fundamentals. To be more specific, the response of commodity prices to the one standard deviation real interest rate shock is more persistent in the first subsample, while the reaction to demand and uncertainty shocks are more pronounced in the second subsample. Note that we have also replaced the common factor with three sectoral factors and apply our core shocks over the full sample period, and two subsample periods, we have observed the important difference in sectoral responses over time – see Figure B1 in the Appendix B.

5.2.2 *TVP-FAVAR model with stochastic volatility*

The previous results were based upon the assumption that the impact of fundamentals on commodity prices was time-invariant. Our subsample analysis, with exogenously identified sub-periods, indicates that this assumption is open to question, hence we now adopt more flexible methods. In this section, we focus upon the time evolution of the relationship between commonalities in commodity returns and macro shocks using a TVP-FAVAR model with stochastic volatility. Such an approach allows us to consider the evolving impact of Chinese demand, recent monetary policy and the role of risk during the financial crisis. Note that for a standard VAR model whose parameters are time-invariant, we can graph one impulse response profile for each shock, see Figure 2. For the time varying parameter models however, there will be a different set of coefficients in every time period. So we will have a different impulse response function at each point in time. Although one can draw a three-dimensional plot for the time varying impulse responses, it is common practice to present the impulse responses for a selected horizon over time and/or at a selected point in time (e.g., Primiceri, 2005; Koop and Korobilis, 2010; Nakajima *et al.*, 2011; Baumeister and Peersman, 2013). Therefore, we plot both the impulse responses for the full sample period, and for up to a ten quarter horizon for three specific time periods.

[INSERT Figure 3 Here]

Figure 3 graphs contemporaneous time varying impulse responses of the global commodity factor to one standard deviation increases in demand, real interest rates and risk. In this figure the posterior median is the solid line and the dotted lines are the 16th and 84th percentiles of the posterior distribution. We find that global business cycle has a consistent positive relationship with commodity price commonalities. This reaction is intuitive since an expansion in the global economy shall increase demand for industrial commodities and drive up prices (Kilian, 2008; Frankel, 2014). This positive relationship can be seen in the top panel of Figure 3 and the relationship intensified in the 2000s. The response of commodities to demand is consistently out-with the zero axis and hence can be considered to be statistically significant from a frequentist perspective. The middle panel of Figure 3 shows a significant negative response of commodities to a real interest rate shock over the entire sample period, based upon the 16th and 84th percentiles.[10] Real commodity prices tend to fall in response to higher real interest rate until commodities are "undervalued," and future prices are expected to rise sufficiently to offset the higher interest rate. Only then shall firms and investors hold inventories, despite the high carrying costs (Frankel, 2008). The effect of monetary policy on real commodity prices is also time-varying. We can see commodity prices respond more negatively to real interest rate shocks during the 2000s. This was a period of rapid commodity price inflation and activist Federal Reserve monetary policy associated with the collapse in the dot.com bubble, credit crunch and the global financial crisis.

Using our more flexible time varying parameter methodology, the third shock upon the common factor that we consider is that of uncertainty. This uncertainty proxy is from the commodity market, as discussed above. We find uncertainty had a substantial and negative impact upon commodity commonalities, see the bottom panel of Figure 3. The acutely time-

[10] Note that a policy induced monetary contraction can temporarily raise the real interest rate via a rise in the nominal interest rate, a fall in expected inflation, or both.

varying impact is closely associated with the Global Financial Crisis, during which financial market volatility rose to levels that have rarely been seen since the Wall Street Crash. Recall that, the reaction of subprime mortgages and securitized products raised serious concerns about the solvency and liquidity of financial institutions. This led in 2008 to a full-blown banking crisis following the failures of Lehman Brothers, and government takeovers of Fannie Mae, Freddie Mac, and AIG (Ivashina and Scharfstein, 2010). Commodities also fell sharply when uncertainty rose during the crisis period, see Figure 1. Although still important, we observe a smaller impact of the uncertainty shock on commodities before and after the crisis in 2008. The latter reduction is consistent with the partial success of a variety of government actions which were implemented to promote the liquidity, solvency of credit markets and financial market stability. As noted earlier uncertainty effects are known to be short lived, and our TVP results highlight that they are especially time specific.

5.2.3 *Sector-specific commonalities in a TVP-FAVAR model*

To account for heterogeneity in commodity prices, we now replace the common factor in our TVP-FAVAR model with three sectoral factors for agriculture raw materials, food and metals. The TVP-FAVAR impulse responses for material, food and metal sectors in Figure 4, share some similarities. For example, we find that aggregate demand shocks are positively related to the real price of commodities across all three sectors throughout most of the sample period; while real interest rate shocks and uncertainty shocks are negatively related to commodity prices for certain periods.

[INSERT Figure 4 Here]

There are important differences however among these three sectors' responses to macro shocks which underscores heterogeneity in the commodity market. The metal sector generally responds more positively to the global business cycle than the material and food sector in Figure 4. One possible explanation for this is that the unexpectedly rapid pace of industrialization and urbanization of emerging economies has dramatically increased the demand for metal commodities, such as copper, which are core materials in constructions and electronics. Issler *et al.* (2014) also presents empirical evidence that cycles in metal prices are synchronized with the global economy. On the other hand, while greater economic activity without commensurate increases in population raises incomes, this is less likely to increase demand for food products overall and there may be substitution effects between different food commodities (Cater *et al.*, 2011).

However, we observe more homogeneous responses among material, food and metal sectors to demand after the crisis. This is consistent with the earlier literature on commodities moving together as an asset class (e.g., Byrne *et al.*, 2013, and West and Wong, 2014). A number of authors study the cause of recent high food prices and increased cross-commodity linkages, and they provide evidence of a positive relationship between biofuel production and food prices, notably in the US (e.g., Mallory *et al.*, 2012; Avalos, 2014). The growth in the subsidized biofuel industry raised concerns among stakeholders about global food shortages and food poverty.

In terms of real interest rate shocks, the zero axes are always out with the error bands for the agriculture raw materials and food, unlike for metals, suggesting that materials and food commodities are more sensitive to interest rate shocks than metals – see the second column of Figure 4. In particular, our sectoral evidence suggests that real interest shocks have a more persistent impact upon food prices, possibly because monetary policy is more closely aligned with food prices than materials and metals. Furthermore, one of the key transmission mechanisms for changes in real interest rates to commodity price fluctuations is through the carrying cost of inventories. During high real interest rates periods, firms' desire to carry food inventories decreased faster as compared to materials and metals. Food may be more interest rate elastic compared to other commodities, since the physical costs of food inventory are already substantial and profit margins are therefore smaller.

Turning to the time varying impact of risk, our measure of commodity price uncertainty adversely affected the price of industrial commodities. This effect was particularly acute towards the end of 2007, see the third column of Figure 4 for the response of the three sectors to uncertainty. The global financial crisis caused a global recession and raised fears about future economic conditions. The heterogeneous responses are reasonable since a large risk shock will reduce production activity and demand for raw materials and metals. Food on the other hand is more impervious to risk and the financial conditions more generally, possibly due to the importance of maintaining food consumption, even in a crisis.

To sum up our results so far, we provide empirical evidence that macro fundamentals affect the returns of a large panel of commodities and these effects vary over time. There is also important heterogeneity in the response of agricultural raw material, food and metal sectors. Our findings are consistent with Ferraro et al. (2015) who find that a country's major commodity export price predicts changes in its nominal exchange rate.

To check the robustness of our results, we re-estimate our TVP-FAVAR models by replacing a number of the variables in our model with alternative proxies, such as Kilian's (2009) global economic activity index, the federal funds rate, realized volatility of commodities and stock market volatility. We find that the responses of commodity commonalities to fundamental shocks are similar to our main results. See the Appendix B Figures B2-B5 for further details. Additionally, we also report the responses of the commodity common and sector factors to three macro shocks at three points in time using the TVP-FAVAR model – see Appendix B Figures B6 and B7. The responses of these shocks are observed at ten year intervals, i.e., 1988Q4, 1998Q4 and 2008Q4.[11] Our empirical evidences underscore the importance of allowing for time variation in studying the effects of macro fundamentals on commodity commonalities.

5.3 *China and the Global Commodity Market*

A number of studies suggest that strong economic growth in China this century has raised global demand for a broad range of commodities, as well as increasing commodity prices (e.g., Kilian, 2009; Roache, 2012; Frankel, 2014). It is widely known that China has significantly increased its market shares of global commodity markets since 2000. Again, prior studies assumed the impact of macro determinants upon commodities has not changed over time. Therefore, we consider the extent to which commonalities in commodity prices are affected by unexpected increases in Chinese economic activity, accounting for heterogeneity and a potentially evolving relationship over time. We use the real growth rate of Chinese industrial production as a proxy for Chinese economic activity. We focus upon the more topical post 2000 period, due partly to data availability.

[INSERT Figure 5 Here]

Figure 6 plots time varying impulse responses of the global commodity factor and three sectoral factors to the one standard deviation increase in Chinese demand immediately after the shock. The posterior median response is once again the solid line and dotted lines are the 16th and 84th percentiles of the posterior distribution. First, we find that unexpected strong demand from China lead to a persistent increase in the common factor of commodities and this effect was more substantive in 2008 and 2012. The response of the common factor to Chinese demand is found in the top left panel of Figure 5. When we consider the response of

[11] There are some notable differences in these responses in the representative periods for the three shocks. For example, we can clearly see increasing responses over time of commodity prices to demand shock; the increasing impact of the real interest rate shock; and also the risk impulse responses becomes highly negative and important in 2008Q4.

commodity sectors to Chinese shocks, we again observe a strong positive impact on metal commodities due to Chinese demand. Materials are only more recently impacted by Chinese demand. Interestingly, we also find Chinese economic activity impacted food prices. In fact, greater real economic activity leads to higher level of incomes, and rising incomes drive greater food consumption, particularly in developing countries in which caloric intake is more responsive to income growth (e.g., Carter *et al.*, 2011). Therefore, China economic activity, and not merely economic activity in the US, appears to drive global food prices.[12]

6. Conclusion

Large swings in commodity prices have brought new momentum to the spirited debate on their commonalities and determinants, and our paper extends this literature. We firstly contribute to the empirical evidence on the co-movement of real primary commodity prices. Unlike existing studies that extract principal components from a large panel of data, we employ a dynamic hierarchical factor model from Moench *et al.* (2013) to decompose the real price of commodities into common, sectoral, sub-sector and idiosyncratic components. We find significant evidence of co-movement in commodity prices and importantly, identify a common factor and three sectoral factors. Our results highlight the importance of modelling common variations at different levels: for instance, common and sectoral factors may share similar trends, but there is also notable heterogeneity.

Next, we empirically relate commodity price commonalities to (*i*) demand, (*ii*) real interest rates and (*iii*) uncertainty. While existing studies often present conflicting evidence of the impact of fundamentals using time-invariant methodologies to examine the drivers of commodity prices co-movement, this study uses a time varying parameter factor augmented vector autoregression (TVP-FAVAR) model with stochastic volatility. This allows us to capture potentially unstable relationships to fundamentals and a time varying impact upon the commodity market.

The results from this analysis can be summarised as follows. First, we find that positive innovations to the global business cycle cause a higher price of commodities over time, especially after 2000s. Second, real interest rate shocks were found to have an important and negative effect on real commodity commonalities. Furthermore, we find that elevated risks negatively impact commodity prices. This uncertainty effect on the real price of

[12] Finally, we have also checked the impulse response of common and sectoral commonalities to Chinese demand shocks at representative points in time: 2003Q4, 2008Q4 and 2013Q4. Consistent with the common perception, we observe a positive response across time for both the common factor and three sectoral factors. The effect is time varying with a peak effect in 2008Q4 – see Appendix B Figure B1.

commodities was most acute from the middle of 2007 and peaked at the end of 2008. This finding is consistent with the idea that many asset classes suffered from the adverse impact of the 2007-2008 global financial crisis. Finally, we extend the literature on the relationship between commodity prices and macro determinants, whilst allowing for commodity heterogeneity. We find sectoral factors for agricultural raw material, food and metal sectors respond differently to macro shocks at different points in time.

In sum our findings provide useful information for macroeconomic policy making, consumption, capital investment, risk and portfolio management. Better understanding what drives the swings in commodity prices can help economic and financial planners anticipate, and adjust to, their consequences. For instance, by identifying the heterogeneity of sector sensitivities to macroeconomic fundamentals changes implies that some commodities can provide a channel for diversification during large swings in global uncertainty. In particular, if the global demand is expected to soar in the future, investors may use this information to devise their investment strategies such as taking short positions for raw materials and metals; and during extreme uncertain periods, one may take short positions in raw materials and metals. Additionally, central banks take explicit account of the volatility of commodity prices in setting monetary policy. Our findings provide useful information for policy makers that the effects of monetary policy vary over time and across sectors. Hence, monetary authority needs to take these into account to have a desirable policy impact by implementing monetary policy. One interesting question will be to find out whether our time-varying framework can improve the predictability of commodity prices. We shall leave these issues for future work.

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Table 1. Data and Model Structure

Sector	Sub-Sector	*N*
Food	Cereals	5
	Meat	3
	Vegetable oil and protein meals (Non-fuel oil)	9
	Others	6
Materials		8
Metals		7
Total		38

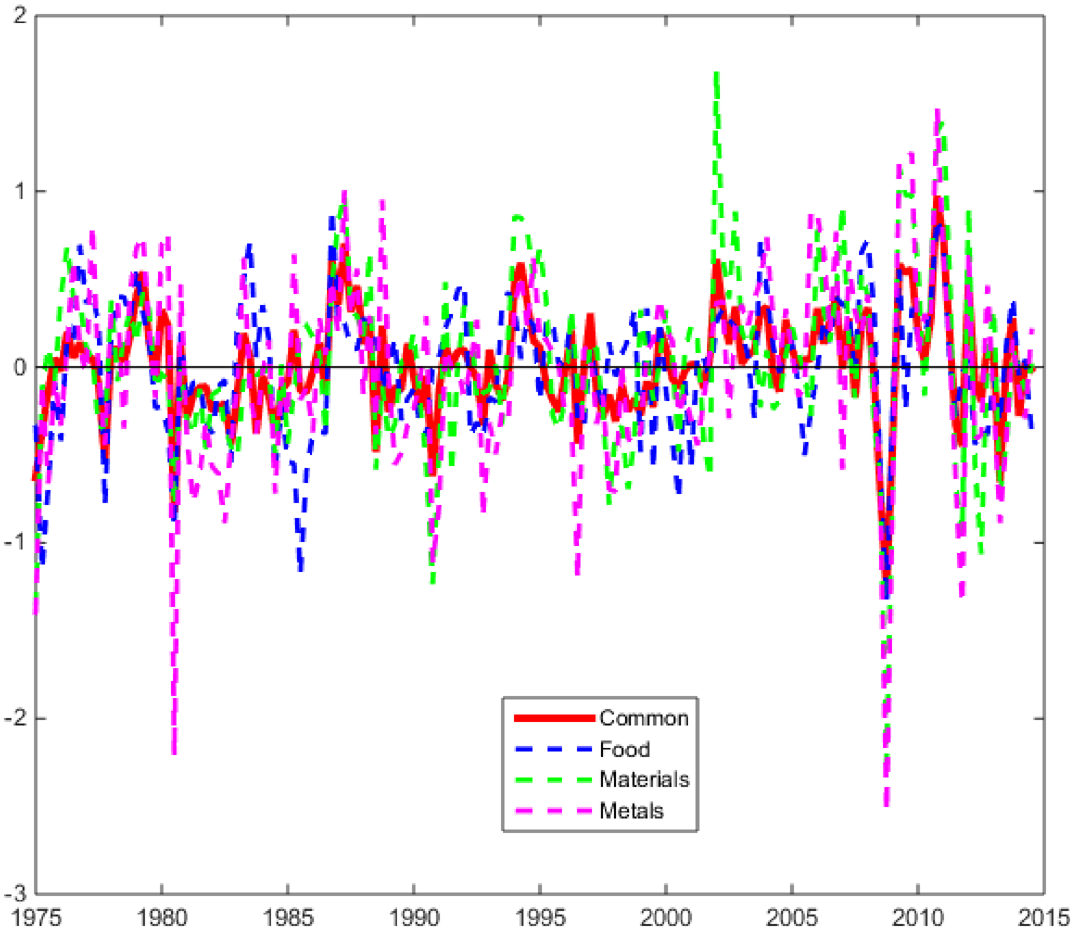
Notes: This table summarizes the different sectors in our data set. These are food, agricultural raw materials, and metal sectors. Sub-sectors for real commodity prices are also included. *N* denotes the number of series in each sector/sub-sector.

Table 2. Variance Decomposition of Commodity Prices

Sector	Sub-Sector	Global [$Share_F$]	Sector [$Share_G$]	Sub-Sector [$Share_H$]	Idiosyncratic [$Share_Z$]
Food	Cereals	0.215 (0.017)	0.177 (0.013)	0.183 (0.013)	0.424 (0.033)
	Meat	0.007 (0.012)	0.006 (0.010)	0.245 (0.170)	0.742 (0.182)
	Non-fuel oil	0.243 (0.028)	0.200 (0.024)	0.037 (0.006)	0.520 (0.045)
	Others	0.024 (0.016)	0.020 (0.013)	0.090 (0.044)	0.866 (0.063)
Materials		0.207 (0.052)	0.096 (0.029)		0.697 (0.059)
Metals		0.330 (0.062)	0.098 (0.023)		0.572 (0.069)

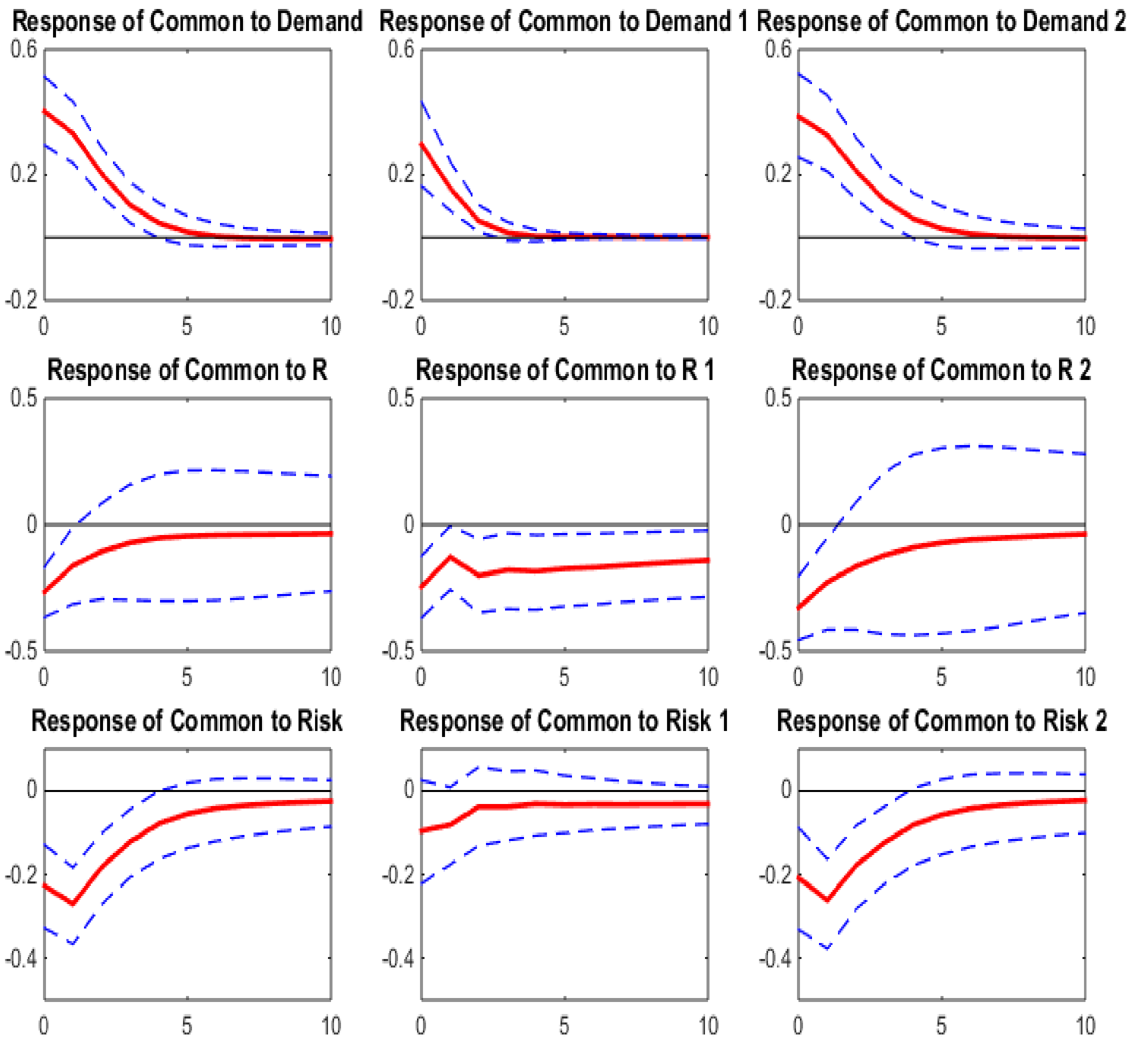
Notes: This table summarizes our four level variance decomposition of real commodity price based upon a dynamic hierarchical factor model (DHFM) presented in equations (1)-(3). The four levels are the global factor [$Share_F$], sector [$Share_G$], sub-sector [$Share_H$] and idiosyncratic shocks [$Share_Z$]. We report the means and in parentheses standard deviations of the estimated variance shares for the model's four levels, including all sectors and sub-sectors of our data set. The sample period is 1974Q1 to 2014Q3.

Figure 1. Commonalities in Commodity Prices



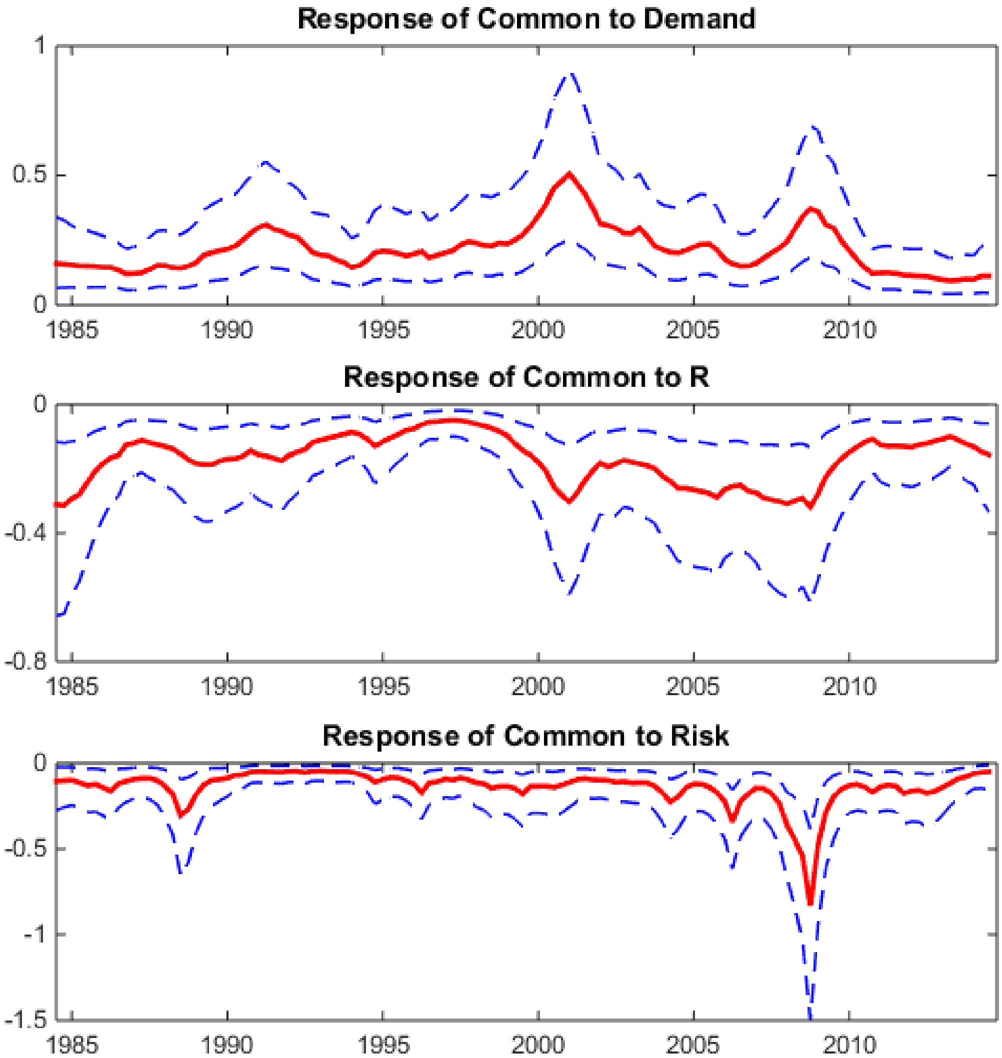
Notes: The graph presents estimated aggregate common factor (Common), along with sectoral factor for the returns in food (Food), agricultural raw materials (Materials), and metal (Metals). The sectoral commonalities are identified Dynamic Hierarchical Factor Model in equations (1), (2) and (3), see Moench *et al.* (2013).

Figure 2. FAVAR Impulse Responses of Common Factor



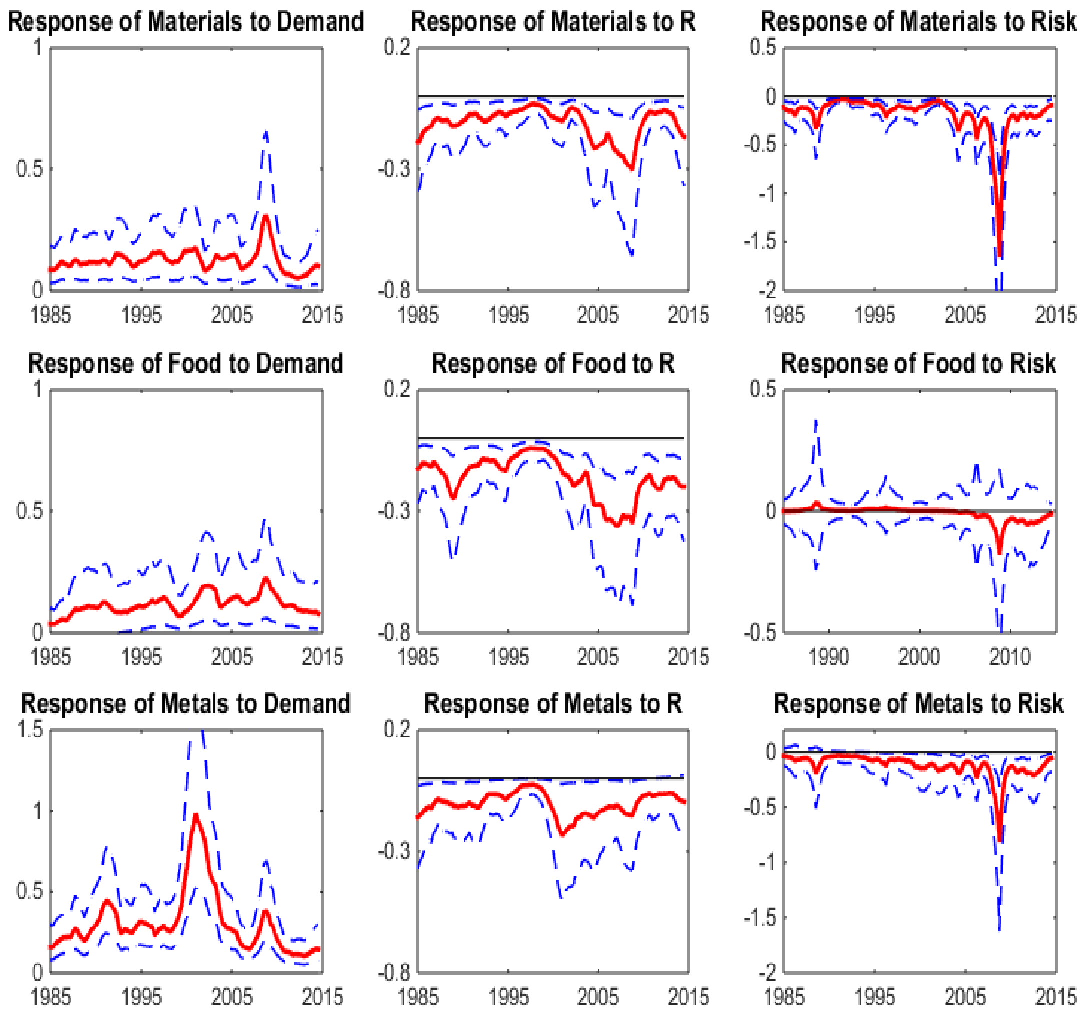
Notes: The nine graphs in Figure 2 plot the median responses of common factor (solid line) to each of the three macro shocks that affect the commonalities in commodity returns for three sample periods. Note that the first column reports the full sample period (1974Q1 to 2014Q3) result, and second and third columns report two sub-samples 1974Q1-1993Q4 (i.e. period 1), and 1994Q1-2014Q3 (i.e. period 2). We also provide 16th and 84th percentile error bands in dashes. The common factor is extracted from the DHFM equation (3).

Figure 3. TVP-FAVAR Common Factor Response



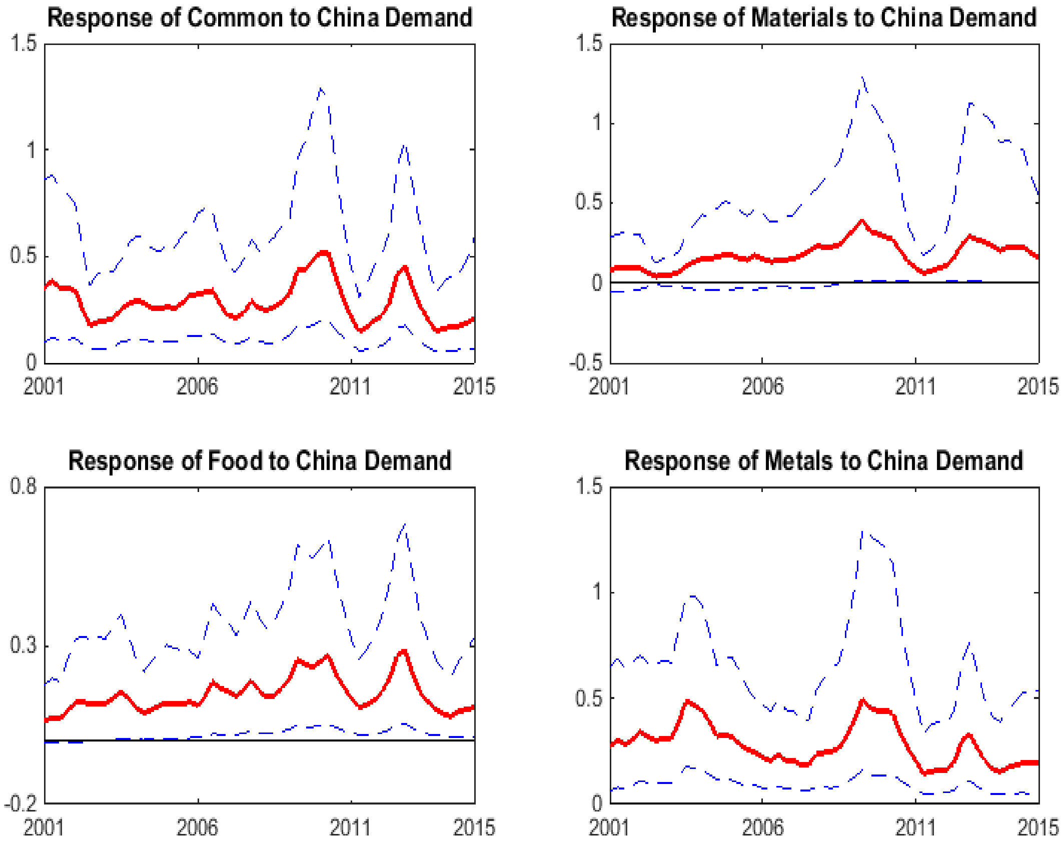
Notes: The three graphs in Figure 3 plot the median impulse responses of the common factor (solid line) to each of the three macro shocks that affect commodity returns. We also provide 16^{th} and 84^{th} percentile error bands in dashes. The estimates are based on the TVP-FAVAR model in equation (11). Each panel measures how a unit impulse of shocks impacts the commodity common factor over time. Here we use the full sample period.

Figure 4. TVP-FAVAR Sectoral Factor Responses



Notes: The nine graphs in Figure 4 plot the median responses of three sector factors to each of the three macroeconomic shocks with 16th and 84th percentile error bands. The three shocks are to demand, the real interest rate and risk. The estimate responses are based on the TVP-FAVAR model in equation (11). Each panel measures how a unit impulse of shock impacts the commonalities of commodity prices over time. Here we use the full sample period to consider the time varying response.

Figure 5. TVP-FAVAR Factor Responses to Chinese Demand Shock



Notes: The four graphs in Figure 5 plot the median responses in commodity returns of common and three sector factors to Chinese demand shocks, plus 16th and 84th percentile error bands. The estimates are based on the TVP-FAVAR model in equation (11). The sample period is based upon data availability.

Appendix A: Data Sources

Table A1. List of Commodities and Data Sources

	Commodity	Description	Source
1	Barley	US (Units: US dollars per metric ton)	WB
2	Maize	11176j-zzfm17: US (Units: US dollars per metric ton)	IMF
3	Rice	57874n-zzf---: Thailand (Units: US dollars per metric ton)	IMF
4	Sorghum	11176trzzf---: US (Units: US dollars per metric ton)	IMF
5	Wheat	11176d-zzf---: US gulf (Units: US dollars per metric ton)	IMF
6	Beef	19376kbzzf---: Australia (Units: US cents per pound)	IMF
7	Lamb	19676pfzzf---: New Zealand (Units: US cents per pound)	IMF
8	Chicken	US (Units: US dollars per kilogram)	WB
9	Coconut oil	56676aizzf---: Philippines (Units: US dollars per metric ton)	IMF
10	Copra	56676agzzf---:Philippines (Units: US dollars per metric ton)	IMF
11	Groundnuts	69476bhzzf---:Nigeria (Units: us dollars per metric ton)	IMF
12	Groundnut oil	69476bizzf---: US (Units: US dollars per metric ton)	IMF
13	Linseed oil	00176nizzf---: US (Units: US dollars per metric ton)	IMF
14	Palm oil	54876dfzzf---: Malaysia (Units: US dollars per metric ton)	IMF
15	Soybeans	11176jfzzf---: US (Units: US dollars per metric ton)	IMF
16	Soybeans meal	11176jjzzf---: US (Units: US dollars per metric ton)	IMF
17	Soybeans oil	11176jizzf---: US (Units: US dollars per metric ton)	IMF
18	Cocoa beans	65276r-zzfm44: US (Units: US dollars per metric ton)	IMF
19	Coffee	38676ebzzf---: US (Units: US cents per pound)	IMF
20	Tea	11276s-zzf---: US (Units: US cents per kilogram)	IMF
21	Banana	US (Units: US dollars per kilogram)	WB
22	Fishmeal	29376z-zzf---: US (Units: US dollars per metric ton)	IMF
23	Sugar	11176iazzfm02: US (Units: US cents per pound)	IMF
24	Cotton	11176f-zzfm40: Liverpool (Units: US cents per pound)	IMF
25	Hides	11176p-zzf---: US (Units: US cents per pound)	IMF
26	Plywood	56676wxzzf---: Philippines (Units: US cents per sheet)	IMF
27	Rubber	54876l-zzf---: Malaysia (Units: US cents per pound)	IMF
28	Hardwood logs	54876vxzzf---: Sarawak (Units: US dollars per cubic meter)	IMF
29	Hardwood sawnwood	54876rmzzf---: Malaysia (Units: US dollars per cubic meter)	IMF
30	Wool coarse	11276hdzzf---: Australia 48 coarse (Units: US cents per kilogram)	IMF
31	Wool fine	11276hezzf---: Australia 64 fine (Units: US cents per kilogram)	IMF
32	Aluminium	15676drzzf---: US (Units: US dollars per metric ton)	IMF
33	Copper	11276c-zzf---: US (Units: US dollars per metric ton)	IMF
34	Gold	11276krzzf---: US (Units: US dollars per troy ounce)	IMF
35	Lead	11276v-zzf---: US (Units: US dollars per metric ton)	IMF
36	Silver	11176y-zzf---: US (Units: unspecified units)	IMF
37	Tin	11276q-zzf---: US (Units: US dollars per metric ton)	IMF
38	Zinc	11276t-zzf---: US (Units: US dollars per metric ton)	IMF

Notes: IMF indicates IMF International Financial Statistics; and WB refers to World Bank Commodity price data.

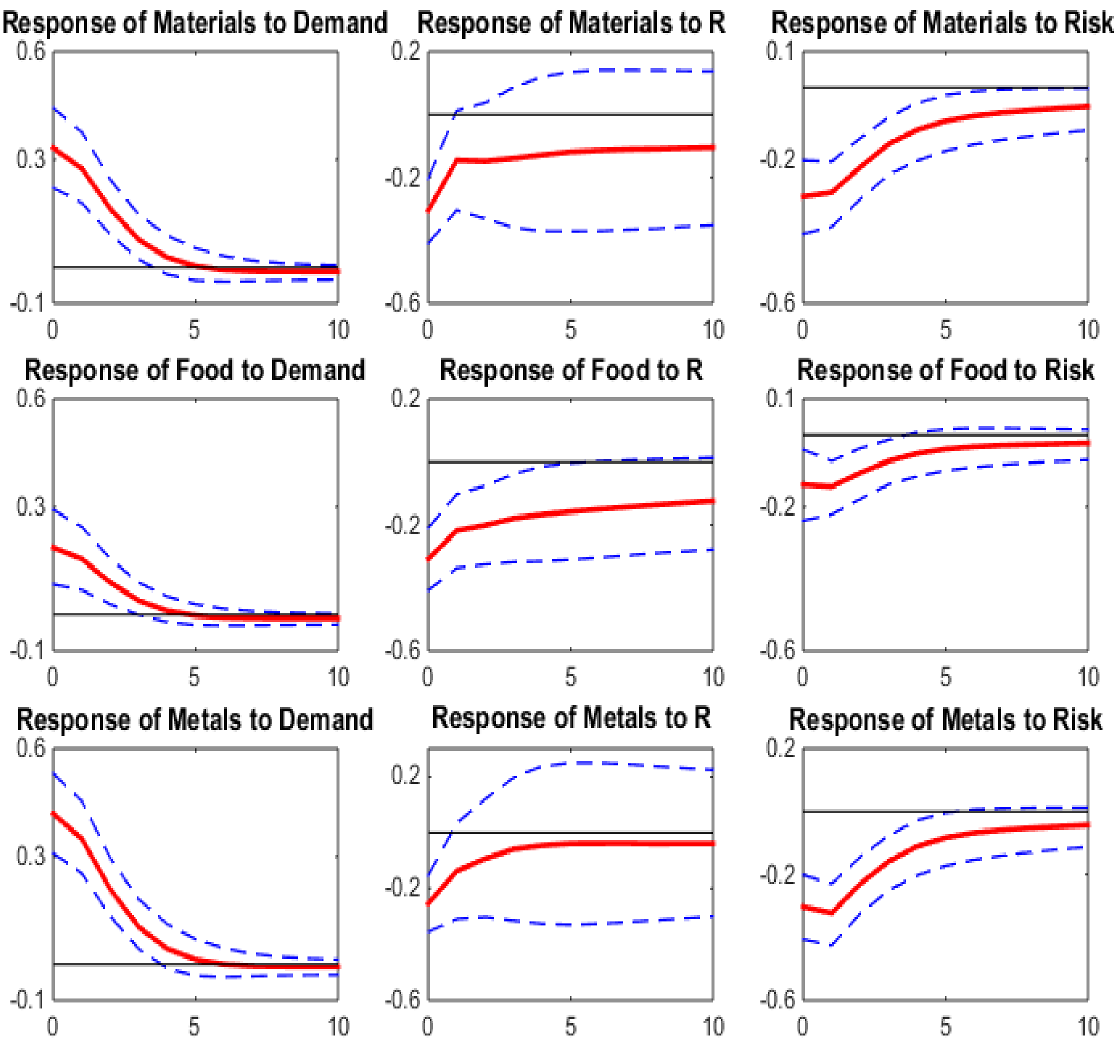
Table A2: Data Sources and Transformations

Variables	Raw Data Series	Transformations	Sources of Data
Real Commodity Prices	38 Commodity Prices	**1.** Compute the real commodity prices by deflating the nominal price index using the US CPI Index, with 1983Q2=100; **2.** Take the first difference in the logarithms of the real commodity prices.	IMF *International Financial Statistics* and the World Bank, see Table A1 for details.
Demand	**1.** Real US Industrial Production	Logarithm growth rate of real US industrial production.	Federal Reserve Bank of St. Louis
	2. Real Chinese Industrial Production	Change year on year of Chinese industrial production	Datastream
	3. Single-voyage freight rates	See Kilian (2009) for detailed information on how to construct this series.	Lutz Kilian's homepage: http://www-personal.umich.edu/~lkilian/reaupdate.txt
Real Interest Rates	**1.** Three Month US Treasury Bill Yields **2.** Federal Funds Rate	Compute the real interest rate by subtracting the inflation rate from the nominal interest rate. The inflation rate is based upon the change in the U.S. CPI Index.	Federal Reserve Bank of St. Louis
Uncertainty	**1.** S&P GSCI GARCH	**1.** Compute the first difference in the logarithms of the daily S&P GSCI Non-Energy Spot Index; **2.** Fit a GARCH model to identify variance; **3.** Take the within quarterly average of the estimated conditional variance to match the frequency of quarterly macroeconomic data.	Datastream
	2. S&P GSCI Variance	**1.** Compute the first difference in the logarithms of the daily S&P GSCI Non-Energy Spot Index; **2.** Compute the within quarterly variance based on daily S&P GSCI returns.	
	3. S&P 500 GARCH	**1.** Compute the first difference in the logarithms of the daily S&P500 index; **2.** Fit a GARCH model to identify variance; **3.** Take the within quarterly average of the estimated conditional variance to match the frequency of quarterly macroeconomic data.	

Appendix B: Additional Results

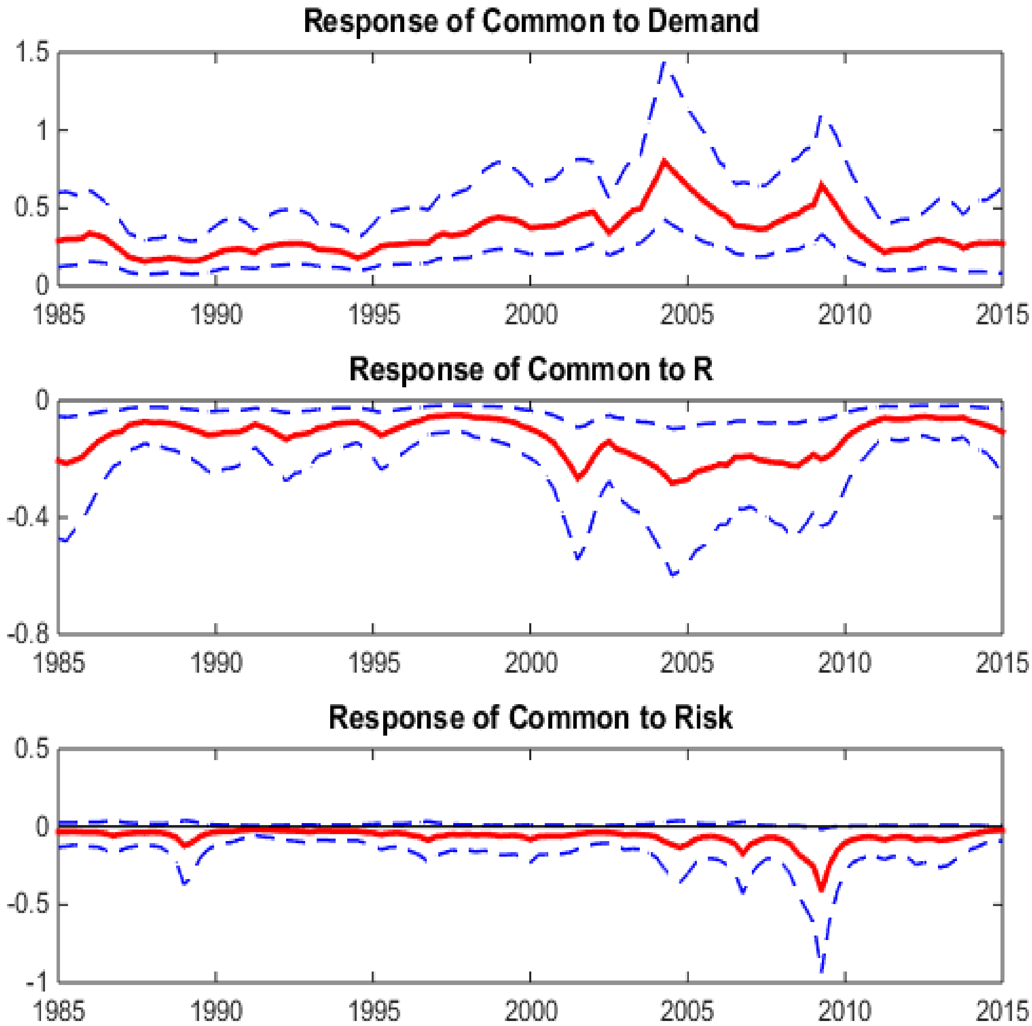
(NOT FOR PUBLICATION)

Figure B1. FAVAR Impulse Responses of Sectoral Factors



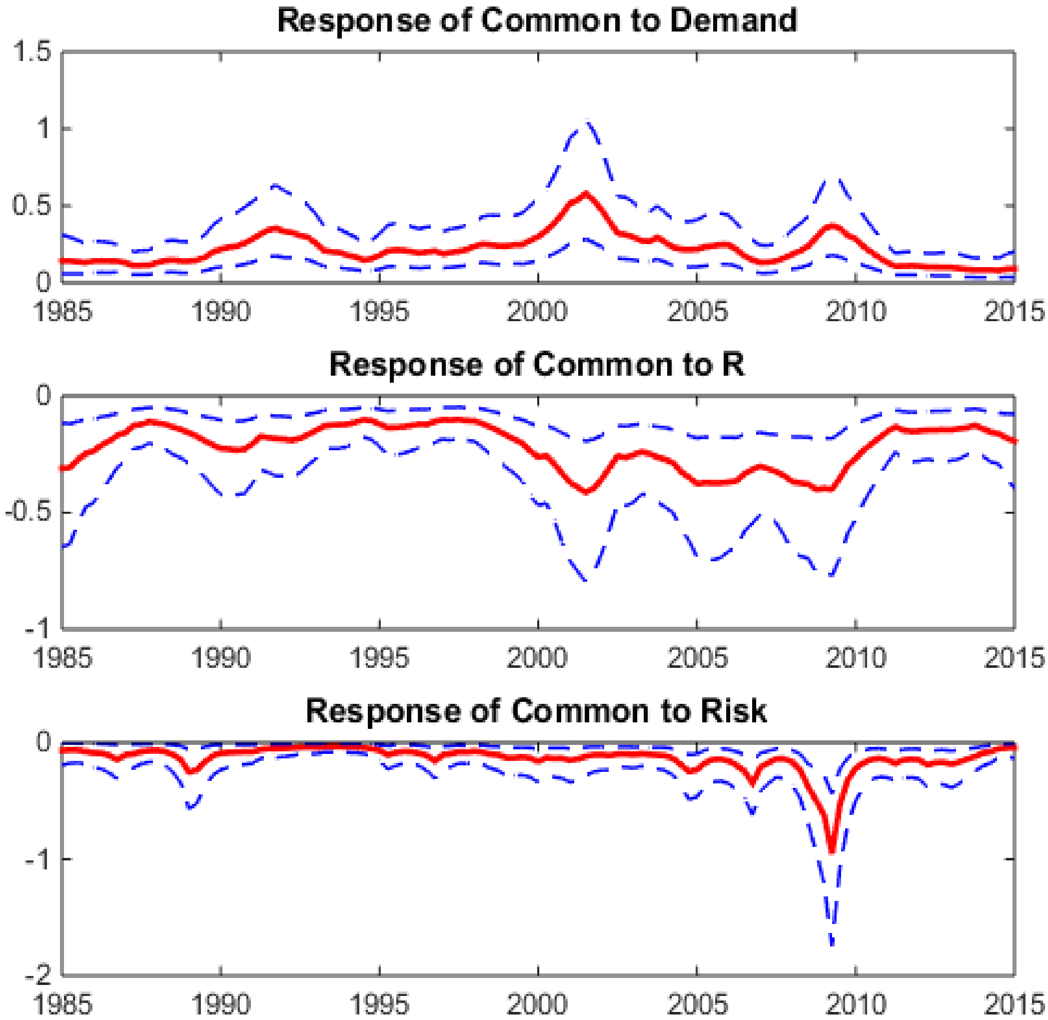
Notes: The nine graphs in Figure B1 plot the median responses of three sector-specific factors (solid line) to each of the three macro shocks that affect the sector commonalities in commodity returns. We also provide 16^{th} and 84^{th} percentile error bands in dashes. The sectoral factors are extracted from the DHFM equation (2).

Figure B2. Robustness Check Using Global Economic Activity



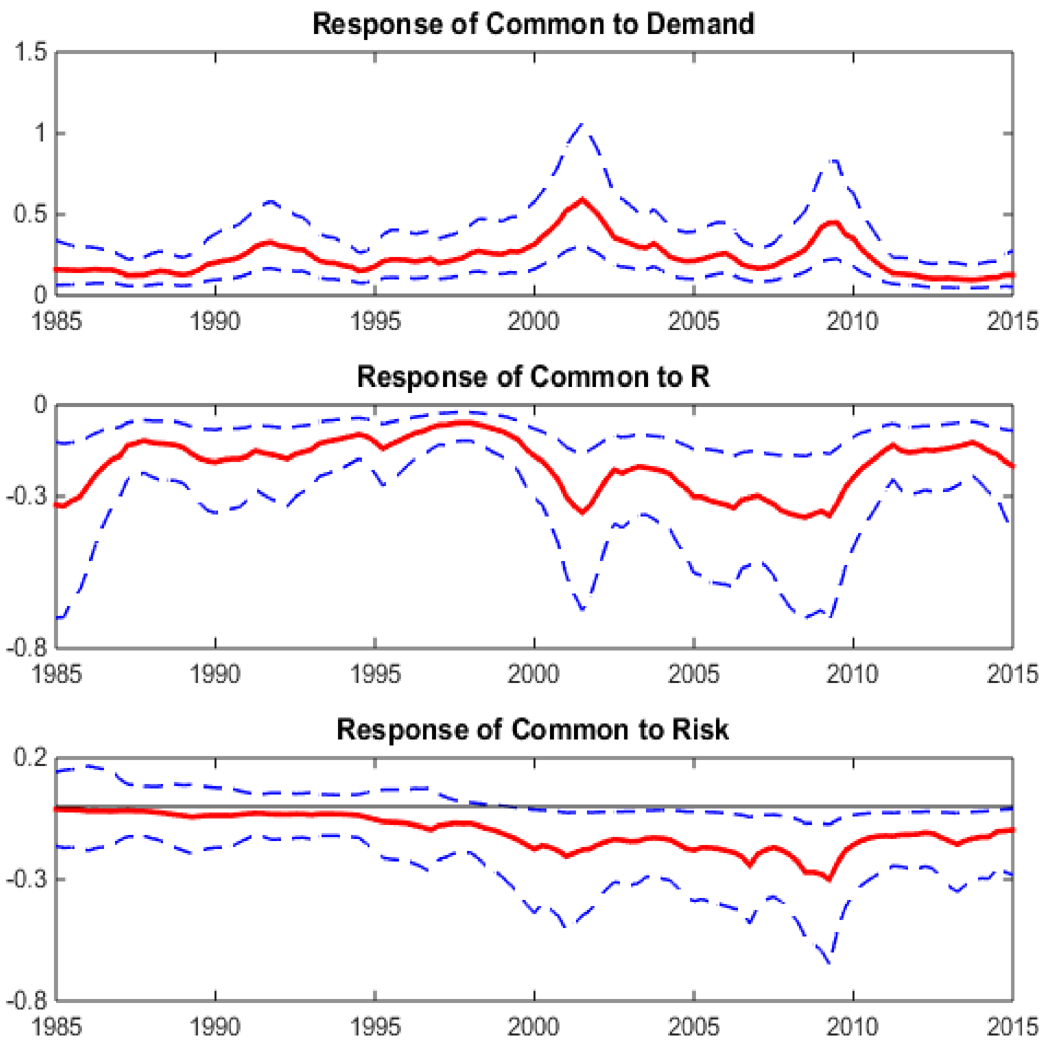
Notes: The three graphs in Figure B2 plot the median impulse responses of the common factor (solid line) to each of the three macro shocks that affect commodity returns. We also provide 16th and 84th percentile error bands in dashes. The estimates are based on the TVP-FAVAR model in equation (11). Each panel measures how a unit impulse of shocks impacts the commodity common factor over time. Here we use an alternative proxy for demand based upon Kilian's index of Global Activity (Demand). The above figure displays similar responses as to that contained in the main text Figure 4.

Figure B3. Robustness Check Using Federal Fund Real Interest Rate



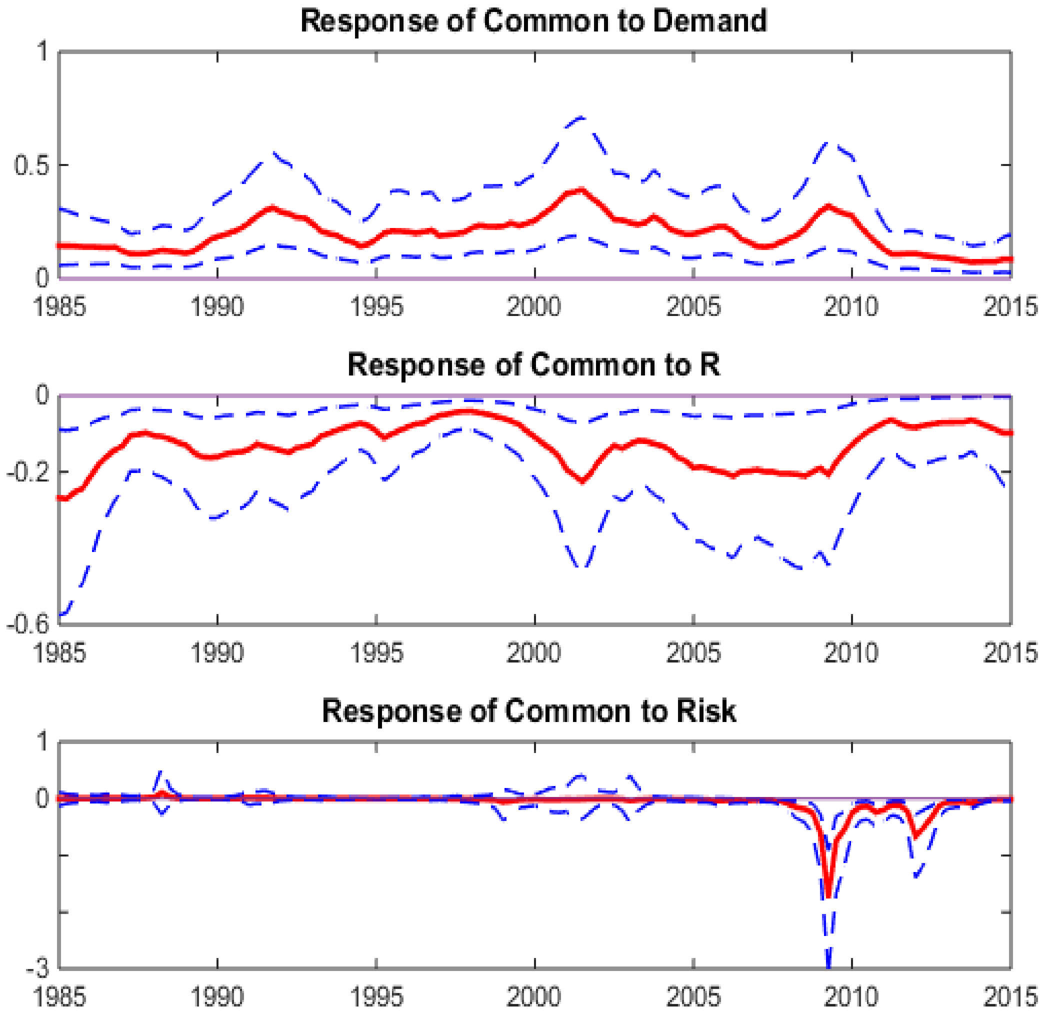
Notes: The three graphs in Figure B3 plot the median impulse responses of the common factor (solid line) to each of the three macro shocks that affect commodity returns. We also provide 16^{th} and 84^{th} percentile error bands in dashes. The estimates are based on the TVP-FAVAR model in equation (11). Each panel measures how a unit impulse of shocks impacts the commodity common factor over time. Here we construct the real interest rate using the Federal Funds rate (R). The above figure displays similar responses as to that contained in the main text Figure 4.

Figure B4. Robustness with Uncertainty based on within variance of S&P GSCI



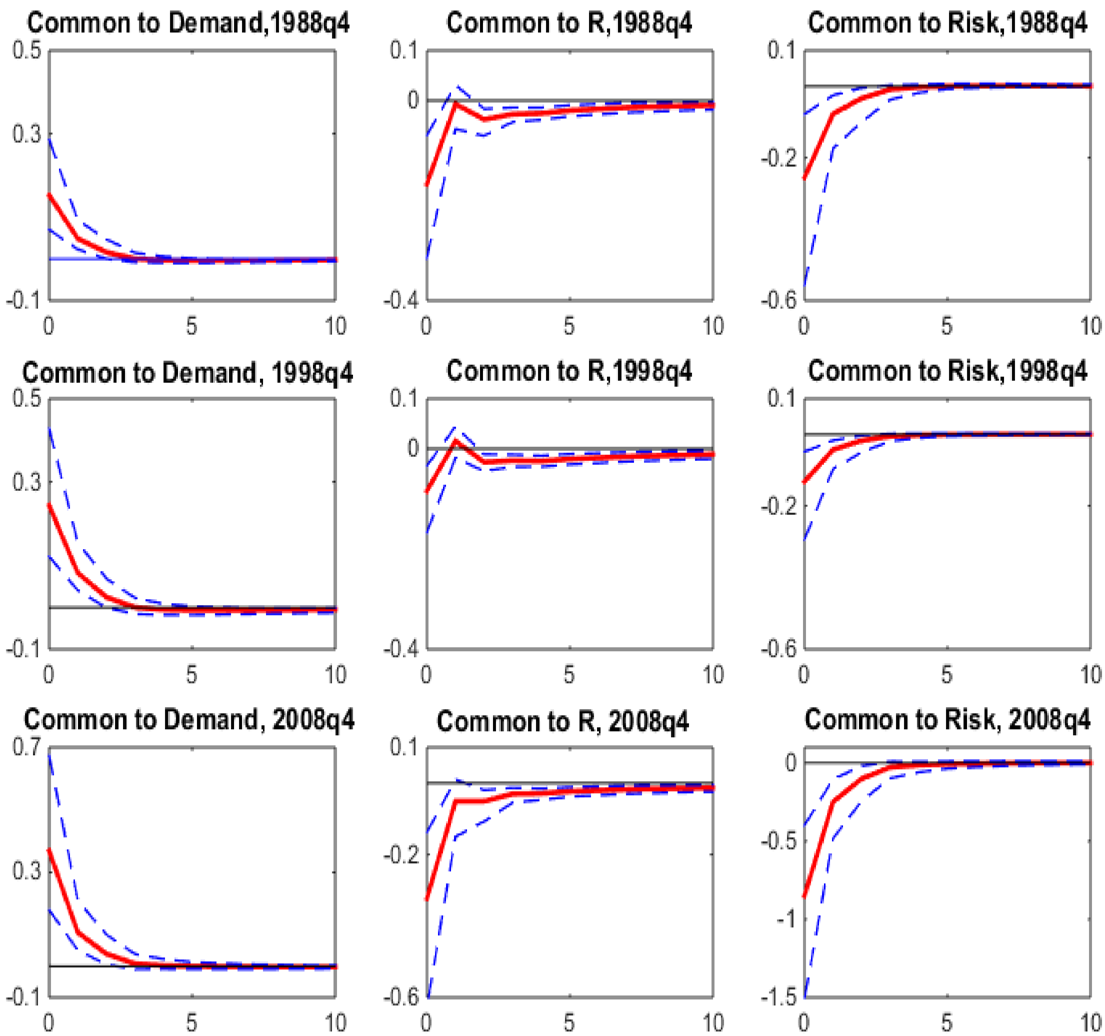
Notes: The three graphs in Figure B4 plot the median impulse responses of the common factor (solid line) to each of the three macro shocks that affect commodity returns. We also provide 16th and 84th percentile error bands in dashes. The estimates are based on the TVP-FAVAR model in equation (11). Each panel measures how a unit impulse of shocks impacts the commodity common factor over time. In this robustness check, we replace the uncertainty measured from S&P GSCI GARCH to within quarter variance of S&P GSCI. The above figure displays similar responses as to that contained in the main text Figure 4.

Figure B5. Robustness Check: Uncertainty based on S&P 500 GARCH



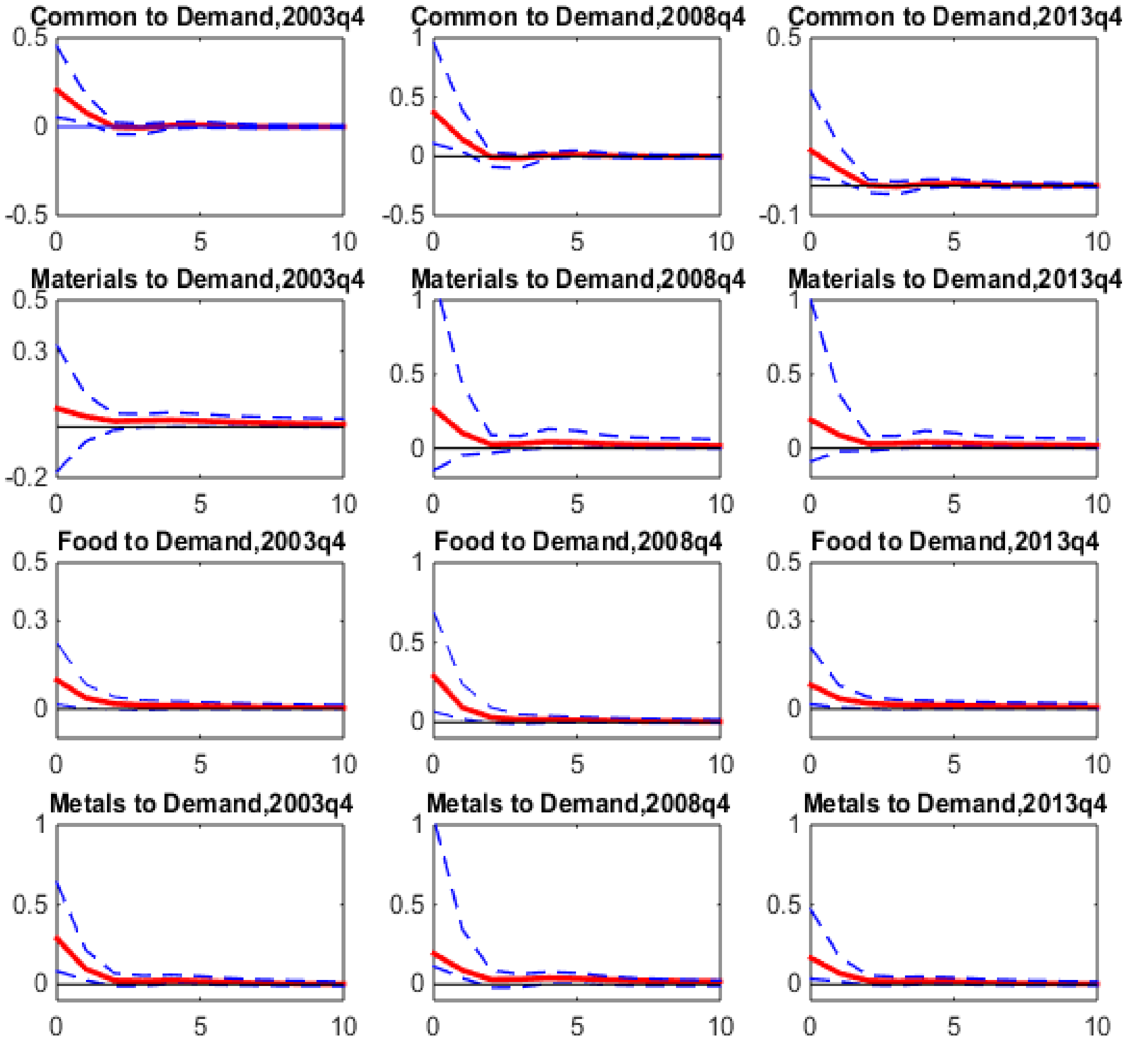
Notes: The three graphs in Figure B5 plot the median impulse responses of the common factor (solid line) to each of the three macro shocks that affect commodity returns. We also provide 16th and 84th percentile error bands in dashes. The estimates are based on the TVP-FAVAR model in equation (11). Each panel measures how a unit impulse of shocks impacts the commodity common factor over time. In our final robustness check we construct the measure of uncertainty from S&P500 GARCH. The above figure displays similar responses as to that contained in the main text Figure 4, although stock market uncertainty effects upon commodities are more transient and period specific.

Figure B6. TVP-FAVAR Common Factor Responses: Specific Time Periods



Notes: The nine graphs in Figure B6 plot the median responses in commodity returns of common factors (solid line) to each of the three macro shocks. We also provide dashes for the 16th and 84th percentile error bands. The impulse responses are at times 1988Q4, 1998Q4 and 2008Q4. The estimates are based on the TVP-FAVAR model in equation (11). Each panel measures how a unit impulse of shocks at time *t* impacts the sector commonalities of commodity prices at time *t* + *s* for different values of *s*. Here we limit s until 10-quarters ahead.

Figure B7. TVP-FAVAR Factor Responses to Chinese Demand Shock: Specific Time Periods



Notes: The nine graphs in Figure B7 plot the median responses in commodity returns of common and sector factors (solid line) to China demand shocks. We also provide dashes for the 16th and 84th percentile error bands. The impulse responses are at times 2003Q4, 2008Q4 and 2013Q4. The estimates are based on the TVP-FAVAR model in equation (11). Each panel measures how a unit impulse of shocks at time *t* impacts the sector commonalities of commodity prices at time *t* + *s* for different values of *s*. Here we have responses (s) until 10-quarters ahead.