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Global commodity prices, economic activity and monetary policy: The relevance of China

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ABSTRACT

After decades of strong economic growth, industrialization and rising living standards, China has become a dominant player in commodity markets. This study attempts to shed light on the role of China in global commodity price dynamics.

The empirical analysis applies (Toda and Yamamoto, 1995, *J Econom*, 66, 225–250) type Granger causality tests and Generalized Impulse Response Functions (GIRF) to examine causal linkages and short-run dynamics between global commodity prices, economic activity, and monetary policy of China from 1998 to 2012.

Our results provide evidence that economic activity is Granger causing both energy and industrial metals prices. As for the GIRF analysis, our findings suggest that energy and industrial metals prices respond positively to an increase in the economic activity and that agricultural as well as energy commodity prices overshoot after a drop in the real interest rate of China. We further find evidence that industrial metals prices tend to be higher when China's exchange rate system is relaxed.

Introduction

China is now the world's most populated nation, world's second largest economy and largest holder of foreign reserves. After decades of strong economic growth, industrialization and rising living standards, China has also become a dominant player in commodity markets.

On the physical side, the country has become the largest producer as well as a consumer of a wide range of commodities spanning agricultural, energy and metal markets. China is considered the largest agricultural economy in the world (USITC, 2011). In 2010, China was the world's largest producer of 11 out of 17 agricultural aggregates used in the Food and Agriculture Organization of the United Nations (FAO, 2013) statistical yearbook. Amongst these categories, China's share of global production accounted for 20.11% in cereals, 28.31% in rice, 17.63% in wheat, 21.73% in root and tuber, 51.70% in vegetable, 22.54% in tree nut, 20.09% in fruit, 19.50% in citrus fruit, 27.33% in meat, 30.13% in egg, milk and processed milk and 35.91% in fish. Although China is largely self-sufficient, it was the world's second largest importer of agricultural commodities after the US in 2009 (USITC, 2011). In the energy sector, China replaced the US as the world's largest primary energy[2] consumer in the year 2011 (BP, 2013). In 2012, China consumed 21.92% of global primary energy, followed by the US with 17.70%. In the same year, the country was the largest coal and second largest oil consumer next to the US, accounting for 50.22% of the world's coal and for 11.71% of global oil consumption. While the lion's share of China's coal consumption is satisfied by its own production, only a small portion of its oil consumption is covered by domestic production, making it the second largest net oil importer after the US in 2009 (EIA, 2012). China is also a dominant player in global metal markets. In 2012, the country was the dominant producer of 22 out of 41 elements and element groups that are of economic value (BGS, 2012). In 2011 and in regard to the London Metals Exchange (LME) traded metals, China accounted for 39.96% of aluminum, 50.18% of lead, 42.47% of tin, 33.66% of zinc and 13.88% of gold mine production worldwide (BGS, 2013). Also in the sphere of metals, China has not only become the largest producer but also world's largest consumer of many metals and minerals (Pitfield et al., 2010).

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[1] The views expressed in this paper are those of the authors and do not necessarily reflect the views of Four Elements Capital Pte. Ltd.

[2] Primary energy comprises commercially traded fuels including oil, natural gas, coal, nuclear energy, hydro-electricity and renewables according to the definition used in the BP Statistical Review of World Energy 2013 (BP, 2013).

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Having emerged as a major player on the physical side, China also developed its commodity futures markets substantially. After the merger of 50 Chinese commodity exchanges into 14 in 1995 and subsequent consolidation into three in 1999, the trading volumes at these three exchanges have grown at an astonishing rate. According to data of the World Federation of Exchanges (WFE, 2013), the aggregate number of commodity contracts traded at the three commodity exchanges Dalian Commodity Exchange (DCE), Shanghai Futures Exchange (SFE) and Zhengzhou Commodity Exchange (ZCE) increased from 0.15 billion traded contracts in 2004 to 1.35 billion contracts in 2012, accounting for 42.84% of the global figure proxied by the total of commodity futures and option contracts traded at WFE member and non-member exchanges. In terms of notional turnover, the joint volume of the three exchanges also increased heavily from 0.71 trillion US dollars in 2004 to 15.29 trillion US dollars in 2012, accounting for 12.93% of the global figure.

Undeniably, China has become a dominant player in both, physical and financial commodity markets. With this development, global commodity markets have become increasingly exposed to macroeconomic developments in China. Many studies have pointed out that the rapid economic growth and industrialization of emerging market economies, particularly China, is pushing commodity demand and thus prices (Hamilton, 2009; He et al., 2010; Li and Lin, 2011; Radetzki, 2006; Roache, 2012). Although US commodity exchanges are still considered to dominate price formation in global commodity futures markets, with its increasing weight in commodity markets, China is acknowledged to play a remarkable and increasingly important role in the pricing of globally traded commodities (Liu and An, 2011).

Given China's weight in commodity markets and while several studies have pointed out that expansionary monetary policy is a significant driver of commodity prices (Akram, 2009; Anzuini et al., 2010; Belke et al., 2013; Frankel, 2008; Saghaian et al., 2002a, 2002b), it is surprising that no previous study has attempted to examine the role of the People's Bank of China's (PBC) monetary policy on global commodity prices.

To fill up the gap, the objective of this study is to shed light on the relevance of China in international commodity price dynamics. By focusing on both China's economic activity and monetary policy, this study explores the role of China in global commodity price dynamics from a macroeconomic perspective in general and analyzes its economic activity and monetary policy in particular. Our empirical analysis looks at the period from 1998 to 2012 and uses monthly data on industrial production and real interest rates to account for China's economic activity and monetary policy respectively. As for commodity prices, the study uses real commodity group spot price indices of the agricultural, energy, industrial metals, livestock and precious metals sector. Applying Toda and Yamamoto (1995) type Granger causality tests, we find that China's economic activity Granger causes global energy and industrial metals prices. Our findings from the Generalized Impulse Response Function (GIRF) analysis further suggest that energy and industrial metals prices respond positively to an increase in the economic activity of China and that agricultural as well as energy commodity prices overshoot after a drop of China's real interest rate. Our results confirm that macroeconomic conditions in China have become an important factor particularly influencing global agricultural, energy and industrial metals price dynamics.

The rest of this paper is organized as follows. The next section reviews the theoretical framework and briefly discusses the relevant literature. Section 3 presents the data and methodology used to investigate causal linkages and short-run dynamics between the variables in our model. Section 4 leads through the empirical results, followed by the conclusion in Section 5.

Theoretical framework and literature review

This study mainly builds on the theoretical model of commodity price overshooting developed by Frankel (1986, 2008).

Drawing on Dornbusch's (1976) exchange rate overshooting hypothesis, Frankel (1986, 2008) developed the commodity overshooting model that provides a theoretical explanation why commodity prices overshoot their long-run equilibrium in response to an expansionary monetary policy shift. The theory assumes that the goods market is broadly divided into a sticky fix-price manufacturer and services sector and a flexible sector with commodities that are traded on fast-moving auction markets which are able to respond instantaneously to macroeconomic shocks. In order to compensate for the slow adjustment of the fix price sector, commodities in the flexible sector change more than proportionally to changes in the monetary policy stance. In response to an expansionary monetary policy shock, i.e. fall in real interest rates, real commodity prices overshoot their new long-run equilibrium. It is necessary that real commodity prices are overvalued so that there will be an expected decrease in the price sufficient to offset the lower real interest rate, and vice versa.

Following Frankel (2008), the theory is derived from two assumptions. First, market participants who observe that the real commodity price today rcp_t lies over its perceived long-run value expect the price to move back to its long-run equilibrium $\overline{rcp}$ over time. As shown in Eq. (1), the expected relative change in the real commodity price $E_t\Delta(cp_{t+1}-pm_{t+1})$, where cp_{t+1} is the nominal commodity price in $t+1$ and pm_{t+1} the price of manufactured goods or the general price level in $t+1$, is expected to regresses back to equilibrium proportionally to the gap between real commodity price today and its long-run value. When the real price is high today, market participants expect a decrease until the long-run equilibrium is reached and vice versa.

$$E_t\Delta(cp_{t+1}-pm_{t+1}) = -\theta(rcp_t-\overline{rcp}) \tag{1}$$

Second, market participants base their decision to hold storable commodities on the arbitrage condition that the cost-adjusted expected rate of return of holding the commodity $E_t\Delta cp_{t+1}+c_t$ should equal the return on alternative assets or the interest rate i_t as illustrated in Eq. (2). The cost of holding commodities c_t includes the convenience yield, the storage costs and a risk premium[3].

$$E_t\Delta cp_{t+1}+c_t = i_t \tag{2}$$

Combining these two assumptions yields the commodity overshooting model represented by Eq. (3). The real commodity price relative to its long-run equilibrium price is negatively related to the nominal interest rate, positively related to the expected price level and, thus, inversely related to the real interest rate $i_t - E_tpm_{t+1}$ relative to the cost of holding the commodity c_t. A fall in the real interest rate induced by an expansion in money supply, increases the real commodity prices above its long-run equilibrium price, i.e. they overshoot, so that the expected increase in commodity prices equals the lower real interest rate and cost of holding commodities. Apparently, as the long-run real equilibrium price and the cost of holding commodities is not constant over time, the relationship between real interest rate and real commodity price does not hold precisely in practice (Frankel, 2008).

$$rcp_t-\overline{rcp} = -\frac{1}{\theta}(i_t-E_tpm_{t+1}-c_t) \tag{3}$$

Building on the work of Dornbusch (1976) and Frankel (1986), Saghaian et. al. (2002b) further extended the commodity price

[3] For a detailed discussion on the cost of holding commodities see Frankel (2008).

overshooting theory to an open economy. In addition to the fix price manufactured goods and services sector and the flexible commodity sector, their model[4] considers the exchange rate as a second flexible sector. This extended model, however, is not applicable in our case because the exchange rate regime of China has not been fully liberalized[5] over the observed period, implying that only the commodity sector can be flexible. Therefore we consider Frankel's (1986, 2008) commodity price overshooting model as our theoretical framework in the subsequent empirical analysis. In order to account for China's shift from a fixed- to a managed floating exchange rate system, we consider a dummy variable in our empirical model.

Several studies have attempted to test the commodity price overshooting theory empirically. One example is Frankel's (2008) empirical work applying bivariate regression analysis to annual data of US real interest rates, several commodity price indices as well as a set of individual commodity prices. His findings suggest that commodity prices significantly overshoot in response to a decrease in real interest rates for the sample ranging from 1950 to 2005. In particular, results show that there is a statistically significant inverse relationship between the real interest rate and all three of the major price indices available since 1950, i.e. Dow-Jones, Commodity Resources Board and Moody's commodity spot price indices. The regression results for 23 individual commodities further indicates that the negative relationship between real commodity prices and real interest rates is reasonably robust across commodity price measures over the sample period. In another study, Akram (2009) applies structural VAR models and uses quarterly data over the period from 1990 to 2007 to investigate how global real interest rates proxied by the US rate and the US dollar contribute to higher commodity prices. The analysis considers the behavior of real prices of crude oil, food, metals and industrial raw materials and additionally considers the production volume in the OECD countries as proxy for world output fluctuations to account for the interaction between global economic activity level, financial variables and commodity prices. In regard to the real interest rate, the findings suggest that commodity prices rise when the real interest rate falls. While real oil prices and real industrial raw material prices tend to display overshooting behavior in response to shocks to the real interest rate, the response of real food and metals prices rather shows a delayed response to interest rate shocks.

Although there is a broad consensus in the literature that China's increasing economic weight matters in global commodity price dynamics (Hamilton, 2009; He et al., 2010; Li and Lin, 2011; Radetzki, 2006; Roache, 2012), only a few attempts have been made to quantify the impact of China's economic activity on global commodity prices (Roache, 2012). One recent study (Roache, 2012) uses monthly data from 2000 to 2011 and applies Granger causality tests and impulse response functions to vector autoregression models to analyze the effect of China's economic activity on global commodity markets. The results provide evidence for a causal relationship running from economic activity, i.e. aggregate activity measured by industrial production, to global oil and lead prices as well as evidence that economic activity shocks of China have a significant and persistent short-run impact on the price of oil and some base metals.

While most studies on the linkage between monetary policy and global commodity prices focus on the effect of the US and while only a few studies have attempted to analyze the impact of China's economic activity on global commodity prices, the main contribution of this study is to investigate both the role of China's monetary policy and economic activity in international commodity price dynamics. Thereby, this study contributes to the literature on the role of China in global commodity price dynamics from a macroeconomic perspective, with the focus on economic activity and monetary policy in particular.

[4] For a detailed description of the model see Saghaian et al. (2002b).

[5] After the Asian financial crisis in 1997, China pegged its currency at a fixed exchange rate to the US dollar. On 21 July 2005 China lifted the peg and officially moved to a managed floating exchange rate system. In fall 2008, the PBC re-pegged the Renminbi to the US dollar before it returned to the managed floating system in the mid of 2010.

Data and methodology

Data

For the empirical analysis, we use monthly data from 1998M01 to 2012M12. The time period starts at the point when China accelerated banking sector reforms and officially replaced its credit quota system by a target system and interest rates started to be increasingly determined by market forces. The analysis considers five distinct commodity group indices as well as industrial production and real interest rate of China to account for economic activity and monetary policy respectively. Data is sourced via Bloomberg.

We use commodity group indices rather than prices of individual commodities because of the advantage that idiosyncratic factors affecting individual commodities have far less influence on an index capturing a basket of different commodities (Belke et al., 2013). In particular, we use the Dow Jones-UBS commodity spot price sector sub-indices of the agricultural, energy, industrial metals, livestock and precious metals group and deflate it by the OECD CPI of China. These indices, jointly compiled by S&P Dow Jones and UBS Investment Bank, are based on futures contracts on physical commodities[6] and are intended to provide a general estimate of trends in commodity prices across these sectors. The relative quantity of the commodity contracts included in each sub-index are based on liquidity as well as production figures and subject to weighting restrictions applied annually. Being dynamically adjusted, these indices capture the economic significance and market liquidity of the included commodities over time.

In order to account for the interaction between economic activity, monetary policy as well as global commodity prices, and as proposed by Akram (2009), we consider industrial production in our empirical model. Although there have been developed alternatives (Kilian, 2009), it is common to use industrial production as a measure of economic activity (Akram, 2009; Reinhart and Borensztein, 1994; Roache, 2012). Since there is no index available, we collect the annual industrial production percentage change from the National Bureau of Statistics of China[7] as a measure for economic activity.

The real interest rate is calculated by subtracting the one-year inflation rate observed over the preceding year from the one-year interest rate. We use the annualized weighted average interbank lending rate from the PBC and inflation rate from the National Bureau of Statistics of China.

In order to account for the exchange rate regime change in China we further consider a dummy variable capturing the move

[6] As of 2014, the composition of the respective Dow Jones-UBS commodity sector index is as follows. Agricultural includes Chicago Wheat, Kansas Wheat, Corn, Soybeans, Coffee, Sugar, Cocoa and Cotton. Energy includes WTI Crude Oil, Heating Oil, Brent Crude Oil, RBOB Gasoline and Natural Gas. Industrial Metals includes Aluminum, Copper, Lead, Nickel and Zinc. Livestock includes Live Cattle, Feeder Cattle and Lean Hogs. Precious Metals include Silver and Gold. For details on index methodology and composition see ⟨http://us.spindices.com/index-family/commodities/dj-commodities⟩.

[7] Starting in 2007, in order to remove the impact of the different dates of "Spring Festival" of each year, the National Statistics Bureau of China jointly releases January and February data on industrial production. In order to align the data up to 2007, we compute the average of the January and February figure and use this average figure for both January and February.

of China from a fixed exchange rate regime to a managed floating exchange rate regime in 2005M07. Fig. 1 clearly illustrates the peg of the Renminbi to the US dollar up to the mid of 2005 and the adoption of the managed floating exchange rate system. However, as shown in the graph, the PBC, in fact, temporarily re-pegged the Renminibi to the US dollar in the period around the financial crisis from 2008M10 to 2010M06. The dummy variable considers the period of the fixed exchange rate regime as well as the stabilization of the CNY/USD exchange rate in the period surrounding the financial crisis, taking on a value of zero in the period from 1998M01 to 2005M07 as well as 2008M10 to 2010M06 and a value of one otherwise.

Table 1 summarizes the descriptive statistics of the variables included in the model. All variables have been transformed to logarithmic form. The coefficient of variation, indicating the standard deviation relative to the mean, shows that the real interest rate of China (*RIR*) has the highest volatility. This largely reflects the relatively strong fluctuations in inflation experienced by China over the observed period. The livestock commodity group price (*CP_LI*) exhibits the lowest volatility amongst the variables in the model.

Table 2 summarizes the correlation coefficients between the variables in the model. As expected, the coefficients show positive correlation between China's economic activity (*EA*) and all of the commodity group prices. Energy prices (*CP_EN*) show the strongest correlation followed by industrial metals (*CP_IN*), livestock (*CP_LI*), agricultural (*CP_AG*) and precious metals (*CP_PR*). Also as expected, the correlation coefficients indicate an inverse relationship between the real interest rate (*RIR*) and all of the commodity group prices. In sum, the analysis of the correlation coefficients shows relatively strong linear relationships between economic activity (*EA*) as well as real interest rates (*RIR*) and commodity prices. While these coefficients reflect the pairwise correlation between the variables, the following analysis sheds light on how these variables are interrelated over time.

Methodology

In the following empirical analysis, we broadly follow the methodology applied by Soytas et. al. (2009) and Nazlioglu and Soytas (2011) to assess causal and short-run dynamics between the variables in our model.

In order to investigate causality linkages, we employ the methodology proposed by Toda and Yamamoto (1995, T&Y hereafter). The T&Y procedure allows running a Vector Auto-Regression (VAR) model formulated in its levels, regardless of the order of integration of the variables. The advantage of this procedure is that there is no need to test for cointegration, which prevents a likely pretest bias. Another advantage of the T&Y procedure is that by using data in its level, loss of information resulting from differencing data can be avoided. The T&Y methodology starts with determining the maximum order of integration $d_{\max}$ of the variables included in the system. In our case, a VAR(p) model of the following specification is set up, where x_t is the $n \times 1$ vector of the variables in its levels, A_0 the $n \times 1$ vector of intercept terms, A_i the $n \times n$ matrix of coefficients, ψ and D_t the $n \times 1$ vector of coefficients and $n \times 1$ vector of dummy variables respectively, and ε_t the $n \times 1$ vector of error terms.

$$x_t = A_0 + A_1 x_{t-1} + \ldots + A_p x_{t-p} + \psi D_t + \varepsilon_t \tag{4}$$

The lag length p is determined by applying the usual lag selection criteria and the respective VAR model is then augmented by the number of additional lags given by the maximal order of integration d_{max} identified in the unit root tests. The model of the form VAR($p+d_{max}$) is then estimated with the variables of the $d_{\max}$ additional lags defined as exogenous variables. In our case, the lag augmented VAR model, including the dummy variable, is specified as following.

$$x_t = A_0 + A_1 x_{t-1} + \ldots + A_p x_{t-p} + \ldots + A_{(p+d_{\max})} x_{t-(p+d_{\max})} + \psi D_t + \varepsilon_t \tag{5}$$

Granger causality can be tested by applying Wald tests on the joint significance on the parameters of the coefficients of the first p coefficient matrices. As long as the order of integration of the variables does not exceed the true lag length of the model, the Wald Test statistic, with an asymptotic chi-square distribution and p degrees of freedom, can be applied to test for restriction on the parameters of the first p coefficient matrices of the lag augmented $VAR(p+d_{\max})$ model. Let $x_t = (CP\_AG_t, CP\_EN_t, CP\_IN_t, CP\_LI_t, CP\_PR_t, EA_t, RIR_t)'$ the 7×1 vector of our model, we can test for Granger causality running from the economic activity (*EA*) and real interest rate (*RIR*) to the agricultural commodity price (*CP_AG*) by testing the joint significance of the coefficients $A_{16,1}, \ldots, A_{16,p}$ and $A_{17,1}, \ldots, A_{17,p}$ respectively. The respective hypotheses can be written as following.

$$\begin{aligned} &H_{0,1}: A_{16,1} = \ldots = A_{16,p} = 0, \text{ No Granger causality} \\ &\qquad \text{running from } EA \text{ to } CP\_AG \\ &H_{0,2}: A_{17,1} = \ldots = A_{17,p} = 0, \text{ No Granger causality} \\ &\qquad \text{running from } RIR \text{ to } CP\_AG \end{aligned} \tag{6}$$

The null hypothesis of no Granger causality is rejected if the Wald test statistic is significant. The augmented Granger causality test provides us with information whether there is a causal relationship between the variables. However, it does not show how each variable reacts to innovations in other variables and whether the effect is time persistent or not.

In order to investigate this relationship, we apply the Generalized Impulse Response Function (GIRF) developed by Koop et al. (1996) and Pesaran and Shin (1998) to the VAR(p) model in levels defined in Eq. (4). Using a VAR model in levels still allows obtaining consistent estimates of parameters describing the system's dynamics (Sims et al., 1990). Comparing impulse response estimators based on VAR model specifications determined by pretests for unit roots and cointegration as well as unrestricted VAR model specifications in levels, Gospodinov et al. (2013) point out that the impulse response estimators obtained from VAR model specification in levels tend to be the most robust for applied empirical work. Considering the VAR model in levels as specified in Eq. (4), where ε_t is an $m \times 1$ vector of well-behaved disturbances with covariance $\Sigma = \sigma_{ij}$, the GIRF can be defined as

$$\psi_j^g(n) = (\sigma_{jj})^{-(1/2)} (S_n \sum e_j), \; n = 0, 1, 2, \ldots, \tag{7}$$

which measures the effect of one standard error shock to the jth equation at time t on expected values of x at time $t+n$. Note that $S_n = A_1 S_{n-1} + \ldots + A_p S_{n-p}, n = 1, 2, \ldots, S_0 = I,\; S_n = 0$ for $n < 0$ and e_j the $m \times 1$ selection vector with unity as its jth element and zero elsewhere. Similar to Soytas et al. (2009) and Nazlioglu and Soytas (2011), we use the GIRF because, unlike the standard approach, this approach does not require orthogonalization of shocks. As the results of the GIRF approach are invariant to the ordering of the variables in the VAR model, it overcomes the orthogonalization problem of the traditional approach. In the next section we lead through the empirical analysis and discuss the major findings.

Empirical analysis

Unit root test and lag length

In the first step of the analysis, we determine the maximum order of integration $d_{\max}$ of the variables included in our model. Thereby a variable is said to be integrated of order n when it achieves

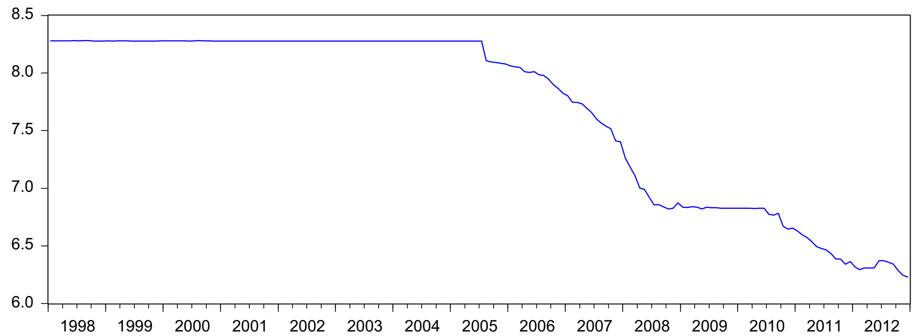

Fig. 1. CNY/USD exchange rate.

Table 1
Descriptive statistics.

	CP_AG	*CP_EN*	*CP_IN*	*CP_LI*	*CP_PR*	*EA*	*RIR*
Mean	5.013	5.472	4.828	4.676	5.049	2.536	1.727
Standard deviation	0.379	0.541	0.438	0.122	0.560	0.288	0.496
Coefficient of variation	0.076	0.099	0.091	0.026	0.111	0.114	0.288
Skewness	0.444	−0.736	0.124	−0.434	0.450	−0.669	−0.866
Kurtosis	1.897	2.695	1.523	2.766	1.803	2.830	4.487
Observations	180	180	180	180	180	180	180

Note: all variables have been logarithmic transformed. Commodity group indices have been deflated by the CPI of China. *CP_AG* represents the real agricultural group price, *CP_EN* the real energy group price, *CP_IN* the real industrial metals group price, *CP_LI* the real livestock group price, *CP_PR* the real precious metals group price, *EA* the economic activity of China and *RIR* the real interest rate of China.

Table 2
Correlation Coefficients.

	CP_AG	*CP_EN*	*CP_IN*	*CP_LI*	*CP_PR*	*EA*	*RIR*
CP_AG	1.000						
CP_EN	0.683***	1.000					
CP_IN	0.794***	0.849***	1.000				
CP_LI	0.561***	0.719***	0.645***	1.000			
CP_PR	0.960***	0.705***	0.822***	0.605***	1.000		
EA	0.209***	0.620***	0.488***	0.417***	0.205***	1.000	
RIR	−0.590***	−0.739***	−0.667***	−0.533***	−0.522***	−0.533***	1.000

*** Represents significance levels at 1%.

stationarity after taking its *n*-th difference. In order to determine the order of integration of the variables, we apply the augmented Dickey and Fuller (1979) (ADF), Elliott et al. (1996) Dickey Fuller GLS detrended (DF-GLS), Phillips and Perron (1988) (PP), Ng and Perron (2001) MZ_{α} and Kwiatkowski et al. (1992) (KPSS) unit root test. Table 3 summarizes the results of the five tests.

Except for *CP_LI*, all of the unit root tests indicate at the 1% level of significance that d_{max} of the included variables is one. Including an intercept in the test equation, DF-GLS and MZα indicate that the null of a unit root applied to the first difference of *CP_LI* cannot be rejected even at the 10% level of significance. However, the ADF, PP as well as KPSS test statistic indicate at the 1% level of significance that *CP_LI* is stationary after taking the first difference. Including a trend and intercept in the test specification, all of the unit root tests confirm at the 1% level of significance that the first difference of *CP_LI* is stationary. Therefore we conclude that d_{max} is one.

In the next step we determine the optimal lag length of the VAR model defined in Eq. (4). As specified by T&Y (1995), we can apply the usual lag selection criteria to our VAR model. Using 13 lags in the lag specification, we apply the Akaike Information Criterion, Final Prediction Error, Hannan–Quinn Information Criterion and the Schwarz Information Criterion. All of the lag order selection criteria indicate a maximum optimal lag length of one. Thus we choose a lag length of one in the following analysis.

VAR estimation and model robustness

On the basis of the optimal lag length, we estimate a VAR(1) as specified in Eq. (4). The 7×1 vector of our model jointly considers the prices of the agricultural, energy, industrial metal, livestock and precious metals group as well as economic activity and real interest rate of China, such that $x_t = (CP\_AG_t, CP\_EN_t, CP\_IN_t, CP\_LI_t, CP\_PR_t, EA_t, RIR_t)'$. The model further considers a dummy variable capturing the effect of the managed floating- against the fixed exchange rate regime of China. The dummy variable has a value of zero in the periods of fixed exchange rate system and a value of one otherwise. The estimated VAR(1) model satisfies the stability condition so that no roots lie outside the unit circle.

Next, we augment the $VAR(p)$ to $VAR(p+d_{max})$ as specified in Eq. (5). The unit root tests indicate that d_{max} is one. Therefore we augment the VAR(1) model to VAR(1+1). As specified in Eq. (5), the additional d_{max} lags are defined as exogenous variable in the lag augmented VAR model. As the VAR system must satisfy the common regression assumptions to be valid, we test the residuals of each equation in the model for autocorrelation and heteroskedasticity.

Table 3
Unit root tests.

	Variable	ADF	DF-GLS	PP	MZα	KPSS
Intercept	*CP_AG*	−0.629(0)	−0.465(0)	−0.639	−0.982(0)	1.544***
	CP_EN	−1.833(0)	−0.199(0)	−1.858	−0.229(0)	1.333***
	CP_IN	−1.166(0)	−0.428(0)	−1.394	−0.675(0)	1.305***
	CP_LI	−2.660*(0)	−1.930*(0)	−2.431	−8.593**(0)	0.956***
	CP_PR	0.408(1)	1.538(1)	0.488	1.478(1)	1.645***
	EA	−2.610*(2)	−0.878(2)	−3.539***	−1.653(2)	0.488**
	RIR	−2.485(0)	−1.215(0)	−2.637*	−3.135(0)	0.809***
	DCP_AG	−13.836***(0)	−12.647***(0)	−13.828***	−88.779***(0)	0.140
	DCP_EN	−12.462***(0)	−4.576***(2)	−12.451***	−27.886***(2)	0.131
	DCP_IN	−12.249***(0)	−4.462***(2)	−12.529***	−26.809***(2)	0.073
	DCP_LI	−14.565***(0)	−0.424(9)	−16.062***	−0.332(9)	0.049
	DCP_PR	−16.302***(0)	−15.983***(0)	−16.677***	−86.005***(0)	0.277
	DEA	−12.415***(0)	−12.453***(1)	−12.564***	−141.918***(1)	0.180
	DRIR	−11.953***(0)	−11.839***(0)	−11.959***	−87.814***(0)	0.069
Trend and intercept	*CP_AG*	−3.488**(0)	−1.681(0)	−3.536**	−5.416(0)	0.210**
	CP_EN	−1.803(0)	−1.666(0)	−1.964	−6.138(0)	0.341***
	CP_IN	−1.586(0)	−1.604(0)	−2.126	−5.286(0)	0.158**
	CP_LI	−3.817**(0)	−3.808***(0)	−3.809**	−25.079***(0)	0.133*
	CP_PR	−3.093(0)	−1.245(1)	−2.888	−3.212(1)	0.321***
	EA	−2.447(2)	−1.557(2)	−3.443**	−5.491(2)	0.298***
	RIR	−2.553(0)	−2.354(0)	−2.853	−11.058(0)	0.125*
	DCP_AG	−13.855***(0)	−13.629***(0)	−13.851***	−88.934***(0)	0.066
	DCP_EN	−12.503***(0)	−11.386***(0)	−12.491***	−86.867***(0)	0.030
	DCP_IN	−12.223***(0)	−11.535***(0)	−12.503***	−87.208***(0)	0.066
	DCP_LI	−14.521***(0)	−5.943***(1)	−15.999***	−42.959***(1)	0.046
	DCP_PR	−16.380***(0)	−16.190***(0)	−16.948***	−85.577***(0)	0.094
	DEA	−12.424***(1)	−12.474***(1)	−12.845***	−142.488***(1)	0.031
	DRIR	−11.950***(0)	−11.873***(0)	−11.919***	−87.862***(0)	0.028

Note: all variables have been transformed to log specification. *D* is the first difference of the variable. Parentheses indicate optimal lag lengths determined by the automatic lag length selection criteria based on SIC with maximum lag length of 13. ADF is the augmented Dickey Fuller test with H0 of unit root. DF-GLS is the Dickey and Fuller GLS detrended test with H0 of unit root. PP is the Phillips and Perron test with H0 of unit root. MZα is the Ng and Perron test with H0 of unit root. KPSS is the Kwiatkowski, Phillips, Schmidt and Shin test with H0 of no unit root.

*** Represents significance levels at 1%.
** Represents significance levels at 5%.
* Represents significance levels at 10%.

Table 4 summarizes the results of the diagnostic tests for the augmented VAR model. The test statistics of the Breusch–Godfrey test (BG) indicate problems with autocorrelation in the *CP_EN*, *CP_PR* and *EA* equation. The diagnostic tests also show problems with heteroscedasticity in the *CP_AG*, *CP_PR*, *EA* and *RIR* equation. In order to yield valid test results[8] in the subsequent hypotheses testing, we apply the Newey–West Heteroskedasticity and Autocorrelation Consistent (HAC) corrected standard errors to the computations of the respective equations.

Toda and Yamamoto type Granger causality tests

In the next step, we apply Wald tests on the first lag coefficient matrix of the lag augmented VAR(1+1) model while ignoring the coefficients in the augmented lag matrix. From the chi-squared statistic of the Wald test, we can infer the presence of Granger causality. The results of this test, with the null of no Granger causality, are shown in Table 5.

The T&Y Granger causality tests indicate that energy (*CP_EN*) as well as industrial metals (*CP_IN*) prices are Granger caused by China's economic activity (*EA*) at the 1% and 5% level of significance respectively. These findings are in line with Roache (2012) who reports significant Granger causality running from the industrial production of China to global oil and lead prices over the period from 2000 to 2011. These findings provide evidence that the economic activity of China is a determinant of global commodity prices, at least in the group of energy and industrial metals. At the 10% level of significance, the test statistic shows

Table 4
Diagnostic tests of VAR(1+1).

Equation	BG	BPG	WHITE	ARCH
CP_AG	1.53	2.00**	2.08**	0.69
CP_EN	2.44*	0.56	0.50	0.15
CP_IN	0.52	0.98	1.06	0.57
CP_LI	1.45	1.01	1.00	0.13
CP_PR	4.20**	2.80***	2.86***	2.75*
EA	3.31**	3.64***	3.28***	1.58
RIR	0.30	2.91***	3.03***	0.90

Note: BG is the Breusch–Godfrey test with H0 of no serial correlation up to lag 2. BPG is the Breusch–Pagan–Godfrey test for H0 of homoskedasticity. WHITE is the White test for H0 of homoskedasticity. ARCH is the Engle test for H0 of no autoregressive conditional heteroskedasticity up to lag 1.

*** Represents significance levels at 1%.
** Represents significance levels at 5%.
* Represents significance levels at 10%.

[8] We also consider the Ramsey's test with one fitted error term to test for functional misspecification. The test statistic indicates problems with functional misspecification in the *CP_EN* as well as the *CP_PR* equation. However, as we focus on the linear model specifications, it is reasonable that this test suggests that some nonlinear effects are not taken into account.

Table 5
Granger causality tests of VAR(1+1).

	CP_AG	*CP_EN*	*CP_IN*	*CP_LI*	*CP_PR*	*EA*	*RIR*
CP_AG	–	0.425	0.799	1.417	2.107	0.000	0.252
CP_EN	0.256	–	1.424	0.085	0.826	7.437***	1.720
CP_IN	0.865	1.585	–	0.000	0.001	4.000**	0.001
CP_LI	0.086	2.709*	0.224	–	4.439**	0.006	0.296
CP_PR	1.009	2.672	0.475	0.027	–	0.062	0.001
EA	3.360*	1.272	3.828*	0.021	1.232	–	0.181
RIR	3.600*	0.017	2.138	0.070	1.556	0.100	–

Note: significance indicates that the column variable Granger causes the row variable.

*** Represents significance levels at 1%.

** Represents significance levels at 5%.

* Represents significance levels at 10%.

that agricultural (*CP_AG*) and industrial metals (*CP_IN*) prices Granger cause economic activity (*EA*) in China. This relationship might be due to the fact that the economy of China is still strongly reliant on the agricultural and manufacturing industry. As agricultural commodities and industrial metals are used as a key input factor in the processing industry, price changes in these raw materials might have a stimulating or dampening effect on economic activity.

As for the monetary policy variable of China, the analysis provides no empirical evidence that the real interest rate of China is Granger causing commodity prices. On the reverse side, however, test results indicate that agricultural commodity prices (*CP_AG*) Granger cause the real interest rate (*RIR*). This relationship is in line with Awokuse and Yang (2003), who report Granger causality running from commodity price to nominal interest rate and inflation. One explanation for this relationship is that fluctuations in agricultural commodity prices may provide signals to policy makers to adjust monetary policy variables, e.g. the interest rate to control inflation. In the case of China, with a relatively flat interest rate, however, it seems to be plausible that changes in commodity prices affect inflation and thus real interest rates. This is because commodities are raw materials that are used as input factor, in the production of higher order goods. A change in the cost of the input factor has an impact on the higher order goods and thus on inflation and real interest rates.

The test results further indicate spillover effects from precious metals (*CP_PR*) and energy (*CP_EN*) to livestock prices (*CP_LI*). While the effect of precious metals is surprising, the impact of energy prices on livestock prices might be explained by an energy cost spillover that is incorporated in the price of livestock.

The estimated coefficients of the dummy variable included in the lag augmented VAR model are presented in Table 6. The coefficients of the dummy variable, capturing the effect of the managed floating-against the fixed exchange rate regime, indicate that industrial metals (*CP_IN*) prices are significantly higher when there is the managed floating exchange rate system in place. One possible explanation for this relationship might be that the value of the Renminbi versus the US dollar tended to increase during the time of a managed floating exchange rate system in the observed period. As the US dollar is the predominant invoicing currency in international commodity transactions, an appreciation of the Renminbi relative to the US dollar implies that the purchasing power of Chinese commodity consumers and thus the demand and prices of industrial metals are pushed up[9]. One reason that only industrial metals prices show a significant result might be that China's net imports of industrial metals were relatively

[9] In addition to the D_t specification of the dummy variable, $D_t \times EX_t$ where EX_t is the CNY/USD exchange rate has been used as an alternative specification. This alternative specification yielded approximately the same results.

Table 6
Dummy variable estimates of VAR(1+1).

	CP_AG	*CP_EN*	*CP_IN*	*CP_LI*	*CP_PR*	*EA*	*RIR*
Coefficient	0.026	0.018	0.045**	0.012	0.010	−0.017	0.022
Standard Error	0.016	0.025	0.018	0.013	0.015	0.032	0.038
t-statistic	1.601	0.718	2.552	0.942	0.667	−0.538	0.581

Note: the respective critical value for the *t*-test is 2.576(1%), 1.96(5%) and 1.645 (10%).

** Represent significance levels at 5%.

large vis-à-vis net imports of other commodity groups. Thus, an appreciation of the Renminbi might have had a proportionately large effect on the price of industrial metals.

Generalized impulse response functions

The augmented Granger causality test provides us with information whether there is a causal relationship between the variables. However, it does not show how each variable reacts to innovations in other variables and whether the effect is time persistent or not. The analysis of the GIRF provides an approach to investigate this relationship. In the following we apply the GIRF analysis to the above estimated VAR(1) model.

Fig. 2 shows the response of the variables included in the VAR (1) model (*CP_AG*, *CP_EN*, *CP_IN*, *CP_LI*, *CP_PR*, *EA*, *RIR*) to a generalized one standard deviation innovation in the economic activity (*EA*) and real interest rate (*RIR*) of China. We use the Monte Carlo simulation procedure with 1000 replications to generate error bands. The dashed line shows the ± 2 standard deviation error band, representing the 5% level of significance.

The first column of the GIRF shows the response of the variables to a shock in the economic activity of China (*EA*). As for the commodity group prices, the analysis indicates that energy (*CP_EN*) and industrial metals (*CP_IN*) prices respond positively to a positive shock in the economic activity of China (*EA*). While the response of the energy price (*CP_EN*) continues to be significant for around 17 months, the feedback of industrial metal prices (*CP_IN*) is less persistent, already becoming insignificant after around seven months. The positive response of these commodity prices to an unexpected shock in the economic activity of China is consistent with the findings of Roache (2012), where global oil and copper prices displayed positive and persistent responses to innovations in the industrial production of China in the time interval from 2000 to 2011.

The GIRF analysis further indicates that the real interest rate of China (*RIR*) responds negatively to an innovation in the economic activity of China (*EA*). One possible explanation for the negative response to an innovation in the economic activity might be that the boost of the economic activity is followed by an increase in the general price level implying a reduction of the real interest rate.

The second column of Fig. 2 indicates that agricultural (*CP_AG*) and energy commodity prices (*CP_EN*) respond negatively to a positive shock in the real interest rate of China (*RIR*) at the 5% and close to the 5% level of significance respectively. The overshooting behavior of commodity prices in response to a drop in the real interest rate is in line with Frankel's (1986, 2008) commodity overshooting model as well as with empirical evidence on the relationship between the real interest rate of the US and different individual- as well as commodity-group prices (Akram, 2009; Frankel, 2008). Our empirical findings indicate China's increasingly important weight in global commodity markets. Not only China's economic activity but also its monetary policy has an impact on global price dynamics, particularly in the sphere of agricultural and energy commodities.

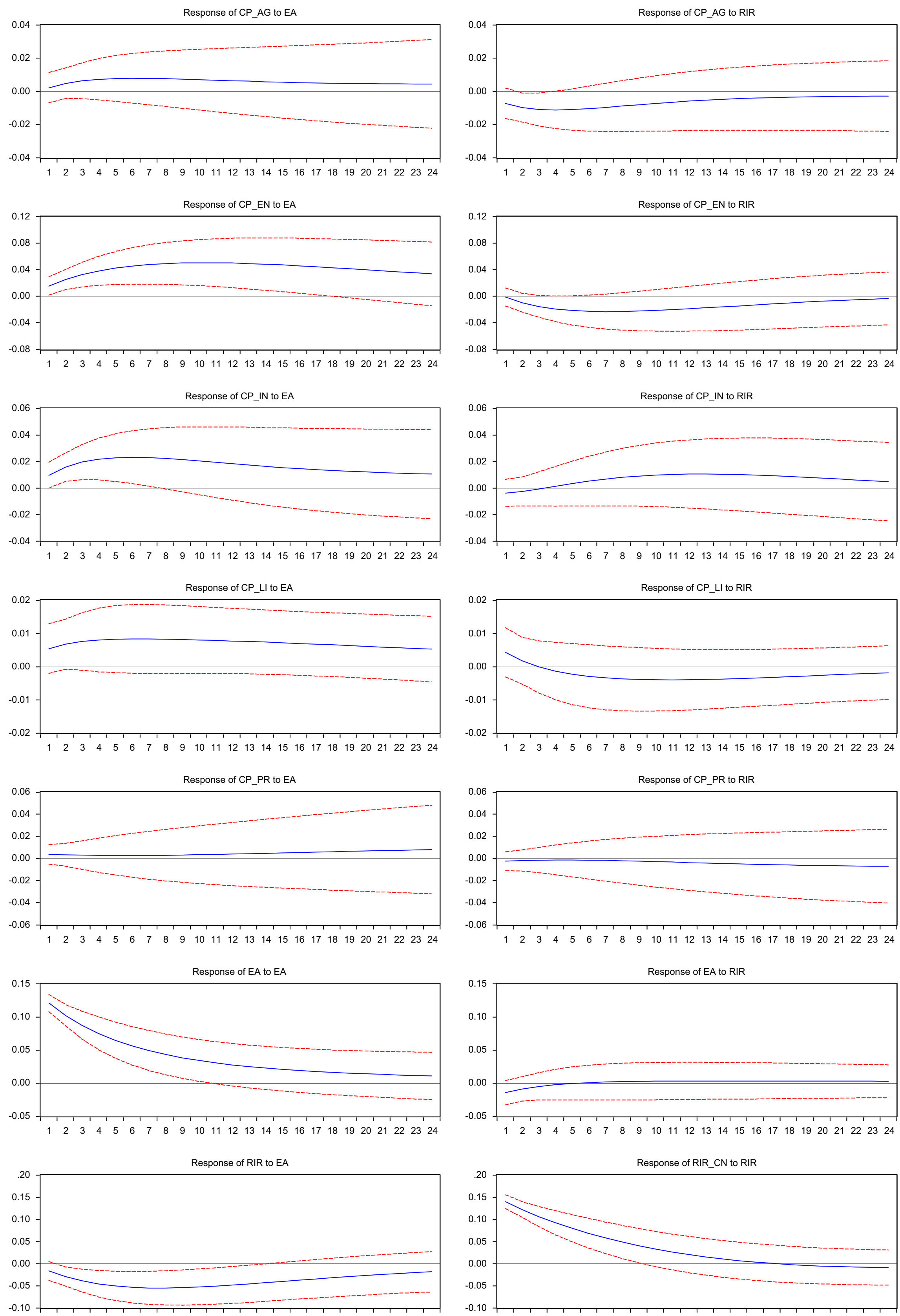

Fig. 2. Generalized response to one standard deviation innovations of EA and RIR of VAR(1).

Conclusion

This study examined the causal linkages and short-run dynamics between commodity prices of the agriculture, energy, industrial metals, livestock and precious metals group, economic activity and real interest rate of China over the period from 1998 to 2012. The time period starts at the point when China accelerated banking sector reforms and officially replaced its credit quota system by a target system and interest rates started to be increasingly determined by market forces.

Results of this study provide significant evidence for a causal relationship between China's economic activity and global energy as well as industrial metals prices. In particular, energy and industrial metals prices are Granger caused by China's economic activity at the 1% and 5% level of significance respectively. As for monetary policy, the analysis finds no significant evidence of a causal relationship between real interest rate and international commodity prices. The coefficient estimates of the exchange rate regime dummy variable indicate that industrial metals prices tend to be significantly higher when the fixed exchange system of China is relaxed. As for the short-run dynamics, the GIRF analysis indicates at the 5% level of significance that both energy and industrial metals prices respond positively to an innovation in the economic activity of China. As for China's monetary policy, the GIRF indicates that agricultural and energy commodity prices overshoot significantly in response to a drop in the real interest rate of China.

These results confirm that particularly agricultural, energy and industrial metals markets have become increasingly interrelated with macroeconomic developments in China. The most apparent reason for this is that China, as illustrated in the introduction, has become a dominant player in both financial and physical commodity markets. Shifts in economic and monetary policies have an impact on China's domestic supply and demand patterns which in turn have a spillover effect on specific commodity prices. Macroeconomic variables, especially economic activity as well as real interest rate, may be useful predictors of future price movements, particularly for commodities of the agricultural, energy and industrial metals sector. Our findings support not only investors in commodity markets to better determine the extent to which they are exposed to changes in macroeconomic conditions of China, but also policy makers to assess the possible effects of economic and monetary policies on commodity prices. Policymakers should be aware that abrupt policy interventions might lead to disruptive fluctuations of commodity prices. These sharp movements can have a severe impact on commodity consumers and producers of commodities as well as a destabilizing effect on the economy as a whole.

When formulating economic and monetary policies, decision makers should consider not only the effects on commodity markets in general, but also the possible up- and down side effects of commodity price changes on different market participants. It is important to note that while commodity producers generally benefit from an increase in prices, consumers usually lose. The negative effect of high commodity prices can be particularly severe for consumers in developing countries. In these countries, a large proportion of households typically spend a relatively large share of their income on primary commodities, agricultural and energy in particular. Policies that bolster commodity prices may have a disproportionately severe effect on the living standards of a large proportion of the population in these countries.

Further research can be extended to examine the impact of China's policies on specific commodities as well as to shed light on the diverging effects of economic activity and monetary policy shifts of China on different groups and individual commodities. From the domestic perspective for China, it would be also interesting to examine the effect of economic and monetary policy shifts on domestic commodity prices.

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