Auburn University
Department of Economics
Working Paper Series

Price Adjustment to the Exchange Rate Shock in World Commodity Markets

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AUWP 2016-01

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March 2016

Abstract

We empirically investigate dynamic responses of 49 IMF primary commodity prices to the US dollar exchange rate shock using recursively identified vector autoregressive models. Our major empirical findings are as follows. First, price adjustments toward the new equilibrium tend to be gradual with a few exceptions. We propose and estimate two measures of price-stickiness, which provide strong evidence of short-run price rigidity in most commodities. Second, our dynamic elasticity analysis implies that price responses are quite heterogeneous even in the long-run. Some commodity prices over-adjust to the exchange rate shock, which implies higher volatility of those prices than that of the exchange rate. Third, for those commodities that over-adjust, prices in the rest of the world would rise significantly when the US dollar depreciates unexpectedly, suggesting a role for price stabilization policies.

Keywords: World Commodity Prices; Price Stickiness; Dynamic Elasticity; Vector Autoregression; Impulse-Response Function

JEL Classification: E31; F31; Q02

*Special thanks go to Randy Beard and Michael Stern for helpful suggestions. We also thank seminar participants at the 2015 Southern Economic Association Meeting.

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1 Introduction

During the recent Great Recession, we observed big swings of the US dollar exchange rate that were accompanied by highly volatile and persistent movements in world commodity prices. In his recent VOX article in December 2014, Jeffrey Frankel argued that commodity prices declined rapidly in 2014 in terms of dollars but went up in terms of other currencies as monetary tightening, i.e., a rise in the interest rate, was anticipated in the US, whereas the European Central Bank and Bank of Japan have continued monetary stimulus. He suggested the following four channels through which monetary policy influences commodity price dynamics: the extraction channel (Hotelling, 1931), the inventory channel (Frankel 1986, Frankel 2014), the financialization channel (Hamilton and Wu, 2014), and the exchange rate channel (Frankel, 2006).[1]

We are interested in the exchange rate channel, though we do not pay particular attention on monetary policy issues. Since world commodities are normally denominated in the US dollar, dollar appreciation implies an increase in commodity prices in the rest of the world, which will then lead to (downward) price adjustments in dollars toward a new equilibrium in world commodity markets. Note that the IMF commodity index exhibits a mirror image of the US dollar exchange rate as can be seen in Figure 1.

Figure 1 around here

Since the seminal work of Obstfeld and Rogoff (1995), the profession has developed the New Open Economy Macroeconomics (NOEM), which introduces sticky-price type economic frictions to open macroeconomic models. For example, prices of tradable goods are sticky in terms of exporter's currency under producer currency pricing (PCP; Obstfeld and Rogoff 1995), while prices are sticky in the importing country's currency under local currency pricing (LCP; Betts and Devereux 2000, Chari, Kehoe, and McGrattan 2002).

When prices are rigid in the short-run, PCP implies 100% pass-through of the exchange rate to import prices, whereas the model results in 0% pass-through to export prices. The converse is true under LCP. Empirical literature, however, finds mixed evidence for these predictions. For example, Campa and Goldberg (2002) report limited evidence on the degree of exchange rate pass-through into the import prices in 23 OECD countries, which thus is inconsistent with both PCP and LCP. Based on such empirical findings, some authors employ models that combine PCP with LCP (Choudhri and Hakura 2015). Overall, nominal rigidity seems to play an important role in determining the degree of pass-through from exchange

[1] The article is available at http://www.voxeu.org/article/commodity-prices-down-dollars-euros.

rates to prices. For a review of the current literature, see Gopinath, Helpman, and Rogoff (2014).

There have been quite a few studies on the degree of pass through in world commodity markets, including Ridler and Yandle (1972), Dornbusch (1987), Fleisig and van Wijnbergen (1985), Giovannini (1988), Gilbert (1989), and Radetzki et al. (1990). But this issue has been somewhat overlooked in the current literature even though the profession started to pay an attention to the linkage between the exchange rate and commodity prices since the Great Recession, as noted in Jeffrey Frankel's aforementioned VOX article.

Since world commodities are highly tradable, one may expect that the Law of One Price (LOP) should hold in world commodity markets at least in the long-run, because commodity arbitrages will occur otherwise (Goldberg and Verboven 2005, Eckard 2004, Pippenger and Phillips 2008).[2] Then, appreciations (depreciations) of the US dollar will result in a fall (rise) in commodity prices in dollars. In the presence of price stickiness, however, actual adjustments of the world commodity prices may not take place immediately in response to exchange rate shocks.

In what follows, we attempt to answer the following questions. First, how quickly do commodity prices adjust to the long-run equilibrium when exchange rate shocks occur? Second, how homogeneous/heterogeneous are the responses? Are long-run exchange rate elasticities of prices near one in absolute value? Third, what are the policy implications of high price volatility triggered by exchange rate shocks?

We employ 49 monthly frequency primary commodity prices from the IMF website. We estimate impulse response functions of the commodity prices to the exchange rate shock using a recursively identified VAR model framework. Also, we define and estimate the dynamic elasticity of the commodity price with respect to the exchange rate. Our major findings are as follows.

First, world commodity prices tend to adjust to their long-run equilibrium slowly when the exchange rate shock occurs. Short-run responses are mostly a lot weaker than those in the long-run, which implies a substantial degree of nominal rigidity in the short-run notwithstanding high tradability of the world commodities. Most prices take roughly 8 to 12 months to converge to their long-run equilibrium. One notable exceptions are oil prices which stabilize in about 4 months.

Second, the price responses vary greatly across commodities. Some commodities such as beef, pork, and logs under-adjust to the exchange rate shock, that is, exchange rate

[2]There is a strand of studies that provides empirical evidence against the LOP, to name a few, Engel and Rogers (1999), Asplund and Friberg (2001), Goldberg and Verboven (2005). But Pippenger and Phillips (2008) point out that these test results might be caused by ignoring some important practical implications of arbitrages.

elasticity estimates of these commodity prices are substantially less than one in absolute value. Some other commodities such as corn, lamb, sugar, hide, and crude oil adjust on par to the exchange rate movement. Prices of the commodities like barley, peanuts, rubber, aluminum, and nickel tend to over-correct exchange rate adjustments.

For those commodities that over-react to the exchange rate shock, local prices in the rest of the world (outside the US) would increase (decrease) permanently in the long-run when the US dollar depreciates (appreciates) unexpectedly. We note that these prices will exhibit very high volatility when exchange rate shocks occur. Putting it differently, we have to pay attention to financial factors, in addition to demand/supply factors, in order to understand recent volatile movements of commodity prices, which may provide useful information for policy-makers who strive to stabilize commodity prices in the local markets.

The rest of the paper is organized as follows. In Section 2, we present our baseline VAR model framework and analytical representations of the dynamic elasticity and our measure of price stickiness. Section 3 reports our major empirical findings. Section 4 concludes.

2 The Empirical Model

Let p_t^i be the natural logarithm of the price of commodity i at time t, denominated in the US dollar, and e_t be the log of the nominal effective exchange rate, defined as the price of one US dollar in terms of a basket of major foreign currencies. Most commodity prices (p_t^i) we consider seem to obey a nonstationary stochastic process, as does the nominal exchange rate (e_t).[3] That is, since most series are integrated I(1) processes, we propose the following regression model with first differenced variables.

$$\Delta p_t^i = c_i + \lambda_i \Delta e_t + \varepsilon_t^i, \tag{1}$$

where c_i denotes the time invariant idiosyncratic intercept, λ_i is the commodity specific coefficient on the dollar appreciation rate, and ε_t^i is the idiosyncratic error term that might capture market-specific disturbances in the demand-supply (fundamental) condition.

To estimate dynamic effects of the exchange rate shock on each commodity price, we extend the model in (1) to the following bivariate vector autoregressive (VAR) model for the nominal exchange rate ($\triangle e_t$) and the commodity price ($\triangle p_t^i$),

$$\mathbf{x}_t = a + \mathbf{B}(L)\mathbf{x}_{t-1} + \mathbf{C}\mathbf{u}_t \tag{2}$$

where $\mathbf{x}_t = [\triangle e_t, \triangle p_t^i]$, $\mathbf{B}(L)$ denotes the lag polynomial matrix, $\mathbf{u}_t$ is a vector of normal-

[3] Unit root test results are available upon request.

ized underlying structural shocks, and **C** is a matrix that describes the contemporaneous relationships between $\triangle e_t$ and $\triangle p_t^i$. By putting $\triangle e_t$ first, we impose an assumption that the US dollar appreciation rate is not contemporaneously influenced by innovations in the commodity price within one month.[4]

We obtain the orthogonalized impulse-response function (OIRF) for $\triangle e_t$ and $\triangle p_t^i$ defined as follows.

$$\begin{aligned} \theta_e^p(j) &= E\left(\Delta p_{t+j} | u_{e,t} = 1, \Omega_{t-1}\right) - E\left(\Delta p_{t+j} | \Omega_{t-1}\right), \\ \theta_e^e(j) &= E\left(\Delta e_{t+j} | u_{e,t} = 1, \Omega_{t-1}\right) - E\left(\Delta e_{t+j} | \Omega_{t-1}\right), \end{aligned} \tag{3}$$

where Ω_{t-1} is the adaptive information set ($\Omega_{t-1} \supseteq \Omega_{t-2} \supseteq ...$) at time $t-1$. Note that we normalize the size of the exchange rate shock to one ($u_{e,t} = 1$). Note also that the OIRFs in (3) are the same as the generalized impulse-response function (GIRF) proposed by **?**, because $\triangle e_t$ is ordered first. We report response function estimates of the *level* variables (p_t and e_t) by cumulatively summing these response functions. That is,

$$\phi_e^p(j) = \sum_{s=0}^{j} \theta_e^p(j), \ \ \phi_e^e(j) = \sum_{s=0}^{j} \theta_e^e(j) \tag{4}$$

We suggest the following dynamic elasticity function of a commodity price at time $t+j$ with respect to the exchange rate.

$$\eta_e^p(j) = \frac{\phi_e^p(j)}{\phi_e^e(j)} \tag{5}$$

Note that $\eta_e^p(j)$ measures the elasticity of the commodity price with the time of impact ($j = 0$) as a reference point, because $\phi(\cdot)$ measures *cumulative* responses from the initial steady state. Also, we propose the following two measures of price stickiness,

$$\omega_e^p = \eta_e^p(\infty) - \eta_e^p(0) \quad \text{or} \quad \varpi_e^p = \frac{\eta_e^p(0)}{\eta_e^p(\infty)}, \tag{6}$$

where $\eta_e^p(0)$ is the initial (contemporaneous) elasticity, while $\eta_e^p(\infty)$ is the long-run elasticity when the price convergences to its long-run equilibrium.[5]

ω_e^p is the difference of the long-run and the initial elasticities, indicating how much more adjustment to be made before the price reaches to the new equilibrium. ϖ_e^p is the ratio of

[4] This seems to be a reasonable assumption, because it is hard to imagine that innovations in a single commodity market generate substantial fluctuations in the US dollar exchange rate.

[5] We report the long-run elasticity based on the 24-month ahead responses. Since virtually all response functions are stabilized within around 1-year, this is not a bad approximation. Alternatively, one may use analytical representations based on the invese matrix of AR representations.

contemporaneous elasticity to the long-run elasticity, which shows the relative impact of the initial elasticity. In what follows, using these two measures, we report a substantial degree of price stickiness in the short-run from a majority of commodity prices even though these are highly tradable world commodities.

3 Empirical Results

3.1 Data Descriptions

We use 49 primary commodity prices and the nominal US dollar exchange rate from January 1980 to November 2014. All commodity prices are denominated in the US dollar, and are obtained from the International Monetary Fund (IMF) website. See Table 1 for data descriptions of all commodities, including 23 items in the Food category (7 cereals, 5 vegetable oils, 4 meats, 3 seafoods, 4 other foods), 4 beverages, 9 agricultural raw materials, 8 metals, and 5 fuel prices. The foreign exchange rate is the trade-weighted average of the value of the US dollar against a subset of the major currencies (TWEXMMTH) obtained from the Federal Reserve Economic Data (FRED).[6]

Table 1 around here

3.2 Price Adjustments and Short-Run Price Stickiness

In Table 2, we report impulse-response function estimates of all 49 commodity prices when there is a one percent unexpected increase in the exchange rate. We report the initial response, $\phi_e^p(0)$ as well as the long-run response, $\phi_e^p(\infty)$, of the commodity price to the exchange rate shock.[7] We also report the long-run response of the exchange rate to its own shock, $\phi_e^e(\infty)$.[8] All point estimates are accompanied by the 95% confidence band by taking 2.5% and 97.5% percentiles from $2,000$ nonparametric bootstrap replications from the empirical distribution.

There's a couple of notable findings. First, exchange rate responses to its own shock are very similar in all 49 VAR models. After the initial 1% shock, the exchange rate continues

[6] Major currency index includes the Euro Area, Canada, Japan, United Kingdom, Switzerland, Australia, and Sweden.

[7] The long-run responses are measured by the response function after two years, which is long enough for deviations to die out.

[8] We don't report $\phi_e^e(0)$ since it is one by construction.

to increases for a while, then settles down to about 1.4%, exhibiting a mild hump-shape response function (see Figure 2). All 95% confidence bands for $\phi_e^e(\infty)$ seem compact and again very similar qualitatively and quantitatively.

Second, unlike the responses of the exchange rate, commodity price responses are quite heterogeneous. For example, $\phi_e^p(0)$ estimates vary from -1.19% to 0.29% with the mean -0.51% and the standard deviation 0.43. The long-run responses $\phi_e^p(\infty)$ range from -0.58% to -3.02% with the mean -1.36% and the standard deviation 0.73. $\phi_e^p(0)$ estimates are insignificant at the 5% level for 24 out of 49 commodity prices and are often negligible.

Note that we observe high degree of price stickiness on impact because most $\phi_e^p(0)$ estimates are less than -1 in absolute value. This is an interesting feature of our findings, because these are highly tradable world commodities. However, the average long-run response $\phi_e^e(\infty)$ is 1.39, which is very close to the average $\phi_e^p(\infty)$, -1.36, in absolute value but with the opposite sign.[9] Therefore, the commodity price in terms of the foreign currency, $p_t + e_t$, remains roughly constant on average in the long-run after the exchange rate shock occurs. Putting it differently, the exchange rate shock effect on the foreign price tends to disappear via long-run price adjustments in the world commodity markets on average.

Table 2 and Figure 2 around here

In Figure 3, we report response function estimates of the prices from the Food-Cereal category to the 1% exchange rate shock. Unlike the homogeneous responses of the exchange rate, we observed quite different responses of cereal prices. Barley price falls by 2.5% in about 8 months, exhibiting an over-adjustment as it decreases more than the increase in the exchange rate in the long-run. Maize (corn) price decreases by about 1.4% in about 12 months which is roughly on par with the exchange rate response, whereas wheat price declines by about 0.8% in about 12 months, which is a lot less than the change in the exchange rate. Overall the commodities in the Cereal category show substantial and statistically significant responses with an exception of wheat (see Table 2).

We also note high degree of short-run nominal rigidity in these prices. Most initial responses of cereal prices to the 1% exchange rate shock are far smaller than 1%, which implies an inelastic short-run price adjustment, $\phi_e^p(0) = \eta_e^p(0) < 1$.[10] For example, $\phi_e^p(0)$ of maize was virtually 0%. Furthermore, initial responses were often insignificant.

[9] We obtained statistically insignificant responses even in the long-run for 18 out of 49 prices, which is about 37% of all world commodity prices we consider.

[10] Note that $\eta_e^p(j) = \phi_e^p(j)$, $j = 0$, by construction, because we use an orthonormal shock to the exchange rate. Of course, this doesn't hold when $j > 0$.

Figure 3 around here

The commodities in the Meat subcategory show negligible and insignificant responses to the exchange rate shock with an exception of lamb (see Figure 4). For example, poultry price shows virtually no meaningful responses with a wide confidence band. Interestingly, the response of lamb price exhibits a mirror image of the exchange rate responses over all time horizon. Its initial response was -1% that exactly offsets the 1% exchange rate shock. The long-run response point estimate was -1.46%, which is quite close to that of the exchange rate in absolute value, which again offsets changes in the exchange rate over time, meaning that lamb price tends to remain roughly constant in the rest of the world.

Figure 4 around here

Agricultural raw materials show a wide range of heterogeneous responses (see Figure 5). Overall, forestry products such as soft logs and soft sawnwood exhibit virtually no adjustments since the impact of the shock. Other products such as cotton and hides show negligible initial responses (price-stickiness) but substantial price correction in about 8 months that are statistically significant. For instance, rubber price decreases only by 0.7% on impact but exhibits a 3% correction within one year.

Figure 5 around here

Prices of the items in the Metals category exhibit overall substantial and significant responses especially in the long-run with an exception of zinc (see Figure 6). Most prices show substantial degree initial adjustments as well. For example, copper and lead prices drop by more than 1% in response to the 1% exchange rate shock. The prices of nickel and aluminum show over-corrections in the long-run, implying a price decrease in local currencies in the rest of the world.

Figure 6 around here

Among prices in the Fuel category, all 4 oil prices decline initially by about 0.8%, then quickly adjust to the long-run equilibrium of about -1.4% decreases in about 4 months, which offsets the increase in the exchange rate (see Figure 7). That is, oil prices show a mildly sluggish adjustment in the short-run, but quickly restore the original local price in local currencies. The response of coal price shows very sluggish adjustment in the short-run, but eventually over-corrects the exchange rate shock in about 8 months.

Figure 7 around here

In a nutshell, we observe substantial degree of short-run price rigidity as well as heterogeneous price adjustments across commodities. For clearer demonstration, we estimate and report a nonparametric kernel distribution of the initial responses from our 49 VAR models in Figure 8, via the following kernel estimator to obtain the kernel density function for $x = \phi_e^p(0)$.

$$\hat{f}(x) = \frac{1}{nh}\sum_{i=1}^{n} k\left(\frac{X_i - x}{h}\right), \tag{7}$$

where n is the number of commodity prices, h is the bandwidth parameter, and $k(\cdot)$ denotes a kernel function.[11]

Note that, given a 1% exchange rate shock, 0% initial response implies complete price rigidity (no adjustment), whereas -1% response implies a thorough adjustment to the shock. As shown in the figure, most initial responses occur between -1% and 0%, which exhibit an incomplete price adjustment in the short-run. Also, a wide dispersion of the distribution implies heterogeneous initial price adjustment dynamics.

Figure 8 around here

3.3 Dynamic Elasticity Analysis

Table 3 reports estimates for the dynamic elasticity in the long-run, $\eta_e^p(\infty)$ along with the 95% confidence band obtained from $2,000$ nonparametric bootstrap replications. We also report the nonparametric kernel density estimate for $\eta_e^p(\infty)$ in Figure 9.

Note that the estimated kernel density overall resembles the normal distribution centered around its mean (-0.98) or median (-1.02). Also, skewness (-0.05) and kurtosis (2.66) are similar as those of the normal distribution. Since $\eta_e^p(\infty) = -1$ means that dollar price

[11] We employ the Epanechnikov kernel and Gaussian kernel, which yield similar results. We choose the optimal h by conventional Silverman's rule of thumb.

changes completely absorb the exchange rate effect on the local prices in the long-run. Put it differently, the LOP holds on average in the long-run.

In order to statistically evaluate the LOP hypothesis, we implement the t-test with the null hypothesis $H_0 : \eta_e^p(\infty) = -1$. The t-statistic was 0.293, that is, the test fails to reject the null (LOP) at any conventional confidence levels.

Figure 9 around here

Dynamic elasticity point estimates vary from 0.05 (Soft Log) to -2.13 (Rubber). Note that $|\eta_e^p(\infty)| > 1$ implies an over-adjustment, because p_t falls by more than the increase in e_t in the long-run. Likewise, $|\eta_e^p(\infty)| < 1$ represents an under-adjustment. That is, even though our empirical evidence implies a just-correction on average, we observe heterogeneous long-run responses across the world commodity markets.

Among the food category commodities, we obtained highly significant dynamic elasticity estimates for all cereal prices with an exception of wheat. Especially, we observe an over-correction for the prices of barley, ground nut, and rice in the long-run, which implies that these prices would exhibit highly volatile movements when the exchange rate shock occurs. That is, countries that have high dependence on these grain products, probably under-developed or developing countries, will face greater fluctuations in domestic prices when exchange rate shocks occur. Maize, soybean meal, and soybean prices seem to (just) correct in the long-run, implying stable domestic prices in local currencies. The dynamic elasticity estimate of wheat price shows an under-adjustment, which is insignificant.

Most other food category prices and beverage prices have small and insignificant elasticity estimates with a couple of exceptions. On the contrary, majority agricultural raw materials, metals, and fuel category prices exhibit highly significant dynamic elasticity estimates, which implies an active adjustment of the commodity price via commodity arbitrages. For example, oil prices show a just-correction from the short- to the long-run, which implies that exchange rate shocks result in virtually no changes in the domestic price in the rest of the world.

Table 3 around here

Lastly, we report our proposed measures of price stickiness in (6). Note that when ω_e^p is different from zero (negative in this exercise) or when ϖ_e^p is smaller than one, price adjustments are greater in the long-run than in the short-run, which may give useful information about price-stickiness in the short-run. Results are reported in Tables 4 and 5 as well as in Figure 10.

As to our first measure ω_e^p, mean (-0.47) and median (-0.37) were very different from its benchmark value 0. Its skewness (-0.01) and kurtosis (2.66) are again close to those of the normal distribution. The t-test statistic was -6.543, which strongly rejects the null hypothesis $H_0 : \omega_e^p = 0$. On the other hand, mean and median of ϖ_e^p estimates were 0.58 and 0.49, respectively, which are far from its benchmark value 1. Skewness was -0.04, thus the distribution is symmetric around its sample mean. Kurtosis was 11.03, implying a fat tail property. The t-test ($t = -2.64$) again rejects the null hypothesis $H_0 : \varpi_e^p = 1$ at any conventional significance levels. The kernel density estimates in Figure 10 are consistent with such statistical analysis.

In a nutshell, irrespective of their highly tradable nature, we found substantial degree of short-run price rigidity in the world commodity markets.

Tables 4, 5, and Figure 10 around here

4 Conclusions

This paper employs a VAR model to study how world commodity prices respond to the exchange rate shock. In the absence of economic frictions, these commodity prices should absorb any changes in the dollar exchange rate, because these (highly tradable) world commodities are denominated in the US dollar. However, our empirical findings imply substantial degree of short-run price stickiness. It takes about 8 to 12 months for most prices to adjust to the new long-run equilibrium.

In this paper, we propose and estimate two measures of short-run price stickiness, ω_e^p and ϖ_e^p, which are functions of the long-run and the short-run exchange rate elasticity of the prices. Via nonparametric kernel density estimates, we report strong evidence of short-run nominal rigidity in the world commodity markets. The t-test also rejects the null hypothesis of zero price rigidity at any conventional significance levels.

Heterogeneous responses of prices were observed across the commodities even within the same category. For example, in the Cereal sub-category, long-run response estimates vary from -0.79% for wheat to -2.54% for peanuts. Barley, peanuts and rice prices over-adjust to the shock, while changes in soybeans, soybean meal, and corn prices absorb changes in the exchange rate in the long-run. Wheat price, on the other hand, adjusts less than the exchange rate.

We further characterize long-run responses of the prices using the dynamic elasticity. The long-run elasticity estimates range from -2.13% for rubber to 0.05% for soft logs. About 15 commodity prices including oil prices have a long-run elasticity that is close to -1, i.e., they just-correct the exchange rate shock effect so that the local price remains the same. About 17 commodity prices including some food prices over-react, implying higher volatility of these prices than the exchange rate. That is, local prices of these goods would rise if the US dollar depreciates unexpectedly, which may call for price stabilization policies.

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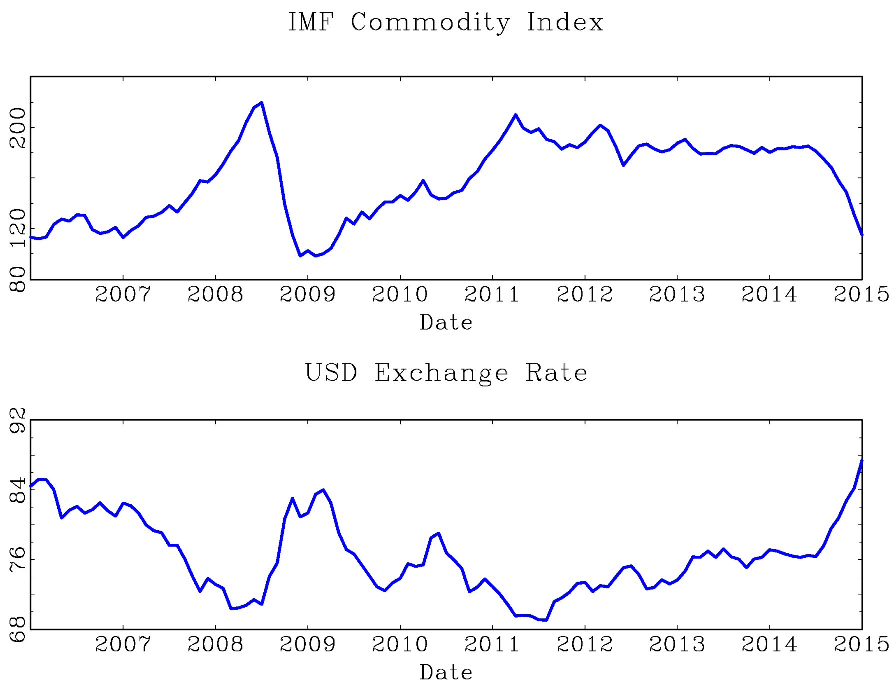
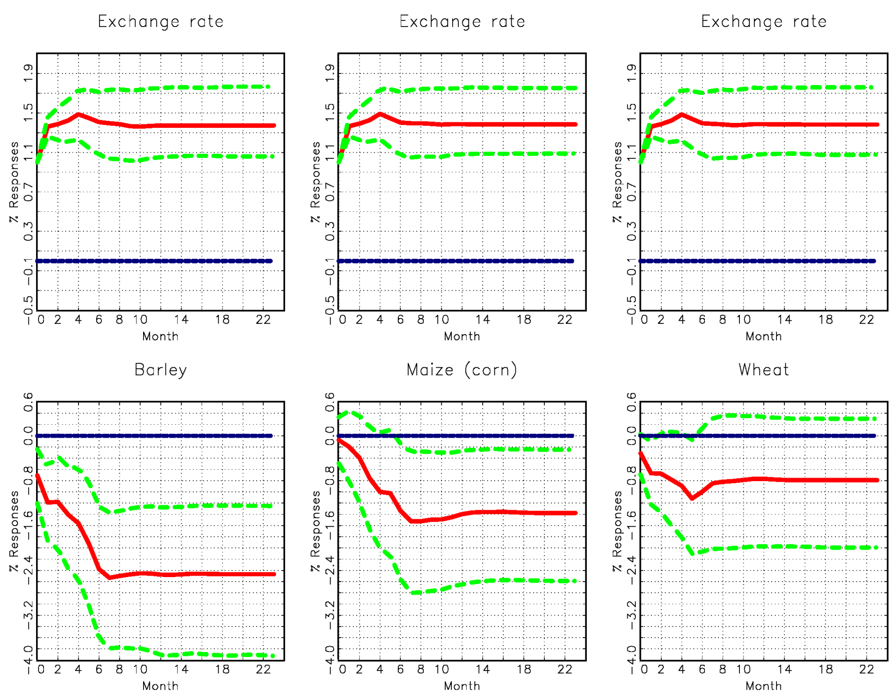
Figure 1: Commodity Price and the USD Exchange Rate



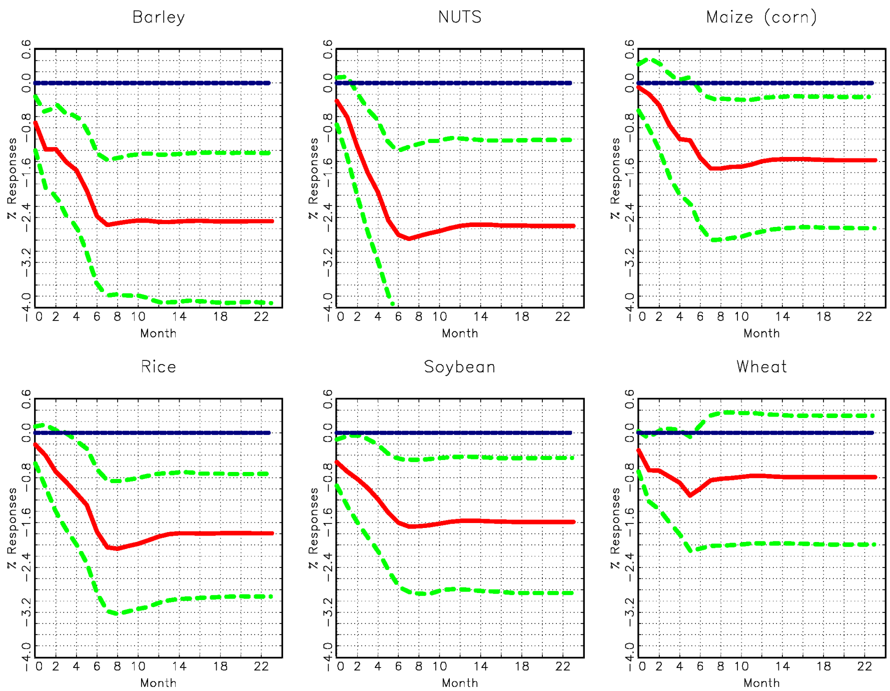
Note: The IMF commodity index was obtained from the IMF website. The USD exchange rate is the nominal effective exchange rate relative to major currencies obtained from the Federal Reserve Economic Data (FRED).

Figure 2: Impulse-Resonse Function Estimates: Exchange Rate/Food-Cereal



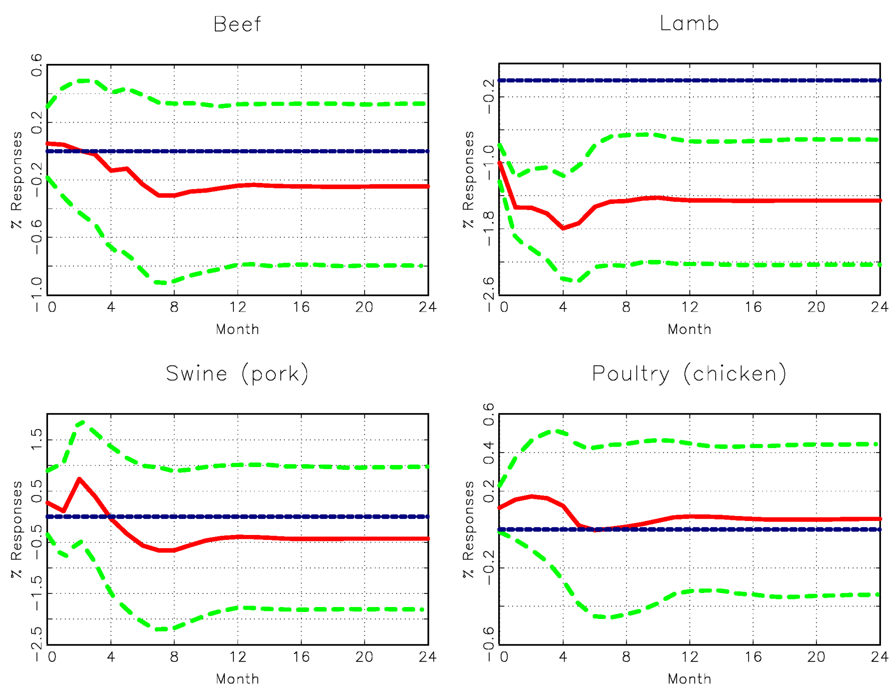
Note: All impulse-response function estimates are obtained from a bivariate VAR with the nominal exchange rate ordered first. 95% confidence bands were obtained from 2,000 nonparametric bootstrap simulations.

Figure 3: Impulse-Response Function Estimates: Food-Cereal



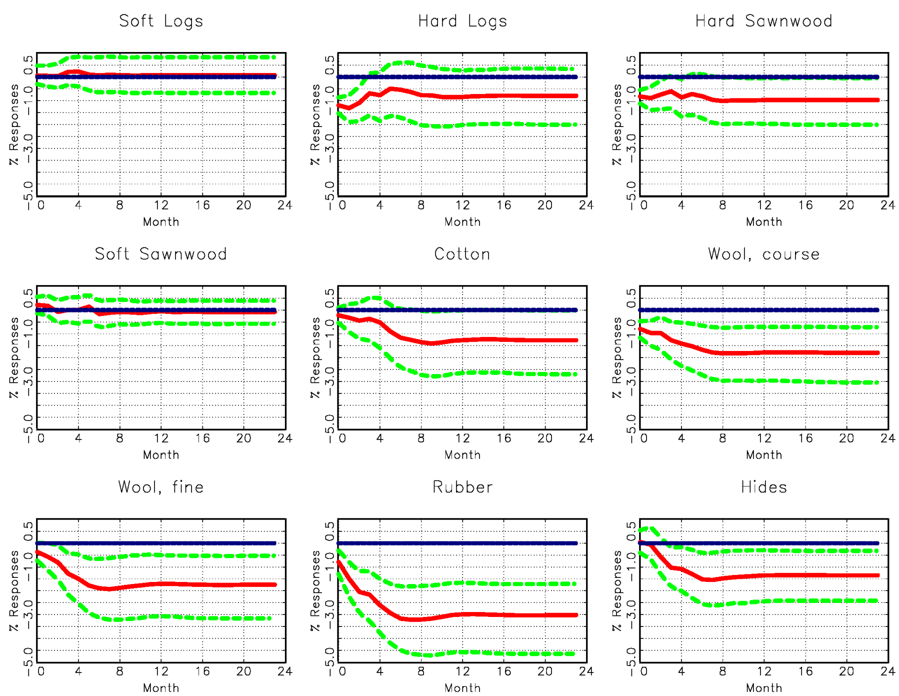
Note: All impulse-response function estimates are obtained from a bivariate VAR with the nominal exchange rate ordered first. 95% confidence bands were obtained from 2,000 nonparametric bootstrap simulations.

Figure 4: Impulse-Response Function Estimates: Food-Meat



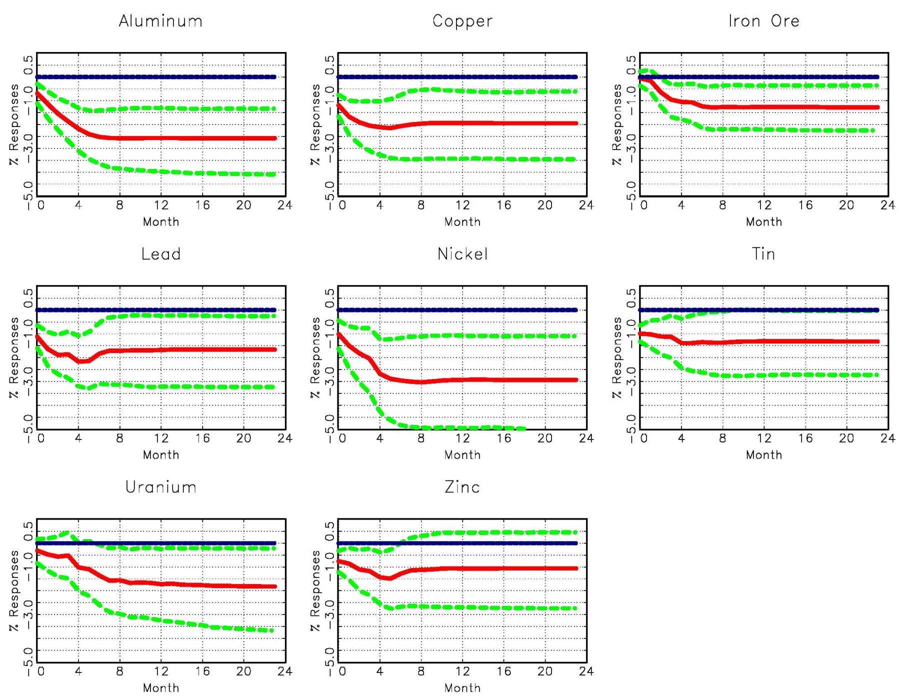
Note: All impulse-response function estimates are obtained from a bivariate VAR with the nominal exchange rate ordered first. 95% confidence bands were obtained from 2,000 nonparametric bootstrap simulations.

Figure 5: Impulse-Response Function Estimates: Ag Raw Material



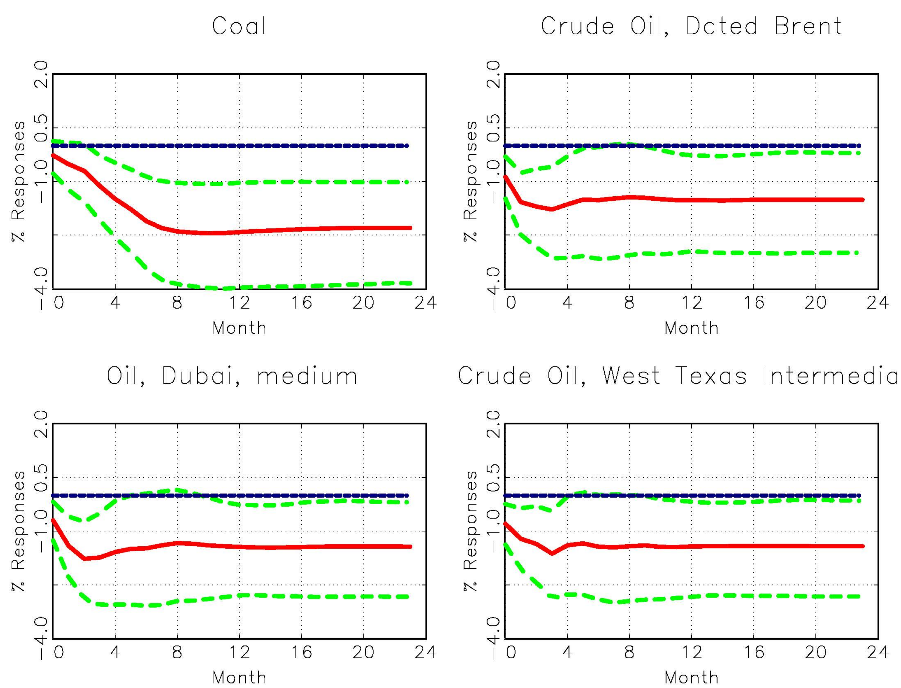
Note: All impulse-response function estimates are obtained from a bivariate VAR with the nominal exchange rate ordered first. 95% confidence bands were obtained from 2,000 nonparametric bootstrap simulations.

Figure 6: Impulse-Response Function Estimates: Metals



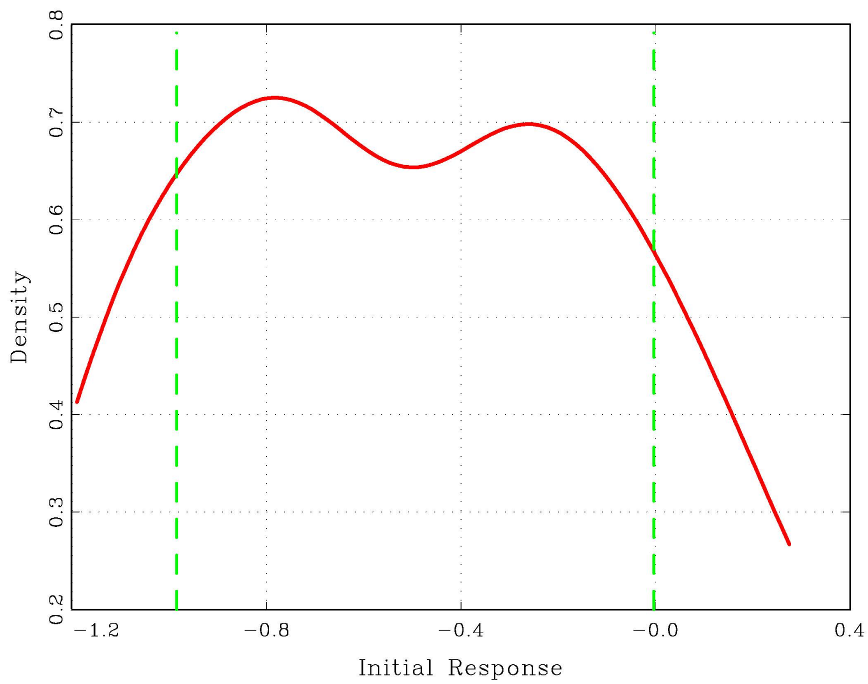
Note: All impulse-response function estimates are obtained from a bivariate VAR with the nominal exchange rate ordered first. 95% confidence bands were obtained from 2,000 nonparametric bootstrap simulations.

Figure 7: Impulse-Response Function Estimates: Fuel



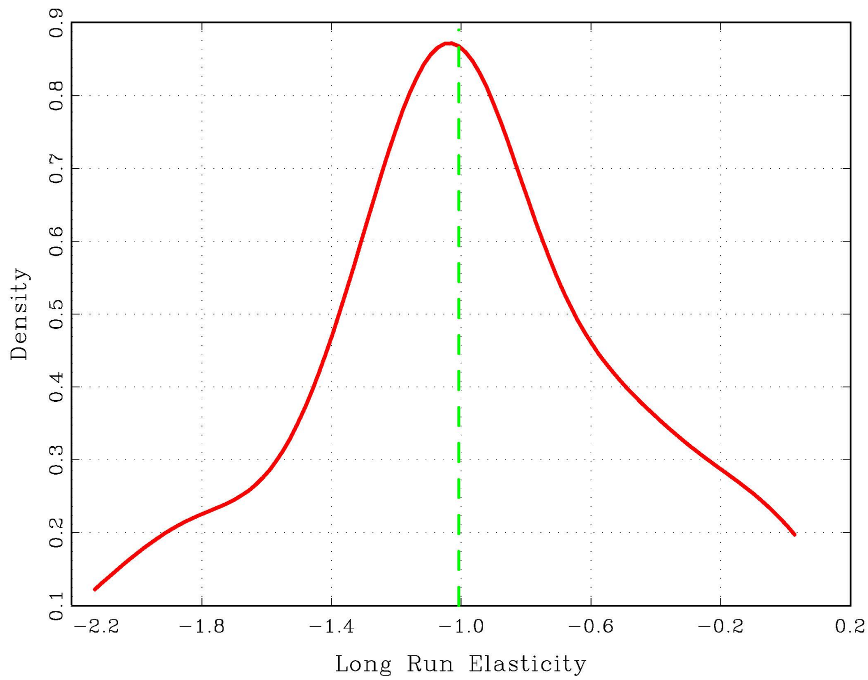
Note: All impulse-response function estimates are obtained from a bivariate VAR with the nominal exchange rate ordered first. 95% confidence bands were obtained from 2,000 nonparametric bootstrap simulations.

Figure 8: Distribution of Initial Responses



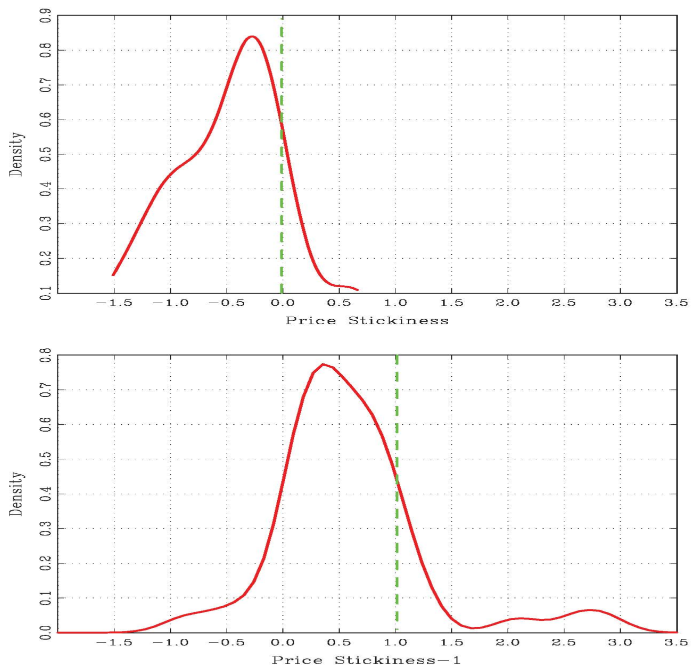
Note: We estimated non-parametric Kernel distribution using the Gaussian Kernel.

Figure 9: Distribution of Long Run Elasticity



Note: We estimated non-parametric Kernel distribution using the Gaussian Kernel.

Figure 10: Distribution of Price Stickiness



Note: We estimated non-parametric Kernel distribution using the Gaussian Kernel. The top panel is for the difference measure of nominal price stickiness ω_e^p and the bottom panel is for the ratio measure of nominal stickiness ϖ_e^p.

Table 1: Data Descriptions

Category	ID	IMF Code	Commodity
Cereal	1	PBARL	Barley, Canadian no.1 Western Barley
	2	PGNUTS	Groundnuts (peanuts), cif Argentina
	3	PMAIZMT	Maize (corn), U.S. No.2 Yellow, FOB Gulf of Mexico
	4	PRICENPQ	Rice, 5 percent broken milled white rice, Thailand price
	5	PSMEA	Soybean Meal, Chicago Soybean Meal Futures
	6	PSOYB	Soybeans, U.S. soybeans, Chicago Soybean futures contract
	7	PWHEAMT	Wheat, No.1 Hard Red Winter, FOB Gulf of Mexico
Vegetable Oil	8	PROIL	Rapeseed oil, crude, fob Rotterdam
	9	POLVOIL	Olive Oil, ex-tanker price U.K.
	10	PPOIL	Palm oil, Malaysia Palm Oil Futures
	11	PSOIL	Soybean Oil, Chicago Soybean Oil Futures
	12	PSUNO	Sunflower oil,US export price from Gulf of Mexico
Meat	13	PBEEF	Beef, Australian and New Zealand 85% lean fores
	14	PLAMB	Lamb, frozen carcass Smithfield London
	15	PPORK	Swine (pork), 51-52% lean Hogs, U.S. price
	16	PPOULT	Poultry (chicken), Whole bird spot price
Seafood	17	PFISH	Fishmeal, Peru Fish meal/pellets 65% protein, CIF
	18	PSALM	Fish (salmon), Farm Bred Norwegian Salmon, export price
	19	PSHRI	Shrimp, No.1 shell-on headless
Other Foods	20	PBANSOP	Bananas, Central American and Ecuador, FOB U.S. Ports
	21	PORANG	Oranges, miscellaneous oranges CIF French import price
	22	PSUGAISA	Sugar, Free Market, Coffee Sugar and Cocoa Exchange
	23	PSUGAUSA	Sugar, U.S. import price
Beverage	24	PCOCO	Cocoa beans, International Cocoa Organization cash price
	25	PCOFFOTM	Coffee, Arabica,New York cash price
	26	PCOFFROB	Coffee, Robusta, New York cash price
	27	PTEA	Tea, Mombasa, Kenya, US cents per kilogram
Ag Raw	28	PLOGORE	Soft Logs, Average Export price from the U.S. for Douglas Fir
	29	PLOGSK	Hard Logs, Best quality Malaysian meranti, import price Japan
	30	PSAWMAL	Hard Sawnwood, Dark Red Meranti, C & F U.K port
	31	PSAWORE	Soft Sawnwood, average export price of Douglas Fir, U.S. Price
	32	PCOTTIND	Cotton, Cotton Outlook 'A Index', CIF Liverpool
	33	PWOOLC	Wool, coarse, 23 micron, Australian Wool Exchange spot quote
	34	PWOOLF	Wool, fine, 19 micron, Australian Wool Exchange spot quote
	35	PRUBB	Rubber, Singapore Commodity Exchange, 1st contract
	36	PHIDE	Hides, Heavy native steers, over 53 pounds, US, Chicago

Category	ID	IMF Code	Commodity
Metals	37	PALUM	Aluminum, 99.5% minimum purity, LME spot price, CIF UK ports
	38	PCOPP	Copper, grade A cathode, LME spot price, CIF European ports
	39	PIORECR	Iron Ore Fines 62% FE spot (CFR Tianjin port), China import
	40	PLEAD	Lead, 99.97% pure, LME spot price, CIF European Ports
	41	PNICK	Nickel, melting grade, LME spot price, CIF European ports
	42	PTIN	Tin, standard grade, LME spot price
	43	PURAN	Uranium, NUEXCO, Restricted Price, Nuexco exchange spot
	44	PZINC	Zinc, high grade 98% pure
Fuel	45	PCOALAU	Coal, Australian thermal coal, 12,000- btu/pound
	46	POILAPSP	Crude Oil (petroleum), Price index, 2005 = 100
	47	POILBRE	Crude Oil (petroleum), Dated Brent, light blend 38 API, fob U.K.
	48	POILDUB	Oil; Dubai, medium, Fateh 32 API, fob Dubai Crude Oil
	49	POILWTI	Crude Oil (petroleum), West Texas Intermediate 40 API

Note: We obtained all commodity price data from the IMF website. The sample period is from January 1980 to November 2014.

Table 2: Impulse-Response Function Estimates

		Commodity Prices				*Exchange Rates*	
ID	IMF Code	$\phi_e^p(0)$	95% $C.I$	$\phi_e^p(\infty)$	95% $C.I$	$\phi_e^e(\infty)$	95% $C.I$
1	PBARL	-0.71	$[-1.20, -0.24]$	-2.47	$[-3.93, -1.25]$	1.37	$[1.06, 1.77]$
2	PGNUTS	-0.32	$[-0.75, 0.10]$	-2.55	$[-4.23, -1.02]$	1.39	$[1.08, 1.77]$
3	PMAIZMT	-0.08	$[-0.49, 0.33]$	-1.38	$[-2.59, -0.25]$	1.38	$[1.09, 1.75]$
4	PRICENPQ	-0.21	$[-0.55, 0.11]$	-1.80	$[-2.92, -0.73]$	1.34	$[1.05, 1.72]$
5	PSMEA	-0.54	$[-0.95, -0.15]$	-1.52	$[-2.86, -0.32]$	1.41	$[1.10, 1.80]$
6	PSOYB	-0.52	$[-0.94, -0.12]$	-1.59	$[-2.85, -0.45]$	1.41	$[1.10, 1.81]$
7	PWHEAMT	-0.31	$[-0.69, 0.03]$	-0.79	$[-1.99, 0.30]$	1.38	$[1.08, 1.76]$
8	PROIL	-1.06	$[-1.49, -0.63]$	-1.84	$[-3.20, -0.55]$	1.40	$[1.09, 1.77]$
9	POLVOIL	-1.10	$[-1.36, -0.86]$	-2.01	$[-2.96, -1.17]$	1.36	$[1.07, 1.72]$
10	PPOIL	-0.54	$[-1.10, 0.00]$	-1.16	$[-2.98, 0.59]$	1.39	$[1.08, 1.75]$
11	PSOIL	-0.37	$[-0.80, 0.05]$	-1.26	$[-2.57, 0.06]$	1.40	$[1.09, 1.79]$
12	PSUNO	-0.26	$[-0.85, 0.25]$	-1.95	$[-3.56, -0.54]$	1.30	$[1.01, 1.66]$
13	PBEEF	0.05	$[-0.18, 0.31]$	-0.25	$[-0.80, 0.33]$	1.39	$[1.09, 1.76]$
14	PLAMB	-1.00	$[-1.23, -0.78]$	-1.46	$[-2.24, -0.72]$	1.38	$[1.08, 1.76]$
15	PPORK	0.27	$[-0.35, 0.90]$	-0.43	$[-1.81, 0.98]$	1.38	$[1.08, 1.76]$
16	PPOULT	0.11	$[-0.01, 0.23]$	0.05	$[-0.34, 0.44]$	1.39	$[1.09, 1.78]$
17	PFISH	-0.82	$[-1.12, -0.53]$	-1.34	$[-2.55, -0.26]$	1.38	$[1.07, 1.74]$
18	PSALM	-1.11	$[-1.37, -0.85]$	-1.54	$[-2.41, -0.83]$	1.39	$[1.09, 1.78]$
19	PSHRI	-0.11	$[-0.36, 0.15]$	-0.61	$[-1.50, 0.31]$	1.37	$[1.07, 1.75]$
20	PBANSOP	0.29	$[-0.73, 1.31]$	-0.74	$[-1.93, 0.48]$	1.36	$[1.08, 1.73]$
21	PORANG	-1.11	$[-1.85, -0.45]$	-0.58	$[-1.93, 0.60]$	1.37	$[1.07, 1.75]$
22	PSUGAISA	-0.59	$[-1.20, 0.00]$	-1.44	$[-3.30, 0.32]$	1.36	$[1.07, 1.72]$
23	PSUGAUSA	-0.05	$[-0.24, 0.15]$	-0.48	$[-1.33, 0.43]$	1.38	$[1.07, 1.73]$
24	PCOCO	-0.63	$[-0.98, -0.28]$	-0.18	$[-1.23, 0.86]$	1.38	$[1.07, 1.75]$
25	PCOFFOTM	-0.06	$[-0.55, 0.41]$	-1.15	$[-2.77, 0.23]$	1.38	$[1.07, 1.75]$
26	PCOFFROB	-0.41	$[-0.81, -0.04]$	-1.47	$[-2.98, -0.19]$	1.39	$[1.07, 1.76]$
27	PTEA	-0.24	$[-0.68, 0.20]$	-0.86	$[-1.97, 0.38]$	1.39	$[1.09, 1.78]$
28	PLOGORE	0.06	$[-0.31, 0.48]$	0.07	$[-0.67, 0.83]$	1.39	$[1.09, 1.76]$
29	PLOGSK	-1.19	$[-1.53, -0.85]$	-0.79	$[-1.99, 0.34]$	1.39	$[1.08, 1.78]$
30	PSAWMAL	-0.82	$[-1.11, -0.55]$	-0.97	$[-2.01, -0.04]$	1.39	$[1.09, 1.76]$
31	PSAWORE	0.22	$[-0.13, 0.56]$	-0.08	$[-0.58, 0.39]$	1.40	$[1.09, 1.79]$
32	PCOTTIND	-0.22	$[-0.54, 0.11]$	-1.26	$[-2.70, -0.01]$	1.42	$[1.10, 1.83]$
33	PWOOLC	-0.80	$[-1.16, -0.46]$	-1.79	$[-3.05, -0.72]$	1.42	$[1.09, 1.81]$
34	PWOOLF	-0.37	$[-0.74, 0.00]$	-1.74	$[-3.16, -0.53]$	1.40	$[1.08, 1.80]$
35	PRUBB	-0.79	$[-1.30, -0.31]$	-3.02	$[-4.66, -1.71]$	1.42	$[1.10, 1.81]$
36	PHIDE	0.05	$[-0.41, 0.55]$	-1.35	$[-2.42, -0.32]$	1.35	$[1.06, 1.72]$

		Commodity Prices				*Exchange Rates*	
ID	IMF Code	$\phi^p_e(0)$	95% $C.I$	$\phi^p_e(\infty)$	95% $C.I$	$\phi^e_e(\infty)$	95% $C.I$
37	PALUM	-0.69	$[-1.11, -0.29]$	-2.57	$[-4.10, -1.33]$	1.42	$[1.09, 1.81]$
38	PCOPP	-1.19	$[-1.66, -0.76]$	-1.94	$[-3.46, -0.61]$	1.37	$[1.06, 1.72]$
39	PIORECR	-0.06	$[-0.36, 0.23]$	-1.27	$[-2.25, -0.36]$	1.42	$[1.09, 1.82]$
40	PLEAD	-1.12	$[-1.60, -0.64]$	-1.66	$[-3.23, -0.25]$	1.35	$[1.04, 1.71]$
41	PNICK	-1.01	$[-1.63, -0.44]$	-2.93	$[-5.01, -1.10]$	1.41	$[1.09, 1.80]$
42	PTIN	-0.99	$[-1.33, -0.64]$	-1.32	$[-2.73, -0.02]$	1.40	$[1.09, 1.78]$
43	PURAN	-0.31	$[-0.84, 0.17]$	-1.82	$[-3.69, -0.22]$	1.46	$[1.11, 1.89]$
44	PZINC	-0.75	$[-1.22, -0.32]$	-1.06	$[-2.74, 0.45]$	1.40	$[1.09, 1.77]$
45	PCOALAU	-0.27	$[-0.78, 0.13]$	-2.30	$[-3.84, -1.02]$	1.33	$[1.03, 1.69]$
46	POILAPSP	-0.81	$[-1.38, -0.27]$	-1.51	$[-2.88, -0.29]$	1.39	$[1.09, 1.78]$
47	POILBRE	-0.88	$[-1.48, -0.30]$	-1.51	$[-3.00, -0.21]$	1.40	$[1.10, 1.79]$
48	POILDUB	-0.70	$[-1.27, -0.17]$	-1.43	$[-2.83, -0.19]$	1.39	$[1.09, 1.78]$
49	POILWTI	-0.80	$[-1.38, -0.24]$	-1.42	$[-2.83, -0.15]$	1.39	$[1.09, 1.77]$

Note: We report responses of level variables that are obtained by cumulative responses of differenced variables. Long-run response functions are measured by the 25-period ahead response function estimates. 95% confidence bands are obtained by taking 2.5% and 97.5% percentiles from 2,000 nonparametric bootstrap iterations.

Table 3: Dynamic Elasticity Estimates

ID	IMF Code	$\eta_e^p(\infty)$	95% C.I.	Id	IMF Code	$\eta_e^p(\infty)$	95% C.I.
1	PBARL	-1.80	$[-2.74, -1.00]$	26	PCOFFROB	-1.06	$[-2.02, -0.15]$
2	PGNUTS	-1.83	$[-2.96, -0.80]$	27	PTEA	-0.62	$[-1.46, 0.27]$
3	PMAIZMT	-0.99	$[-1.81, -0.18]$	28	PLOGORE	0.05	$[-0.48, 0.62]$
4	PRICENPQ	-1.34	$[-2.09, -0.56]$	29	PLOGSK	-0.57	$[-1.37, 0.25]$
5	PSMEA	-1.08	$[-1.90, -0.24]$	30	PSAWMAL	-0.70	$[-1.35, -0.03]$
6	PSOYB	-1.13	$[-1.93, -0.35]$	31	PSAWORE	-0.05	$[-0.40, 0.28]$
7	PWHEAMT	-0.57	$[-1.38, 0.22]$	32	PCOTTIND	-0.88	$[-1.74, -0.01]$
8	PROIL	-1.32	$[-2.22, -0.42]$	33	PWOOLC	-1.26	$[-1.95, -0.55]$
9	POLVOIL	-1.47	$[-2.13, -0.89]$	34	PWOOLF	-1.25	$[-2.02, -0.43]$
10	PPOIL	-0.84	$[-2.11, 0.42]$	35	PRUBB	-2.13	$[-2.90, -1.34]$
11	PSOIL	-0.90	$[-1.75, 0.05]$	36	PHIDE	-1.00	$[-1.71, -0.24]$
12	PSUNO	-1.50	$[-2.90, -0.39]$	37	PALUM	-1.82	$[-2.63, -1.03]$
13	PBEEF	-0.18	$[-0.58, 0.24]$	38	PCOPP	-1.42	$[-2.29, -0.48]$
14	PLAMB	-1.05	$[-1.59, -0.53]$	39	PIORECR	-0.90	$[-1.58, -0.27]$
15	PPORK	-0.31	$[-1.35, 0.70]$	40	PLEAD	-1.24	$[-2.18, -0.20]$
16	PPOULT	0.04	$[-0.25, 0.32]$	41	PNICK	-2.08	$[-3.33, -0.85]$
17	PFISH	-0.98	$[-1.80, -0.19]$	42	PTIN	-0.94	$[-1.90, -0.02]$
18	PSALM	-1.11	$[-1.62, -0.62]$	43	PURAN	-1.25	$[-2.29, -0.17]$
19	PSHRI	-0.44	$[-1.14, 0.22]$	44	PZINC	-0.76	$[-1.88, 0.34]$
20	PBANSOP	-0.55	$[-1.46, 0.33]$	45	PCOALAU	-1.73	$[-2.79, -0.77]$
21	PORANG	-0.42	$[-1.32, 0.46]$	46	POILAPSP	-1.08	$[-2.04, -0.21]$
22	PSUGAISA	-1.06	$[-2.29, 0.25]$	47	POILBRE	-1.08	$[-2.07, -0.15]$
23	PSUGAUSA	-0.35	$[-0.96, 0.30]$	48	POILDUB	-1.03	$[-1.99, -0.14]$
24	PCOCO	-0.13	$[-0.91, 0.63]$	49	POILWTI	-1.02	$[-1.95, -0.11]$
25	PCOFFOTM	-0.83	$[-1.90, 0.19]$				
	Mean: -0.98		Median: -1.02		skewness = -0.05	Kurtosis = 2.66	

Note: The long-run dynamic elasticity $\eta_e^p(\infty)$ is calculated by $\phi_e^p(\infty)/\phi_e^e(\infty)$. Long-run response functions are again measured by the 25-period ahead response function estimates. 95% confidence bands are obtained by taking 2.5% and 97.5% percentiles from 2,000 nonparametric bootstrap iterations. We employed the t-test and $t = 0.293$.

Table 4: Price Stickiness Estimates: ω_e^p

ID	IMF Code	$\eta_e^p(\infty) - \eta_e^p(0)$	Id	IMF Code	$\eta_e^p(\infty) - \eta_e^p(0)$
1	PBARL	-1.09	26	PCOFFROB	-0.64
2	PGNUTS	-1.51	27	PTEA	-0.38
3	PMAIZMT	-0.92	28	PLOGORE	-0.01
4	PRICENPQ	-1.13	29	PLOGSK	0.62
5	PSMEA	-0.54	30	PSAWMAL	0.12
6	PSOYB	-0.60	31	PSAWORE	-0.27
7	PWHEAMT	-0.26	32	PCOTTIND	-0.67
8	PROIL	-0.25	33	PWOOLC	-0.46
9	POLVOIL	-0.37	34	PWOOLF	-0.88
10	PPOIL	-0.29	35	PRUBB	-1.34
11	PSOIL	-0.53	36	PHIDE	-1.05
12	PSUNO	-1.24	37	PALUM	-1.12
13	PBEEF	-0.23	38	PCOPP	-0.23
14	PLAMB	-0.05	39	PIORECR	-0.84
15	PPORK	-0.59	40	PLEAD	-0.11
16	PPOULT	-0.07	41	PNICK	-1.07
17	PFISH	-0.16	42	PTIN	0.04
18	PSALM	0.01	43	PURAN	-0.93
19	PSHRI	-0.34	44	PZINC	-0.01
20	PBANSOP	-0.84	45	PCOALAU	-1.45
21	PORANG	0.68	46	POILAPSP	-0.27
22	PSUGAISA	-0.47	47	POILBRE	-0.21
23	PSUGAUSA	-0.30	48	POILDUB	-0.33
24	PCOCO	0.50	49	POILWTI	-0.22
25	PCOFFOTM	-0.78			
	Mean: -0.47	Median: -0.37	Skewness: -0.01	Kurtosis: 2.66	

Note: We employed the t-test and $t = -6.543$

Table 5: Price Stickiness Estimates: ϖ_e^p

ID	IMF Code	$\eta_e^p(0)/\eta_e^p(\infty)$	Id	IMF Code	$\eta_e^p(0)/\eta_e^p(\infty)$
1	PBARL	0.39	26	PCOFFROB	0.39
2	PGNUTS	0.18	27	PTEA	0.38
3	PMAIZMT	0.08	28	PLOGORE	1.24
4	PRICENPQ	0.16	29	PLOGSK	2.08
5	PSMEA	0.50	30	PSAWMAL	1.17
6	PSOYB	0.46	31	PSAWORE	-4.04
7	PWHEAMT	0.54	32	PCOTTIND	0.24
8	PROIL	0.81	33	PWOOLC	0.63
9	POLVOIL	0.75	34	PWOOLF	0.29
10	PPOIL	0.65	35	PRUBB	0.37
11	PSOIL	0.41	36	PHIDE	-0.05
12	PSUNO	0.17	37	PALUM	0.38
13	PBEEF	-0.30	38	PCOPP	0.84
14	PLAMB	0.95	39	PIORECR	0.06
15	PPORK	-0.88	40	PLEAD	0.91
16	PPOULT	2.87	41	PNICK	0.49
17	PFISH	0.84	42	PTIN	1.05
18	PSALM	1.00	43	PURAN	0.25
19	PSHRI	0.25	44	PZINC	0.99
20	PBANSOP	-0.53	45	PCOALAU	0.16
21	PORANG	2.61	46	POILAPSP	0.75
22	PSUGAISA	0.56	47	POILBRE	0.81
23	PSUGAUSA	0.15	48	POILDUB	0.68
24	PCOCO	4.84	49	POILWTI	0.78
25	PCOFFOTM	0.07			
	Mean: 0.58	Median: 0.49	Skewness: -0.04	Kurtosis: 11.03	

Note: We employed the t-test and $t = -2.64$