The Heterogeneous Responses of the World Commodity Prices to Exchange Rate Shocks

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Abstract

We empirically investigate dynamic responses of 49 world commodity prices to exchange rate shocks 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 two measures of price-stickiness that exhibit a high degree of short-run price rigidity in most commodities. Second, our dynamic elasticity analysis implies that commodity price responses are quite heterogeneous even in the long-run. Some commodity prices over-correct for the exchange rate shock, which implies higher volatility for those prices than the exchange rate. Third, for those commodities that over-react, domestic prices would rise significantly when the US dollar depreciates unexpectedly, perhaps suggesting a role for price stabilization policies.

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

JEL Classification: E31; F31; Q02

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1 Introduction

During the recent Great Recession, we observed big swings of the US exchange rate that were accompanied by highly volatile movements in world commodity prices (See Figure 1). In his recent VOX article in December 2014, Jeffrey Frankel argued that commodity prices declined rapidly in 2014 mainly due to the anticipation of a rise in the interest rate in the US via the following four channels: 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 particularly interested in the exchange rate channel, noting that world commodity prices tend to exhibit a mirror image of the US dollar exchange rate as can be seen in Figure 1. Since world commodities are normally denominated in the US dollar, an appreciation of the US dollar results in an increase in the foreign price of the commodity in the rest of the world, which will induce adjustments in the commodity price. Since most world commodities are highly tradable, it is natural to assume that the law of one price (LOP) holds at least in the long-run. This paper investigates the dynamics of the price adjustment process in the world commodity market in response to unexpected changes in the US dollar exchange rate.

Figure 1 around here

Since the seminal work of Obstfeld and Rogoff (1995), the profession has developed 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 local consumers' currency under local currency pricing (LCP; Betts and Devereux 2000, Chari, Kehoe, and McGrattan 2002).

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 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, sticky prices seem to play an important role for the pass-through mechanism. Gopinath, Helpman, and Rogoff (2014) offer a review of this literature.

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

What about the exchange rate pass-through to world commodity prices? There have been many studies on this issue, 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 the world commodity market at least in the long-run, because commodity arbitrages will occur otherwise (Goldberg and Verboven 2005, Eckard 2004, Pippenger and Phillips 2008).[2] Then an appreciation (depreciation) of the US dollar will result in a fall (rise) in dollar denominated commodity prices. In the presence of price stickiness, however, actual adjustments of the world commodity prices may not take place immediately in response to an exchange rate shock.

In what follows, we attempt to answer the following questions. First, how quickly do commodity prices adjust to the long-run equilibrium when there's an exchange rate shock? Is the speed of adjustment constant over time? Secondly, how homogeneous are the long-run responses of commodity prices to the exchange rate shock? Are long-run price elasticities near one in absolute value? Third, what are the policy implications of the volatility of the commodity price?

We used monthly frequency world commodity prices from the IMF data base and estimated impulse response functions of commodity prices to exchange rate shocks using a recursively identified VAR framework. We further estimated dynamic exchange rate elasticities of the commodity prices. Our major findings are as follows. First, commodity prices tend to slowly adjust to their long-run equilibrium when the exchange rate shock occurs. Initial responses are typically much weaker than longer run responses, which implies a high degree price stickiness in the short-run. Most prices take 8 to 12 months to stabilize. One notable exception is oil prices which stabilize in about 4 months. Second, the responses of commodity prices exhibit high degree heterogeneity. Some commodities such as beef, pork, and logs under-correct to the exchange rate shock, that is, the price elasticities of these commodities are substantially less than one in absolute value. Some others, like corn, lamb, sugar, hide, and crude oil adjust on par with the exchange rate movement. Prices of the commodities like barley, peanuts, rubber, aluminum, and nickel over-correct.

[2]There is a strand of studies that suggests evidence of the failure of the law of one price, such as Engel and Rogers (1999), Asplund and Friberg (2001), Goldberg and Verboven (2005). But Pippenger and Phillips (2008) maintain that all tests that fail to support the LOP are due to the result of ignoring important practical implications of arbitrage.

For those commodities that over-react to the exchange rate shock, their 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. That is, US dollar exchange rate shocks would generate high volatility in these commodity prices. Put differently, not only fundamental demand/supply factors, but also financial factors may be responsible for the highly volatile movements in commodity prices we observed recently, which calls for attention from policy-makers to financial markets dynamics in order to help 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 of 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 measure 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 log differences in 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 normalized underlying shocks, and $\mathbf{C}$ 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

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

appreciation rate is not contemporaneously influenced by commodity price inflation within one month.[4]

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

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

where Ω_{t-1} is the adaptive information set at time $t-1$. Note that we normalize the size of the exchange rate shock to be one ($u_{e,t} = 1$). Note also that the OIRFs in (3) are the same as the generalized impulse-response function (GIRF) proposed by Pesaran and Shin (1998), 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 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 considering the time of impact ($j = 0$) as a reference point, because $\phi(\cdot)$ measures cumulative responses of differenced variables from the initial steady state. All estimates are accompanied by the 95% confidence bands by taking 2.5% and 97.5% percentiles from 2,000 nonparametric bootstrap from empirical distributions.

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 elasticity, while $\eta_e^p(\infty)$ is the long-run elasticity when the responses are stabilized.[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

[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 invese matrix of AR representations.

ratio of initial response to the long-run elasticity. This shows the percentage of the initial elasticity to the long-run elasticity. In what follows, we use these two measures and report a substantial degree price stickiness in the short-run from a majority of commodity prices even though these goods are highly tradable world commodities.

3 Data Descriptions and Empirical Findings

We use 49 primary world commodity prices and the nominal US dollar exchange rate from January 1980 to November 2014. All commodity prices are denominated in the US dollar. We obtained the commodity price data 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

3.1 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. The long-run responses are measured by the response function after two years, which is long enough for the deviation to die out. We also report the long-run response of the exchange rate to its own shock, $\phi_e^e(\infty)$. All point estimates are accompanied by the 95% confidence bands that are obtained by 2,000 nonparametric bootstrap replications.

There are couple of notable findings. First, exchange rate responses to the exchange rate shock are very similar in all 49 VAR models. After the initial 1% shock, the exchange rate increases for a while, then settles down to about 1.4%, exhibiting a mild hump-shape response function (see Figure 2, for example). All 95% confidence bands for $\phi_e^e(\infty)$ seem compact and again very similar qualitatively and quantitatively. Second, unlike the exchange rate

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

responses, the response function estimates of the commodity prices are quite heterogeneous. For example, the initial responses $\phi_e^p(0)$ vary from -1.19% to 0.29% with the mean -0.51% and 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 standard deviation 0.73. The initial responses are insignificant at the 5% level for 24 out of 49 commodity prices and often negligible. Note that we observe high degree 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 $\phi_e^p(\infty)$ in absolute value but with the opposite sign.[7] Note that, on average, the commodity price in terms of the foreign currency, $p_t + e_t$, remains roughly constant in the long-run after the exchange rate shock occurs. Put it differently, the exchange rate shock on the foreign price is cancelled out via long-run adjustments of the commodity prices on average.

Table 2 around here

In Figure 2, we report three sets of impulse-response function estimates from the Food-Cereal category. As we mention previously, the responses of the exchange rate to the 1% exchange rate shock are very similar. They all show mild degree hump-shape responses and stabilize around 1.4% in less than a year.

Responses of the cereal price, however, are not uniform. The barley price falls 2.5% in about 8 months, exhibiting an over-reaction as it responses more than the exchange rate changes in the long-run. The maize (corn) price falls 1.4 % in about 12 months which is on par with the exchange rate response, whereas the wheat price falls 0.8% in about 12 months a lot less than exchange rate response. 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 price stickiness in the short-run. Most initial responses of cereals are far less than 1%. For example, $\phi_e^p(0)$ of the maize price was virtually 0%. Furthermore, initial responses were often insignificant.

Figure 2 around here

[7] 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.

The commodities in the Meat subcategory show negligible and insignificant responses to the exchange rate shock with an exception of lamb (see Figure 3). For example, the poultry price show virtually no meaningful responses with the very narrow confidence band. Interestingly, the response of the lamb price exhibits a mirror image of the exchange rate response all the time. It's initial response was -1% that exactly offsets the 1% exchange rate shock. The long-run response point estimate was -1.46%, which is quite similar to that of the exchange rate in absolute value, which again offsets the innovation in the exchange rate.

Figure 3 around here

Agricultural raw materials show a wide range of heterogeneous responses. See Figure 4. Overall, forestry products such as soft logs and soft sawnwood show virtually no responses since the impact of the shock. Other products in this category show negligible initial responses (price-stickiness) but substantial price correction in about 8 months that are statistically significant. For instance, the rubber price drops only about 0.7% on impact but exhibits 3% correction within a year.

Figure 4 around here

The prices of the items in the Metals category exhibit overall large and significant responses especially in the long-run with an exception of Zinc. See Figure 5. Most prices show substantial degree initial corrections as well. For example, the copper and the lead prices drop by more than 1% responding to the 1% exchange rate shock. The prices of nickel and aluminum show over-corrections in the long-run, implying a price fall in the rest of the world.

Figure 5 around here

Among prices in the Fuel category, all 4 oil prices decline initially by about 0.8%, then quickly reach to the long-run equilibrium of about -1.4% decreases in about 4 months, which offsets the increase in the exchange rate. See Figure 6. That is, oil prices show a mildly sluggish adjustment in the short-run, but quickly restore the price in the rest of the world. The response of the coal price show very sluggish adjustment in the short-run, but eventually over-correct the exchange rate shock in about 8 months.

Figure 6 around here

In a nutshell, we obtained substantial degree of short-run price rigidities and quite heterogeneous price adjustment dynamics. To show these findings more clearly, we estimate and report nonparametric kernel distribution of the initial responses from our 49 VAR models in Figure 7. Note that, given a 1% exchange rate shock, 0 initial response implies complete price rigidity (no adjustment), whereas -1 implies a full adjustment. As is shown in the figure, most initial responses occur between -1 and 0 which show incomplete price adjustments. Also, a wide dispersion of the distribution implies heterogeneous initial price adjustment dynamics.

Figure 7 around here

3.2 Dynamic Elasticity Analysis

Estimates for the dynamic elasticity in the long-run, $\eta_e^p(\infty)$, are reported in Table 3, along with 95% confidence bands obtained from 2,000 nonparametric bootstraps. We also report the nonparametric kernel density estimates in Figure 8. The distribution overall resembles the normal distribution centered around -1. Mean (-0.98) and median (-1.02) estimates are very close to -1, while skewness (-0.05) and kurtosis (2.66) are similar as those of the normal distribution. We also employed 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 at any conventional confidence levels.

We also note that dynamic elasticity estimates show a quite wide range of values from 0.05 (Soft Log) to -2.13 (Rubber). Note that $|\eta_e^p(\infty)| > 1$ implies an over-correction, because p_t falls more than the increase in e_t in the long-run. Likewise, $|\eta_e^p(\infty)| < 1$ represents an under-correction. That is, even though our empirical evidence implies a just-correction on average, highly heterogeneous long-run adjustments were observed across prices.

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 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. Dynamic elasticity estimate of wheat shows an under-correction, which is insignificant.

Most other food category prices and beverage prices show 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 in response to the exchange rate shock. For example, oil prices show a just-correction from the short- to the long-run, which implies that exchange rate shock cause virtually no change in the domestic price in the rest of the world.

Table 3 and Figure 8 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 ϖ_e^p is smaller than one, the adjustment occurs more actively in the long-run rather 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 9.

As to our first measure ω_e^p, estimated mean (-0.47) and median (-0.37) were very different from its benchmark value 0. Its skewness (-0.01) and kurtosis (2.66) are close to those of the normal distribution. The t-test statistic was -6.543, which strongly rejects the null hypothesis $H_0 : \omega_e^p = 0$. The mean and the median estimates of ϖ_e^p 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. Again, we implemented the t-test for the null hypothesis $H_0 : \varpi_e^p = 1$. The test statistic was -2.64 and the null was rejected at any significance levels. The Kernel density estimates in Figure 9 are consistent with these sample moments.

In a nutshell, irrespective of high degree tradability, we found substantial degree of price rigidities in the world commodity markets in the short-run.

Tables 4, 5, and Figure 9 around here

4 Conclusions

This paper employs a VAR model to study how world commodity prices respond to exchange rate shocks. In the absence of economic friction, world commodity prices should adjust completely to changes in the exchange rate, because world commodities are denominated in the US dollar. Even though world commodities are highly tradable, we find a substantial degree of short-run price stickiness in a majority of cases. It takes 8 to 12 months for most prices to reach a new long-run equilibrium, even though long-run responses are quite heterogeneous across commodities. We also introduce two measures of price stickiness, ω_e^p and ϖ_e^p, which is a function of the long-run and the short-run price elasticity with respect to the exchange rate. Our test rejects the null hypothesis of zero price rigidity at any conventional significance levels.

We also find that the responses of commodity prices differ even within the same category. For example, in the Cereal category, the long-run response varies from -0.79% for wheat to -2.54% for peanuts. Barley, peanuts and rice prices over-correct, while soybeans, soybean meal and corn prices just adjust to the exchange rate change. Wheat price under-corrects. On the contrary, oil prices show homogeneous responses within their category.

Also, we introduced the concept of dynamic elasticity and further characterized the heterogeneous responses. Long-run elasticities range from -2.13% for rubber to 0.05% for soft logs. About 15 commodity prices including oil prices have long-run elasticity close to -1, i.e., they adjust to the exchange rate shock so that the local price remains the same. About 17 commodity prices including some food prices over-react, implying that these prices are more volatile 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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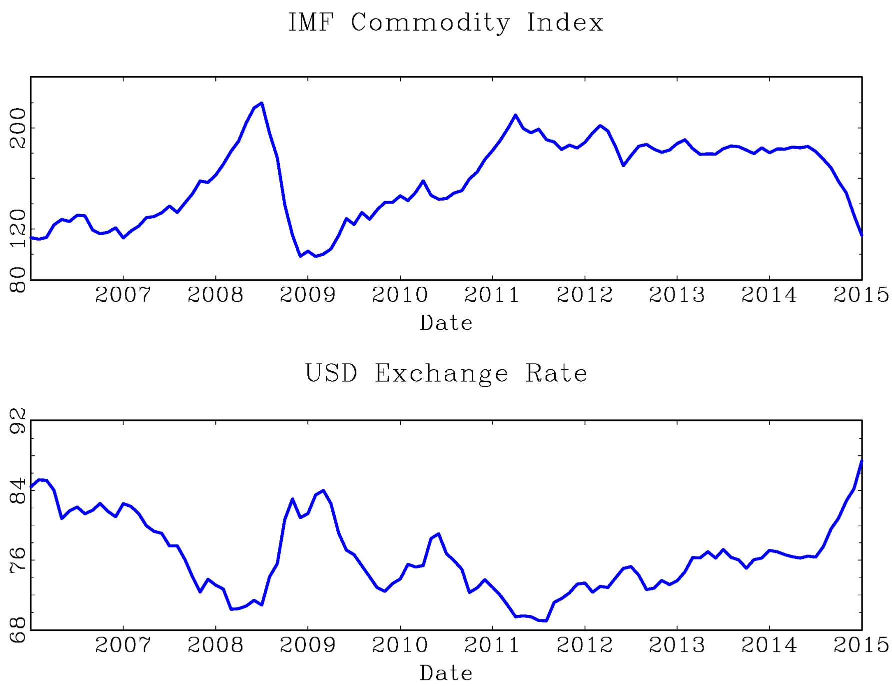
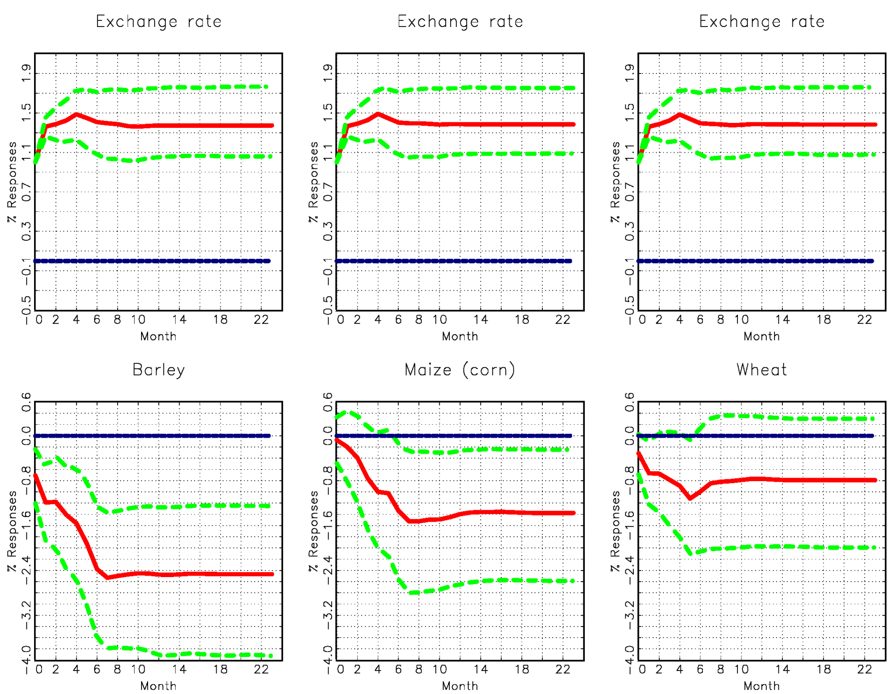
Figure 1: Commodity Price and the USD Exchange Rate



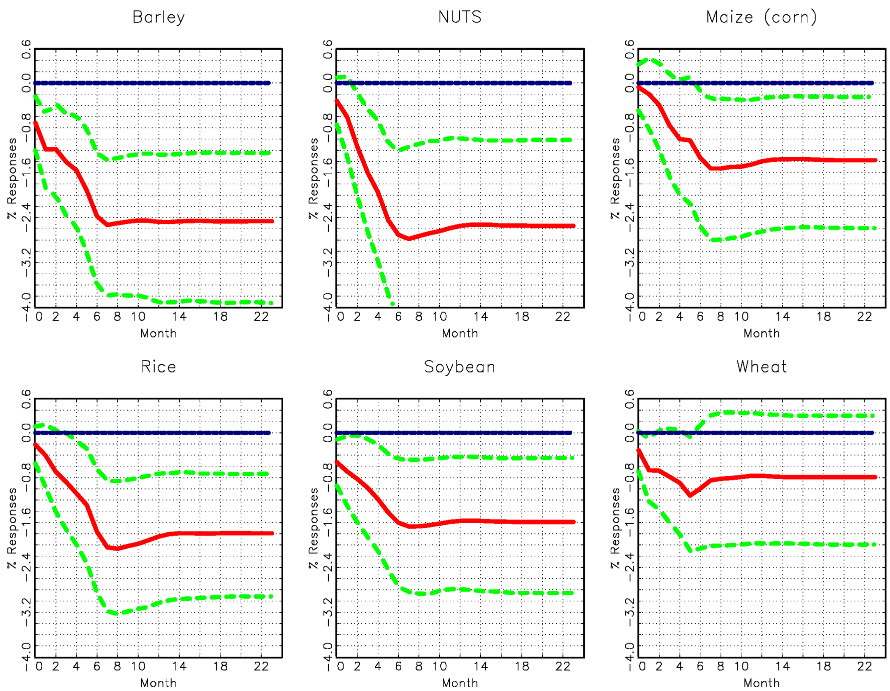
Note: The IMF commodity index was obtained from the IMF website. The USD exchange rate is the nominal effective exchange rate relative to major currencies obtained from the Federal Reserve Economic Data (FRED).

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



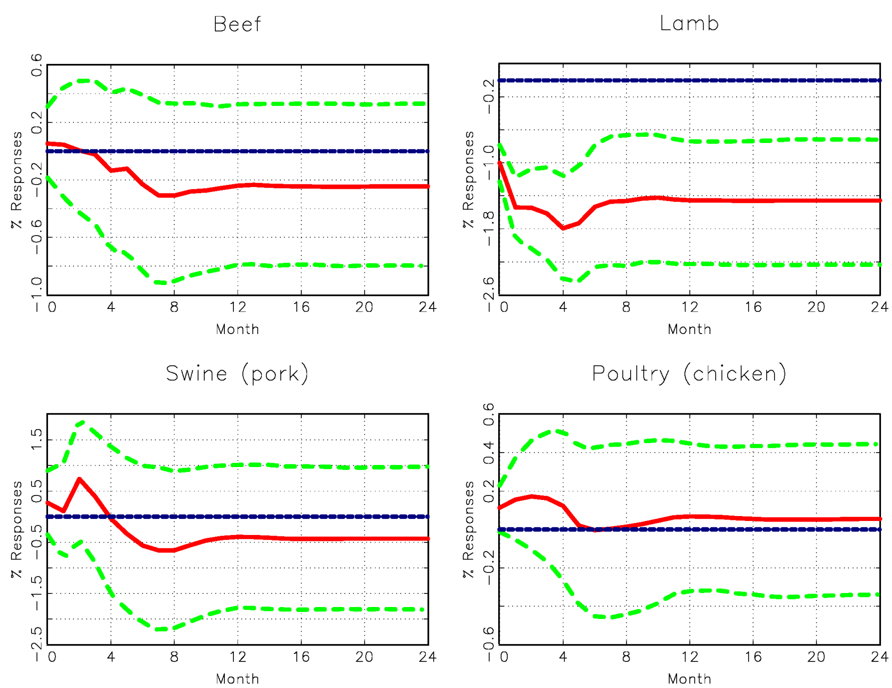
Note: All impulse-response function estimates are obtained from a bivariate VAR with the nominal exchange rate ordered first. 95% confidence bands were obtained from 2000 nonparametric bootstrap simulations.

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



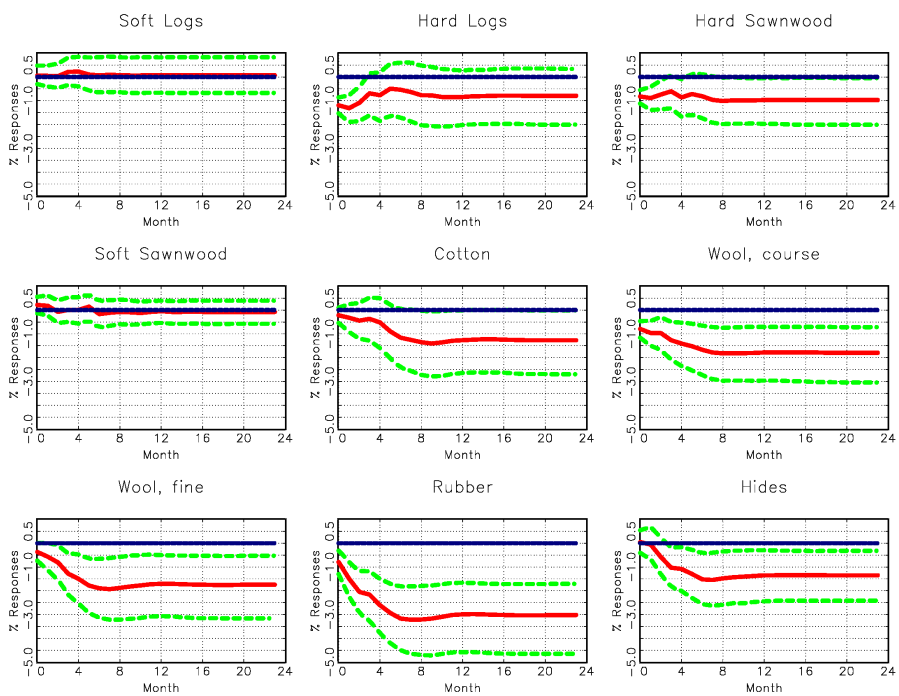
Note: All impulse-response function estimates are obtained from a bivariate VAR with the nominal exchange rate ordered first. 95% confidence bands were obtained from 2000 nonparametric bootstrap simulations.

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



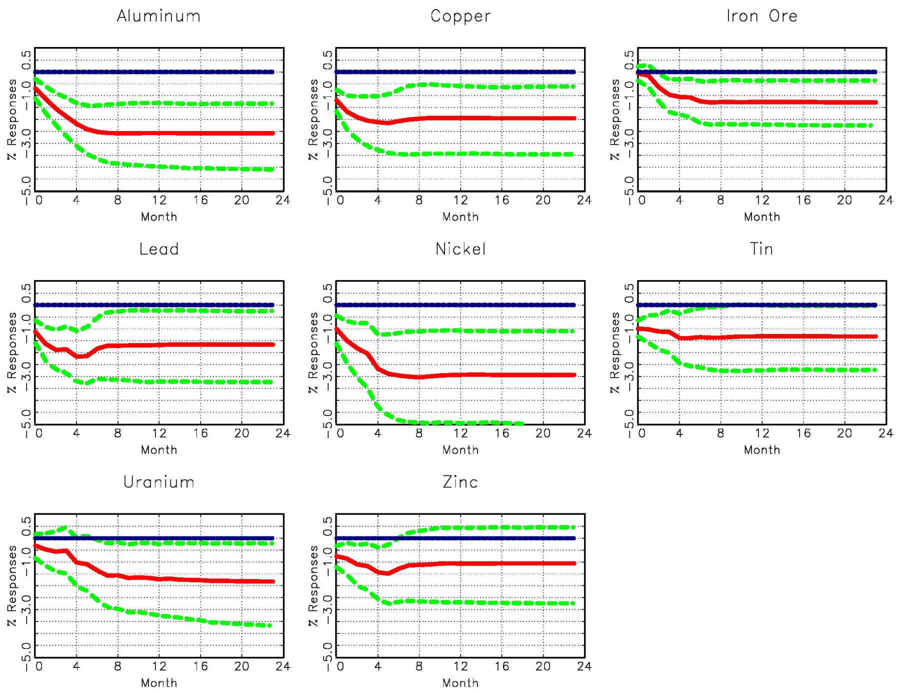
Note: All impulse-response function estimates are obtained from a bivariate VAR with the nominal exchange rate ordered first. 95% confidence bands were obtained from 2000 nonparametric bootstrap simulations.

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



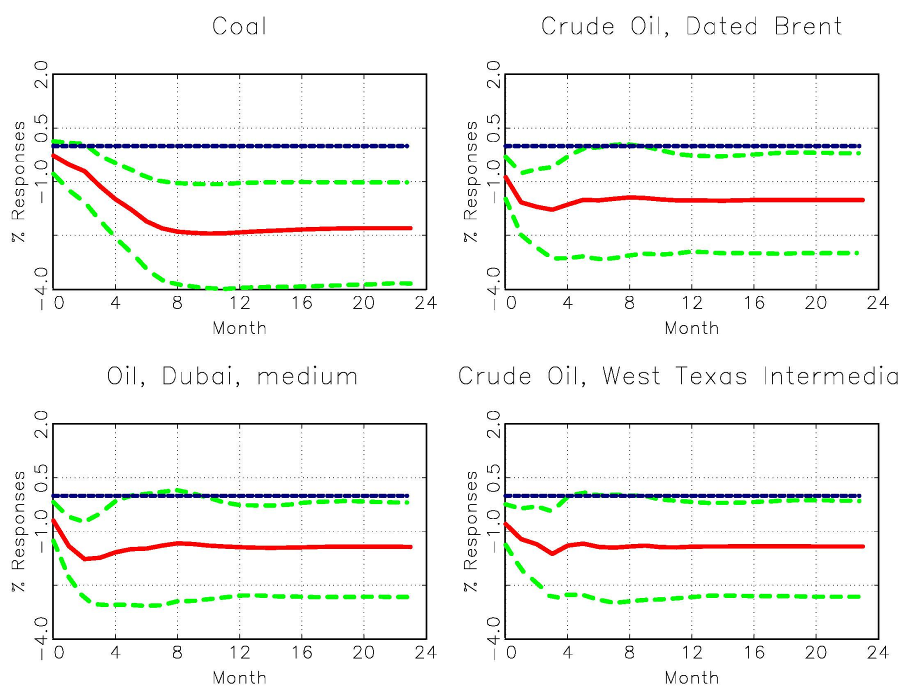
Note: All impulse-response function estimates are obtained from a bivariate VAR with the nominal exchange rate ordered first. 95% confidence bands were obtained from 2000 nonparametric bootstrap simulations.

Figure 6: Impulse-Response Function Estimates: Metals



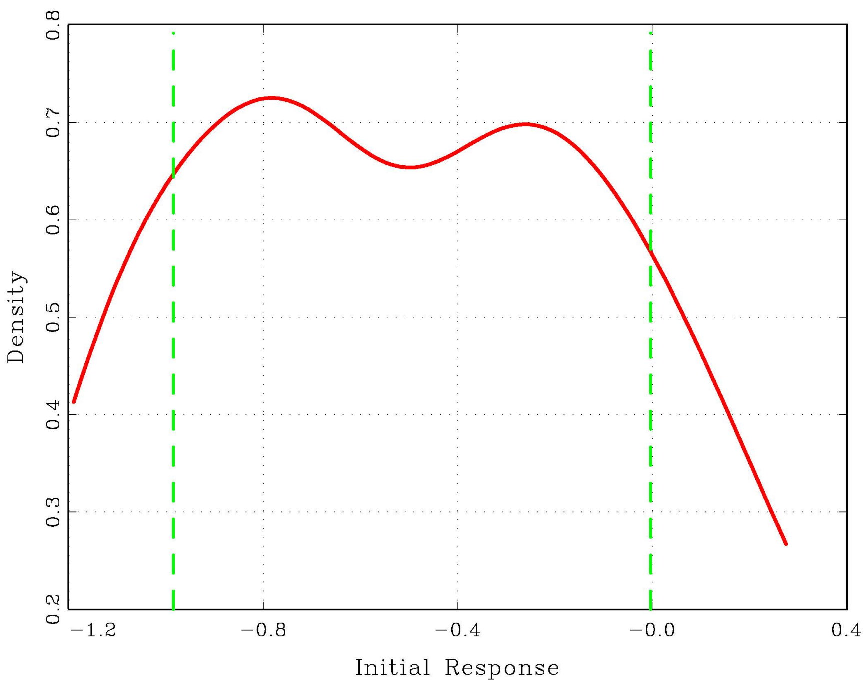
Note: All impulse-response function estimates are obtained from a bivariate VAR with the nominal exchange rate ordered first. 95% confidence bands were obtained from 2000 nonparametric bootstrap simulations.

Figure 7: Impulse-Response Function Estimates: Fuel



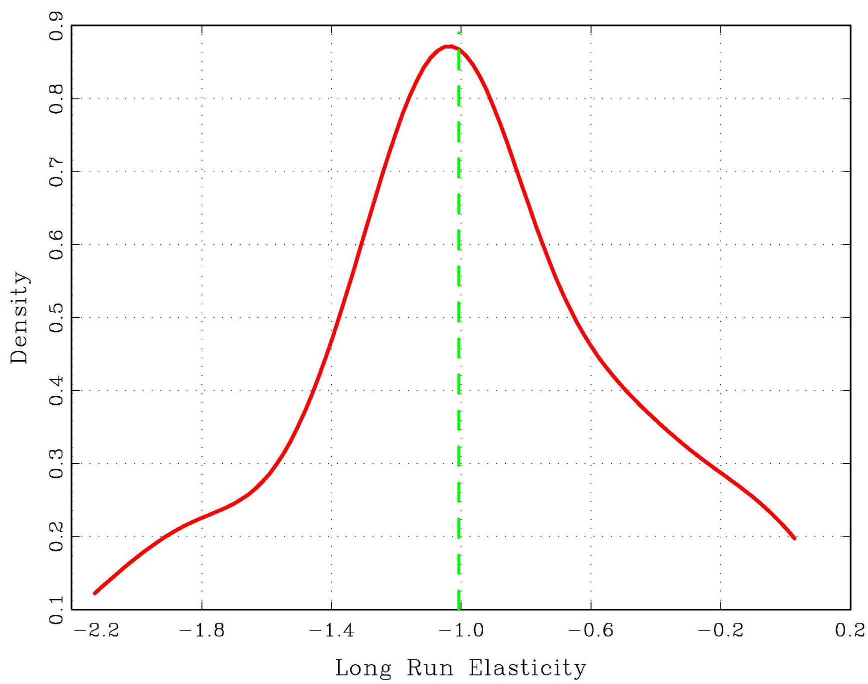
Note: All impulse-response function estimates are obtained from a bivariate VAR with the nominal exchange rate ordered first. 95% confidence bands were obtained from 2000 nonparametric bootstrap simulations.

Figure 8: Distribution of Initial Responses



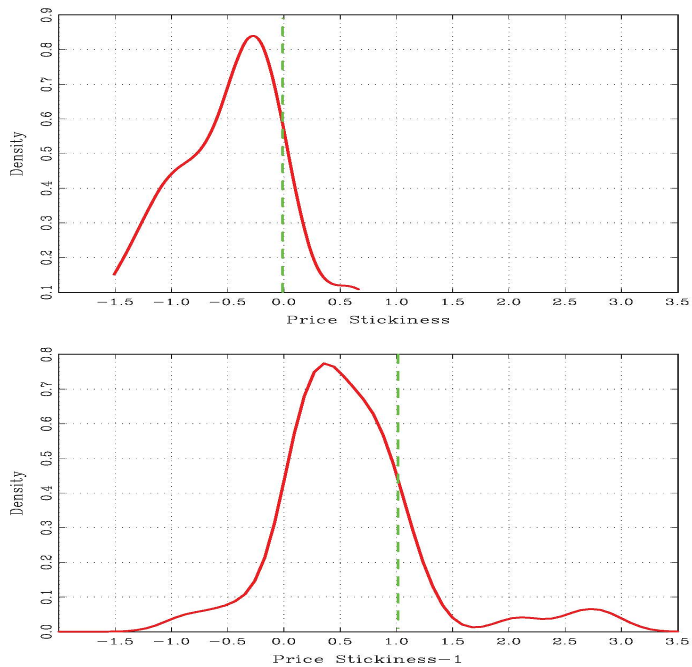
Note: We estimated non-parametric Kernel distribution using the Gaussian Kernel.

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 difference stickiness measure ω_e^p and the bottom panel is for the ratio stickiness measure 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	$\phi_e^p(0)$	95% $C.I$	$\phi_e^p(\infty)$	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 summing 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 2000 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 2000 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 $t = -2.64$