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Investigating Properties of Commodity Price Responses to Real and Nominal Shocks

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Abstract

This paper studies dynamic adjustments of 49 world commodity prices in response to innovations in the nominal exchange rate and the world real GDP. After we estimate the dynamic elasticity of the prices with respect to these shocks, we obtain the kernel density of our estimates to establish stylized facts on the adjustment process of the commodity price toward a new equilibrium path. Our empirical findings imply, on average, that the law of one price holds in the long-run, whereas the substantial degree of short-run price rigidity was observed in response to the nominal exchange rate shock. The real GDP shock tends to generate substantial price fluctuations in the short-run because adjustments of the supply can be limited, but have much weaker effects in the long-run as the supply eventually counterbalances the increase in the demand. Overall, we report persistent long-lasting effects of the nominal exchange rate shock on commodity prices relative to those of the real GDP shock.

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

JEL Classification: E31; F31; Q02

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1 Introduction

World commodity prices often exhibit highly persistent and volatile movements. As Deaton (1999) points out, correctly understanding the stochastic nature of commodity prices is crucial for enhancing the welfare of many developing countries that depend on the export of a few commodities. For example, if deviations of the commodity price from its equilibrium path are *short-lived*, the government may employ stabilization policies to mitigate the transitory impacts of the shock that caused the deviation. On the other hand, if the commodity price contains a unit root so that shocks result in a *permanent* change in the commodity price, policy-makers need to re-formulate their development strategies to incorporate such changes.

Early research in the commodity price literature has focused on the Prebisch-Singer hypothesis (PSH; Prebisch (1950), Singer (1950)). PSH implies a downward *deterministic* trend in the relative price of primary commodities to manufactured goods, continually deteriorating the terms of trade of those commodity-dependent countries. Sapsford (1985), Grilli and Yang (1988), and Helg (1991), among others, reported overall supportive evidence of PSH using commodity price *indices*, whereas Cuddington (1992), Bleaney and Greenaway (1993), and Newbold, Pfaffenzeller, and Rayner (2005) obtained very limited evidence using *disaggregated* commodity price data instead of using aggregate indices. More recently, Kellard and Wohar (2006), Harvey, Kellard, Madsen, and Wohar (2010), and Ghoshray (2011) reported some nonlinear evidence in favor of PSH, allowing multiple structural breaks for a number of commodity prices.

A strand of researchers has estimated the persistence of commodity price shocks. For instance, Cashin, Liang, and McDermott (2000) claim that shocks to world commodity prices typically generate highly persistent effects. In a similar study, Cashin, McDermott, and Pattillo (2004) estimated bias-adjusted half-lives of the terms of trade shock for 42 sub-Saharan African countries. Although they reported *finite* half-life *point* estimates for majority (29 out of 42) countries, the point estimates were quite different across countries, ranging from 0.89-year to 34-year half life. Furthermore, most of their bias-corrected 90% confidence bands extended to positive infinity, meaning that statistical inferences on the length of the half-life are difficult due to high standard errors. Ghoshray (2013) also argued that the persistence of shocks varies widely across individual commodities and over time.

Researchers also have investigated the synchronization (comovement) of primary commodity prices. See, among others, Cashin, McDermott, and Scott (2002), Byrne, Fazio, and Fiess (2013), and West and Wong (2014). These comovement studies are closely related with an array of research works that analyze the source of underlying driving forces (common factors) in the world commodity market. For example, Frankel (2008) highlighted the important role of the real interest rate in commodity price dynamics, while Chen, Rogoff, and Rossi (2010) point out the relationship between commodity prices and the foreign exchange rate of the so-called commodity currency such as Canadian dollars.

Another related researches estimate *latent common factors* applying the method of the principal component to a large panel of time series data. See, among others, Chen, Jackson, Kim, and Resiandini (2014), West and Wong (2014), Byrne, Fazio, and Fiess (2013). For instance, Chen, Jackson, Kim, and Resiandini (2014) demonstrated that the first common factor, estimated from a large panel of commodity price data, is closely related with the nominal exchange rate of the US dollar. Since these commodities are denominated in US dollars, their results confirm that the dollar exchange rate serves a common underlying driving force of world commodity prices.

In the present paper, we investigate statistical properties of price fluctuations in the world commodity market by estimating dynamic adjustment paths of the commodity price toward a new equilibrium path in response to unexpected changes in the nominal exchange rate and the world real GDP growth. We focus on these two primary factors to maintain a simple and homogeneous model structure for 49 world commodity prices. Other potentially important factors such as storage costs, inventory levels, and short-term demand-supply conditions, see Williams and Wright (1991) and Deaton and Laroque (1992), are treated as idiosyncratic factors that are contained in the stationary error term.

Using a vector autoregressive (VAR) model for the nominal exchange rate, the world real GDP, and the commodity price, we estimate the impulse-response function of 49 world commodity prices in response to the exchange rate shock and the real GDP shock. We then define and estimate the dynamic elasticity of the commodity price with respect to these shocks. Instead of analyzing individual responses, we establish a number of stylized facts on commodity price dynamics utilizing kernel density estimates of the dynamic elasticity over time.

Our major findings are as follows. First, we observed the substantial degree of short-run *price stickiness* when the nominal exchange rate shock occurs. In the long-run, however, exchange rate changes are roughly absorbed by changes in the commodity price in dollars so that the commodity price stays constant in the rest of the world. That is, the *law of one price* (LOP) holds on average in the long-run, reflecting highly tradable nature of world commodities.

Second, the world real GDP shock (demand shock) tends to generate substantial price fluctuations on impact because adjustments of the supply can be quite limited in the short-run. The long-run elasticity with respect to the real GDP shock tends to be smaller than its short-run counterpart, because the supply can adjust fully to the shock and eventually counterbalances the increase in the demand in the long-run.

Third, we propose a measure of price stickiness. Kernel density estimates of this measure imply that the nominal exchange rate shock plays a more important role in explaining price dynamics in the long-run, whereas the real GDP shock contributes more to the short-run price dynamics. We also propose a measure of the contribution of the exchange rate shock relative to the real GDP shock, which confirms these findings. That is, nominal shocks in our empirical model have a more persistent long-lasting effect on commodity prices.

As Rogoff (1996) notes in his PPP puzzle, nominal shocks are considered to be short-lived, whereas real shocks yield slower adjustments toward the new equilibrium. On the contrary, Engel and Morley (2001) claimed that persistence of the real exchange rate is mainly driven by nominal shocks. Cheung, Lai, and Bergman (2004) also provided similar results. Our results are overall consistent with their findings.

The present paper also improves the work of Cashin, Liang, and McDermott (2000) and Cashin, McDermott, and Pattillo (2004) who used a univariate model that measures the persistence of the commodity price shock irrespective of the source of the shock. For example, we would expect a very different convergence path if unexpected changes in the commodity price was triggered by the exchange rate shock instead of the real GDP shock.

The rest of the paper is organized as follows. Section 2 presents our baseline VAR model framework. We also define the dynamic elasticity with respect to structural shocks. Section 3 provides a data description and reports our major empirical findings. Section 4 concludes.

2 The Econometric Model

We use a tri-variate vector autoregressive (VAR) model for the nominal exchange rate (e_t), the world real GDP (y_t), and the commodity price (p_t). All variables are log-transformed. p_t is ordered last in the VAR, meaning that other variables can influence it contemporaneously.[1]

Given p_t, unexpected increases in e_t (appreciations of the US dollar) result in higher commodity prices in the rest of the world ($e_t + p_t$). However, if p_t decreases sufficiently and offsets the increase in e_t, commodity prices in the rest of the world stay constant. When y_t rises unexpectedly, this serves as a positive demand shock in the commodity markets, resulting in an increase in p_t if the market supply fails to completely offset such an increase in the demand for commodities.

Since these variables are better approximated by an integrated process, that is, a nonstationary stochastic process, we employ VAR models after differencing the variables. Abstracting from deterministic terms, we propose the following model.

$$x_t = \sum_{j=1}^{p} A_j x_{t-j} + C u_t, \tag{1}$$

where $x_t = [\Delta e_t, \Delta y_t, \Delta p_t]^{'}$, A_j denotes the j^{th} lag polynomial coefficient matrix, and C is the lower-triangular matrix that governs the contemporaneous relationship between the variables in x_t. $u_t = [u_t^e \; u_t^y \; u_t^p]'$ is a vector of mutually orthonormal structural shocks, that is, $E u_t u_t^{'} = I$.

We obtain the orthogonalized impulse-response function (OIRF) for $\triangle e_t$ and $\triangle p_t$ to a one percent exchange rate shock u_t^e as follows.

$$\begin{aligned} \rho_e^p(j) &= E\left(\Delta p_{t+j} | u_{e,t} = 1, I_{t-1}\right) - E\left(\Delta p_{t+j} | I_{t-1}\right) \\ \rho_e^e(j) &= E\left(\Delta e_{t+j} | u_{e,t} = 1, I_{t-1}\right) - E\left(\Delta e_{t+j} | I_{t-1}\right), \end{aligned} \tag{2}$$

where I_{t-1} is the adaptive information set at time $t-1$. Response functions of the *level* variables are obtained by cumulatively summing these response functions.

$$\psi_e^p(j) = \sum_{s=0}^{j} \rho_e^p(j), \;\; \psi_e^e(j) = \sum_{s=0}^{j} \rho_e^e(j), \tag{3}$$

[1]Responses of p_t are robust to alternative ordering of e_t and y_t.

that is, $\psi_e^p(j) = E(p_{t+j}|u_{e,t} = 1, I_{t-1})$ and $\psi_e^e(j) = E(e_{t+j}|u_{e,t} = 1, I_{t-1})$, because $p_{t-1} = e_{t-1} = 0$.[2]

p_t and e_t are log-transformed series, therefore $\psi_e^p(j)$ and $\psi_e^e(j)$ are expected growth rates of the commodity price and the exchange rate over j period when the exchange rate shock occurs at time t.[3] We define the following dynamic elasticity of the commodity price at time $t+j$ with respect to the exchange rate as follows.

$$\eta_e^p(j) = \frac{\psi_e^p(j)}{\psi_e^e(j)} \tag{4}$$

Similarly, we define the dynamic elasticity of a commodity price with respect to the real GDP.

$$\eta_y^p(j) = \frac{\psi_y^p(j)}{\psi_y^y(j)}, \tag{5}$$

where $\psi_y^p(j)$ and $\psi_y^y(j)$ are the response function of the level variables p_t and y_t at time $t+j$, respectively, when there is a shock to the real GDP. $\eta_e^p(0)$ and $\eta_y^p(0)$ denote the contemporaneous dynamic elasticity, while $\eta_e^p(\infty)$ and $\eta_y^p(\infty)$ are the long-run dynamic elasticity of the commodity price.

We also propose a measure of stickiness of the commodity price as follows.

$$\kappa_e = \frac{\psi_e^p(0)}{\psi_e^p(\infty)}, \ \kappa_y = \frac{\psi_y^p(0)}{\psi_y^p(\infty)} \tag{6}$$

For example, κ_e is the share of the initial response of the commodity price to the exchange rate shock relative to its long-run response, whereas κ_y is a similarly defined measure when there is a real GDP shock. Note that these measures provide information on price rigidity when each of these shocks occur. A small positive κ_e or κ_y implies a higher degree of price rigidity, whereas high positive values mean that price adjustments mostly take place on the impact of the shock. A negative number implies that the sign of the response changes over time, which often comes with a wide confidence band that implies an insignificant response.

Lastly, we define the following index to measure the contribution of the exchange rate shock for the j-period ahead forecast variations in the commodity price relative

[2] Recall that x_t is demeaned prior to estimations.
[3] That is, $\ln Z_{t+j} - \ln Z_t \approx (Z_{t+j} - Z_t)/Z_t$.

to the world real GDP (demand) shock.

$$\phi(j) = \frac{|\eta_e^p(j)|}{|\eta_e^p(j)| + |\eta_y^p(j)|} \tag{7}$$

Naturally, the relative contribution of the world demand shock is defined by $1 - \phi(j)$.

In what follows, we employ the following nonparametric kernel density function for $x = \eta_e^p(j),\ \eta_y^p(j),\ \kappa_e,\ \kappa_y,\ \phi(j)$.

$$\hat{f}(x) = \frac{1}{nh} \sum_{i=1}^{n} k\left(\frac{X_i - x}{h}\right), \tag{8}$$

where n is the number of commodity prices, h is the bandwidth parameter, and $k(\cdot)$ denotes a kernel function.[4] We choose the optimal h by conventional Silverman's rule of thumb.

3 Data Descriptions and Empirical Findings

3.1 Data Descriptions

We obtained 49 primary world commodity prices (p_t) from the International Monetary Fund (IMF) website. The data set includes 23 food prices (7 cereals, 5 vegetable oils, 4 meats, 3 seafoods, and 4 other foods), 4 beverage prices, 9 agricultural raw material prices, 8 metal prices, and 5 fuel prices. For details, see Table A1 in the appendix. All commodity prices are denominated in the US dollar. We transformed original monthly frequency commodity prices to quarterly frequency series by taking the end of period value, because the world real GDP growth rate (Δy_t; 00199BPXZF), obtained from the International Financial Statistics (IFS) CD-ROM, is available in quarterly frequency. Observations span from 1980:I to 2013:IV.

The nominal exchange rate (e_t) is the trade-weighted average US dollar index for major currencies (TWEXMMTH) that include the Euro area, Canada, Japan, United Kingdom, Switzerland, Australia, and Sweden. We obtained the monthly frequency data from the Federal Reserve Economic Data (FRED) for the same sample period, then transformed it to quarterly data.

[4] We employ the Epanechnikov kernel and Gaussian kernel, which yield similar results.

3.2 Empirical Findings

We first estimate the tri-variate VAR model in (1) for each commodity price (p_t), then obtain the orthogonalized cumulative impulse-response function estimates as defined in (2) and (3).

It should be noted that responses of the nominal exchange rate (e_t) and the real GDP (y_t) to their *own* shock are quantitatively very similar no matter what p_t is used in (1). On average, e_t increases by 1.08% in the long-run in response to $u_t^e = 1\%$. The standard deviation of the responses was 0.02%, which implies a very tight distribution of the estimate across commodities. The average response of y_t in the long-run was 4.60% when there is a one percent shock to u_t^y. The distribution is again very tight with 0.18% standard deviation. That is, we obtained robust estimates for $\psi_e^e(\infty)$ and $\psi_y^y(\infty)$. Initial responses, $\psi_e^e(0)$ and $\psi_y^y(0)$, were also quantitatively very similar across commodities.[5]

On the other hand, responses of commodity prices (p_t) to u_t^e and u_t^y, that is, $\psi_e^p(\cdot)$ and $\psi_y^p(\cdot)$ exhibit a high degree of heterogeneity across commodities, which will be discussed in what follows.

Figure 1 reports some example impulse-response function estimates for corn (PMAIZMT) and Brent oil (POILBRE) prices along with their associated 95% confidence intervals that are obtained from 500 nonparametric bootstrap simulations. Corn price decreases by 0.76% on impact when one standard deviation exchange rate shock ($u_t^e = 3.63\%$) occurs, whereas Brent oil price decreases by 4.24% when the same shock occurs. In terms of the dynamic elasticity, these responses correspond to -0.21 and -1.17 for corn and Brent oil prices, respectively. That is, corn price exhibits a contemporaneously inelastic response, which implies a substantial degree of short-run price stickiness. On the other hand, Brent oil price slightly over-corrects (more than one-for-one adjustment) the exchange rate shock in the short-run. The long-run elasticity estimates are -1.23 for corn price and -0.99 for Brent oil price, respectively.[6] That is, corn price over-corrects the exchange rate shock, while Brent oil price just-corrects it in the long-run.

In response to a one standard deviation real GDP shock ($u_t^y = 1.58\%$), corn and Brent oil prices increase by 0.44% and 2.41% on impact, while they rise around by

[5] All results are available upon request.

[6] We estimate the long-run elasticity by taking the elasticity estimate for $j = 40$ (10 years) which is long enough for the responses to converge.

7.04% and 5.34% in the long-run, respectively. The corresponding dynamic elasticity estimates for corn price are 0.28 and 0.95 in the short-run and in the long-run, respectively. On the other hand, the dynamic elasticity of Brent oil price are 1.52 in the short-run and 0.72 in the long-run. Note that Brent oil price over-reacts to the real GDP shock in the short-run, but its long-run response is somewhat muted.

Figure 1 around here

In what follows, we establish a number of stylized facts on world commodity price responses to the nominal exchange rate and the real GDP shocks based on empirical distributions of the dynamic elasticity estimates.

Figure 2 reports kernel density estimates of the dynamic elasticity with respect to the exchange rate. We also report the point estimate for each of 49 commodity prices as well as its percentiles, $p_{0.05}$, $p_{0.50}$, and $p_{0.95}$ (p_x is the x percentile), that are obtained from 500 nonparametric bootstrap simulations in Tables A2 and A3 in the appendix. Note that $p_{0.05}$ and $p_{0.95}$ constitute the 90% nonparametric confidence band for each commodity price.

The median (mean) value of the contemporaneous elasticity, $\eta_e^p(0)$, was -0.66 (-0.59), while those of the long-run elasticity, $\eta_e^p(\infty)$, was -0.94 (-0.94). It should be noted that $\eta_e^p(j) = -1$ implies that changes in the exchange rate (e_t) are completely absorbed by changes in the commodity price (p_t). That is, the commodity price stays constant in terms of the rest of the world price ($p_t^* = e_t + p_t$), which is consistent with the law of one price (LOP) proposition. Naturally, we choose $\eta_e^p(j) = -1$ as a benchmark for a just-correction case. Given that, the median (or mean) of $\eta_e^p(0)$ implies a sluggish price adjustment in the short-run, whereas the median (or mean) of $\eta_e^p(\infty)$ is roughly consistent with LOP in the long-run.

To statistically evaluate the possibility of price-stickiness, we implemented a two-sided t-test with the null hypothesis of zero degree of price-stickiness, $H_0 : \eta_e^p(j) = -1$. The test rejects the null hypothesis for the contemporaneous ($j = 0$) elasticity at the 1% significance level ($t = 5.84$), while it fails to reject the null for the long-run ($j = \infty$) elasticity at any conventional significance level ($t = 0.86$). That is, we obtained very strong evidence of short-run price rigidity. In the long run, the elasticity estimates are centered around the benchmark value (-1), which means that commodity prices, on average, counterbalances the effect of the exchange rate shock in the long-run.

These findings overall imply that LOP holds on average in the world commodity market, even though there exists a non-negligible degree of heterogeneity across individual commodities. The kernel density estimates are fairly wide both in the short-run and in the long-run.

Figure 2 around here

In Figure 3, we report kernel density estimates of the dynamic elasticity with respect to the real GDP. The median (mean) is 0.89 (0.85) and 0.25 (0.23) for $\eta_y^p(0)$ and $\eta_y^p(\infty)$, respectively. Complete results are reported in Tables A4 and A5 in the appendix. We select $\eta_y^p(j) = 0$ as a benchmark elasticity, which may happen when the real GDP (demand) shock is completely absorbed by corresponding changes in the supply of the commodity.

As we can see in Figure 3, dynamic elasticity tends to be greater in the short-run than in the long-run. This means that commodity markets tend to rely on price adjustment in the short-run when there's a positive real GDP shock (demand shock), because short-run adjustments in the supply can be limited. On the other hand, positive demand shocks seem to greatly promote the supply of commodities in the long-run, which then curb further rapid rises in the commodity price. Consequently, the long-run dynamic elasticity tends to be smaller than the short-run elasticity when there's a real GDP shock.

Recall that the exactly opposite was true when exchange rate shocks occur. That is, these findings provide empirical evidence that nominal shocks can have more *pronounced* long-lasting effects on the commodity price than real shocks, which is consistent with the findings of Engel and Morley (2001) and Cheung, Lai, and Bergman (2004).

Also, we note that the standard deviation of the long-run elasticity (0.64) is much smaller than that of the short-run elasticity (1.64), which implies a greater degree of homogeneity of the long-run responses than the short-run responses to the real GDP shock.

Again, we implement a two-sided t-test with the null hypothesis, $H_0 : \eta_y^p(j) = 0$. The t-statistic was 3.65 and 2.49 in the short-run and in the long-run, respectively. Even though the test rejects the null hypothesis for both cases, the t-statistic is greater (smaller p-value) for the short-run elasticity, meaning that the test provides a stronger evidence against the null hypothesis in the short-run.

Figure 3 around here

Figure 4 presents kernel density estimates of the price rigidity measure in (6), $\kappa_e = \psi_e^p(0)/\psi_e^p(\infty)$ and $\kappa_y = \psi_y^p(0)/\psi_y^p(\infty)$. We first note that most κ_e estimates are positive (43 out of 49) and are distributed around its median value 0.64. Ruling out obvious outliers, the estimated distribution is quite compact and supports a partial adjustment ($\kappa_e < 1$) in the short run. Put it differently, we report substantial degree of sluggish adjustments of commodity prices when there is an exchange rate shock.

On the other hand, κ_y estimates are widely distributed around its median 0.30 with a large standard deviation (1.42). Large κ_y estimates in *absolute value* imply that prices fluctuate substantially in the short-run when real GDP shocks occur, whereas the impacts of the real GDP shock becomes muted in the long-run possibly due to sufficiently large adjustments of the supply of commodities that counterbalance the increase in the demand. Note that results in Figure 4 are overall consistent with our interpretations on results in Figures 2 and 3.

In a nutshell, these density estimates imply that the nominal exchange rate shock plays a more important role in explaining commodity price dynamics in the long-run relative to the real GDP shock, which contributes more to short-run dynamics of commodity prices.

Figure 4 around here

We further investigate these properties in depth by estimating the kernel density of the relative contribution of the exchange rate using the index in (7), $\phi(j) = |\eta_e^p(j)| \,/\, \left[|\eta_e^p(j)| + |\eta_y^p(j)|\right]$. See Figure 5. The median (mean) $\phi(j)$ estimate is 0.35 (0.38) contemporaneously ($j = 0$), while the median (mean) increases to 0.62 (0.62) in the long run.[7] That is, these estimates imply that the exchange rate shock contributes more to long-run price dynamics, whereas the real GDP (demand) shock influences the commodity price more dominantly in the short-run.

These findings are again consistent with our previous empirical results. Nominal exchange rate shocks have limited effects on commodity prices in the short-run exhibiting price rigidity, whereas commodity prices fluctuate greatly on impact when real GDP

[7]We report full reports in Tables A6 and A7 in the appendix.

shocks occur, because adjustments in the supply of commodities can be sluggish in the short-run.

In the long run, on the other hand, LOP forces world commodity prices to respond more substantially to changes in the exchange rate via commodity arbitrages. On the other hand, the effect of the real GDP shock becomes weak as adjustments in the supply of commodities curb the influence of increases in the world real GDP.

Figure 5 around here

Lastly, we repeat kernel density function estimations using real commodity prices as a robustness check analysis. For this, we deflated all commodity prices using the US consumer price index (CPI) because all commodities are denominated in the US dollar. We obtained quantitatively very similar results, which is not surprising because dynamics of nominal commodity prices are similar to real prices because the CPI exhibits much less variations compared with individual commodity prices. All results are reported in Figure 6.

Figure 6 around here

4 Concluding Remarks

This paper estimates and compares dynamic responses of 49 world commodity prices to unexpected changes in the nominal exchange rate and the world real GDP growth rate. Instead of looking at individual responses, we utilize kernel density function analysis to establish a number of stylized facts on commodity price adjustments toward a new equilibrium after these shocks occur. Our major findings are as follows.

First, we report strong evidence of short-run price rigidity in the world commodity market when nominal exchange rate shocks occur. However, changes in the exchange rate, on average, are absorbed by corresponding changes in commodity prices in the long-run so that the commodity price stays constant in the rest of the world. That is, the law of one price holds in the long-run.

Second, the world real GDP shock has a substantial positive effect on the commodity price in the short-run. On average, the commodity price increases by over 0.8% in the short-run when there's a 1% shock. However, we obtained a fairly flat kernel density function that implies a high degree of heterogeneity across international commodity markets. On the other hand, the real GDP shock has a very weak impact on commodity prices in the long-run, as the supply of commodities eventually counterbalances the changes in the demand triggered by the real GDP shocks in the long-run.

Third, we propose a measure of price rigidity, which is a share of the short-run response of the commodity price relative to its long-run response. Our kernel density analysis implies a high degree of price stickiness when the exchange rate shock occurs. In response to the real GDP shock, we find much weaker and heterogeneous evidence of price rigidity across commodities.

Lastly, we define and estimate the contribution index of the nominal exchange rate shock relative to the real GDP shock to fluctuations in commodity prices. Our results imply that the nominal exchange rate plays relatively more important role in explaining commodity price dynamics in the long-run, whereas the real GDP shock contributes more to short-run price fluctuations.

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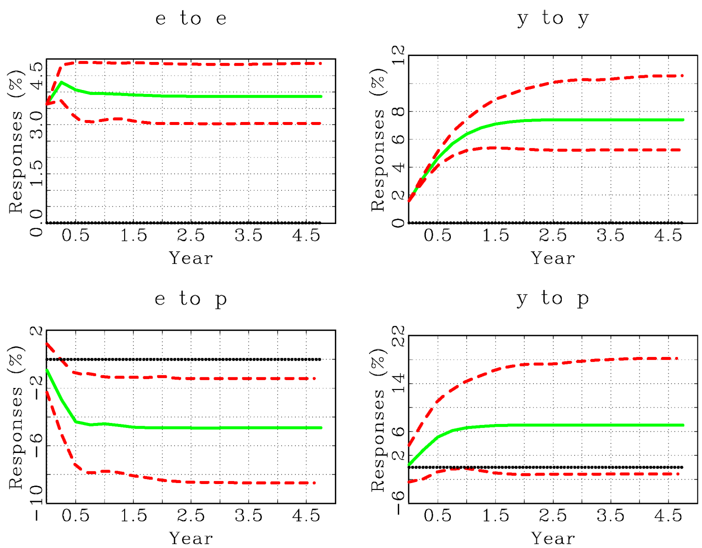
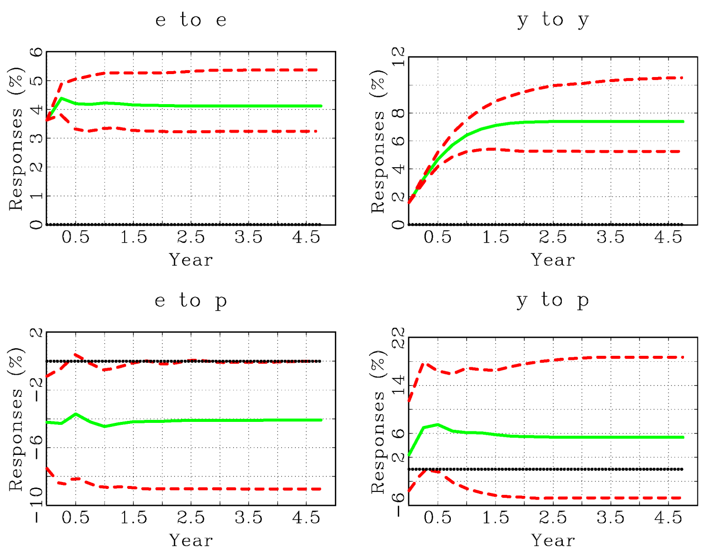
Figure 1. Examples of the Impulse-Response Function Estimates to One Standard Deviation Shocks

$$\psi_e^e(j) = \sum_{s=0}^{j} \rho_e^e(s),\ \ \psi_e^p(j) = \sum_{s=0}^{j} \rho_e^p(s),\ \ \psi_y^y(j) = \sum_{s=0}^{j} \rho_y^y(s),\ \ \psi_y^p(j) = \sum_{s=0}^{j} \rho_y^p(s)$$

(a) Corn



(b) Brent

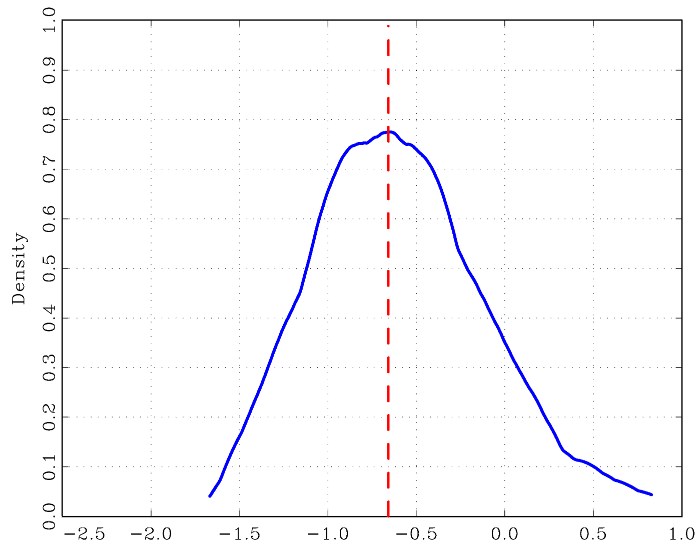


Note: The magnitude of the shock is one standard deviation of each variable, 3.634% and 1.581% for the exchange rate return and the world real GDP growth rate, respectively. Point estimates (solid lines) are reported with 95% confidence bands (dashed lines) that are obtained by 500 nonparametric bootstrap simulations.

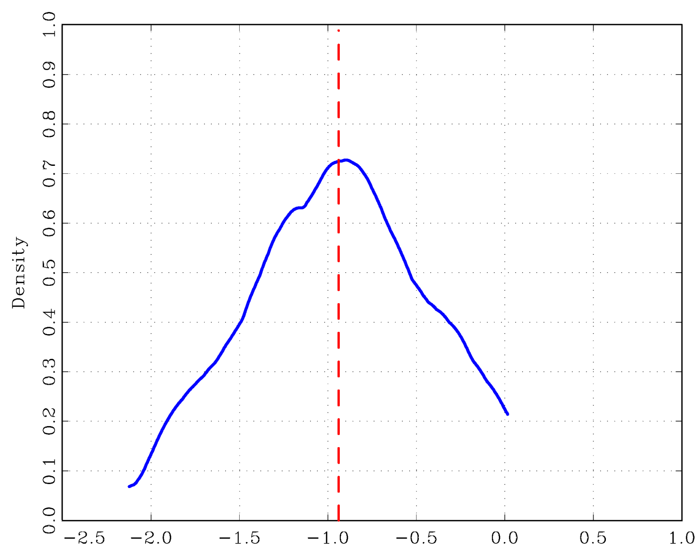
Figure 2. Kernel Density Estimations of the Dynamic Elasticity: Exchange Rate Shock

$$\eta_e^p(j) = \frac{\psi_e^p(j)}{\psi_e^e(j)},\ \psi_e^p(j) = \sum_{s=0}^{j} \rho_e^p(s),\ \psi_e^e(j) = \sum_{s=0}^{j} \rho_e^e(s)$$

(a) Contemporaneous Elasticity $\eta_e^p(0)$



(b) Long-Run Elasticity $\eta_e^p(\infty)$

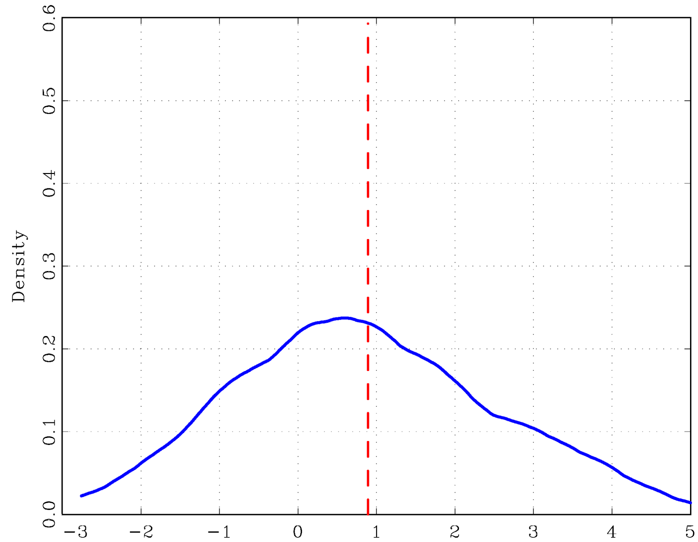


Note: We use the Epanechnikov kernel to estimate the kernel density functions. The vertical dashed line is the median value of the point estimate, -0.658 and -0.939 for $\eta_e^p(0)$ and $\eta_e^p(\infty)$, respectively. The t-statistic for the null hypothesis of zero price-stickiness (-1) was 5.841 and 0.855 for $\eta_e^p(0)$ and $\eta_e^p(\infty)$, respectively. That is, the test strongly supports the short-run price rigidity, whereas the null is accepted for the long-run elasticity.

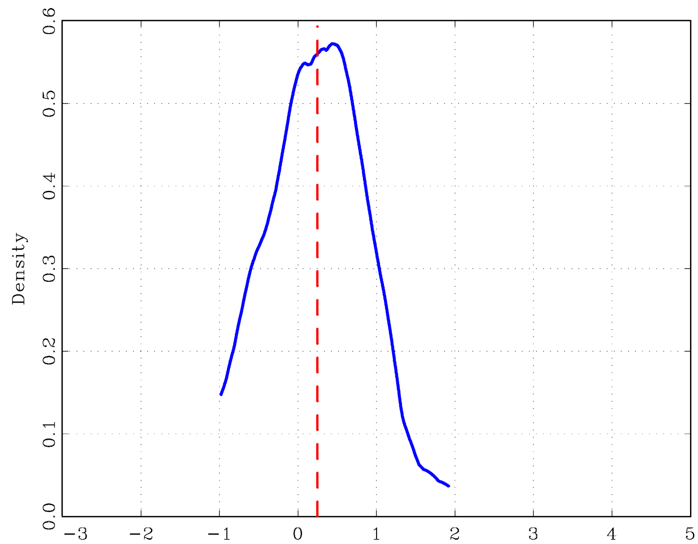
Figure 3. Kernel Density Estimations of the Dynamic Elasticity: Real GDP Shock

$$\eta_y^p(j) = \frac{\psi_y^p(j)}{\psi_y^y(j)},\ \psi_y^p(j) = \sum_{s=0}^{j} \rho_y^p(s),\ \psi_y^y(j) = \sum_{s=0}^{j} \rho_y^y(s)$$

(a) Contemporaneous Elasticity $\eta_y^p(0)$



(b) Long-Run Elasticity $\eta_y^p(\infty)$

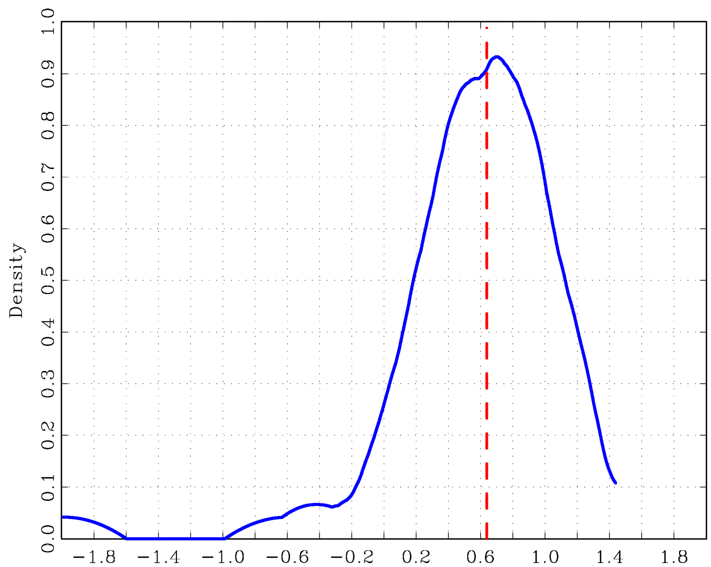


Note: We use the Epanechnikov kernel to estimate the kernel density functions. The vertical dashed line is the median value of the point estimate, 0.855 amd 0.229 for $\eta_y^p(0)$ and $\eta_y^p(\infty)$, respectively The standard deviation was 1.637 and 0.640 for $\eta_y^p(0)$ and $\eta_y^p(\infty)$, respectively, indicating more homogeneous responses across commodities in the long-run. The t-statistic for the null hypothesis of no effect (0) was 3.648 and 2.485 for $\eta_y^p(0)$ and $\eta_y^p(\infty)$, respectively. That is, the test implies a stronger effect of the demand shock in the short-run than in the long-run, even though the test rejects the null in both cases.

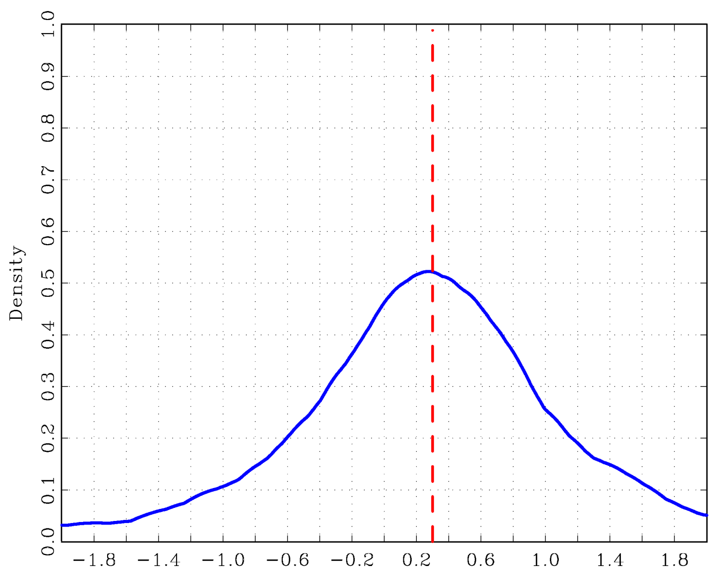
Figure 4. Kernel Density Estimations of the Price Rigidity Measure

$$\kappa_e = \frac{\psi_e^p(0)}{\psi_e^p(\infty)},\ \kappa_y = \frac{\psi_y^p(0)}{\psi_y^p(\infty)},\ \psi_e^p(j) = \sum_{s=0}^{j} \rho_e^p(s),\ \psi_y^p(j) = \sum_{s=0}^{j} \rho_y^p(s)$$

(a) Exchange Rate Shock κ_e



(b) Real GDP Shock κ_y

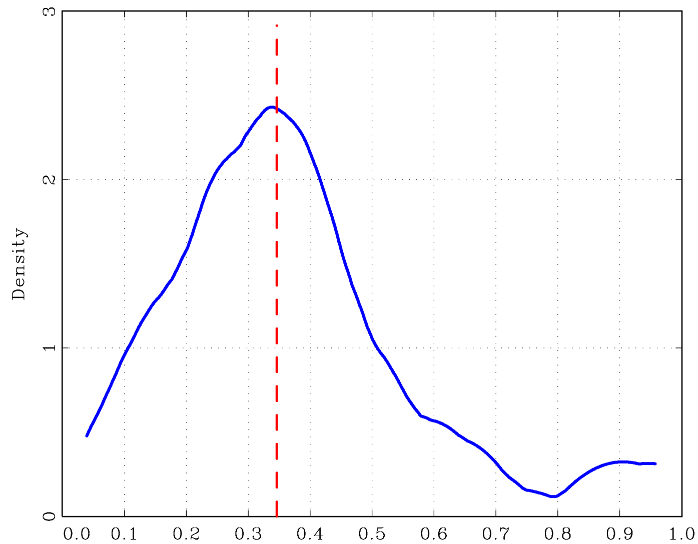


Note: We use the Epanechnikov kernel to estimate distributions. The vertical dashed line is the median value of the point estimate, 0.638 and 0.299 for κ_e and κ_y. The standard deviation was 0.548 and 1.423 for κ_e and κ_y. We obtained strictly positive κ_e estimates for 43 out of 49 commodities, whereas κ_y estimateis were positive only for 32 commodities.

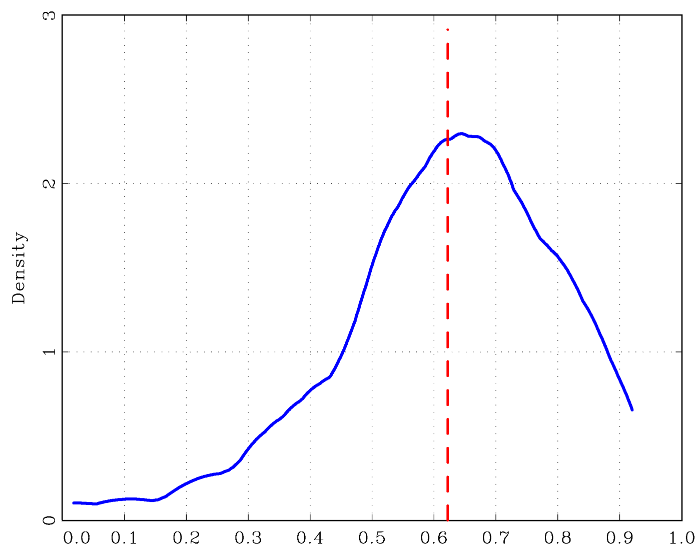
Figure 5. Kernel Density Estimations of the Relative Dynamic Elasticity

$$\phi(j) = \frac{\left|\eta_e^p(j)\right|}{\left|\eta_e^p(j)\right| + \left|\eta_y^p(j)\right|}$$

(a) Contemporaneous Relative Elasticity $\phi(0)$



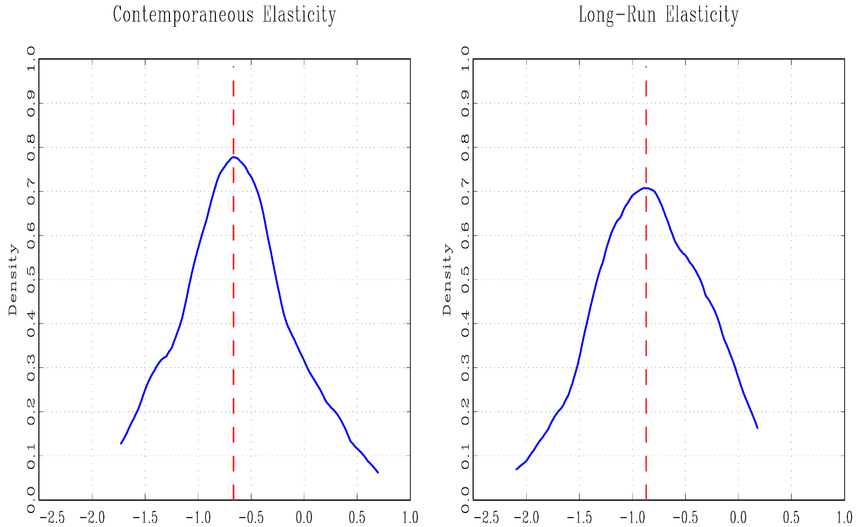
(b) Long-Run Relative Elasticity $\phi(\infty)$



Note: We use the Epanechnikov kernel to estimate distributions. The vertical dashed line is the median value of the point estimate, 0.346 and 0.622 for $\phi(\infty)$and $\phi(\infty)$, respectively. That is, the exchange rate shock plays a more important role relative to the real GDP shock in the long-run, while the opposite is true in the short-run.

Figure 6. Kernel Density Estimation Results with Real Commodity Prices

(a) Exchange Rate Shock



(b) Real GDP Shock

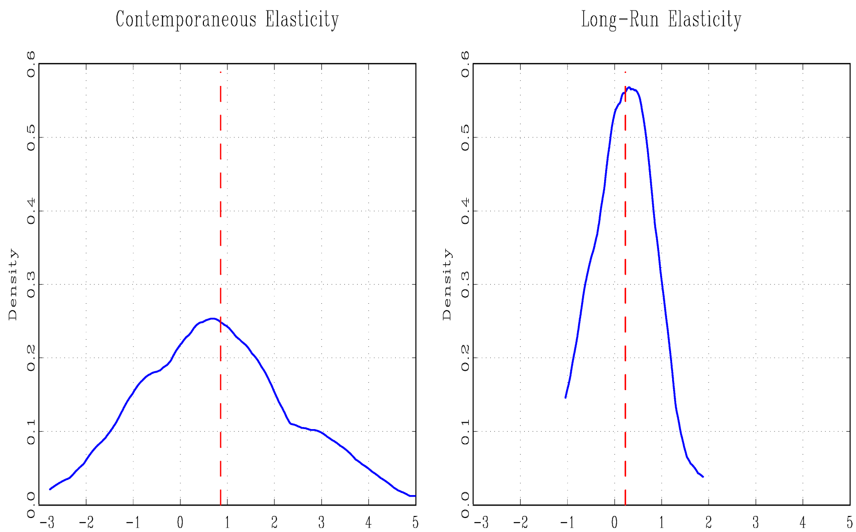
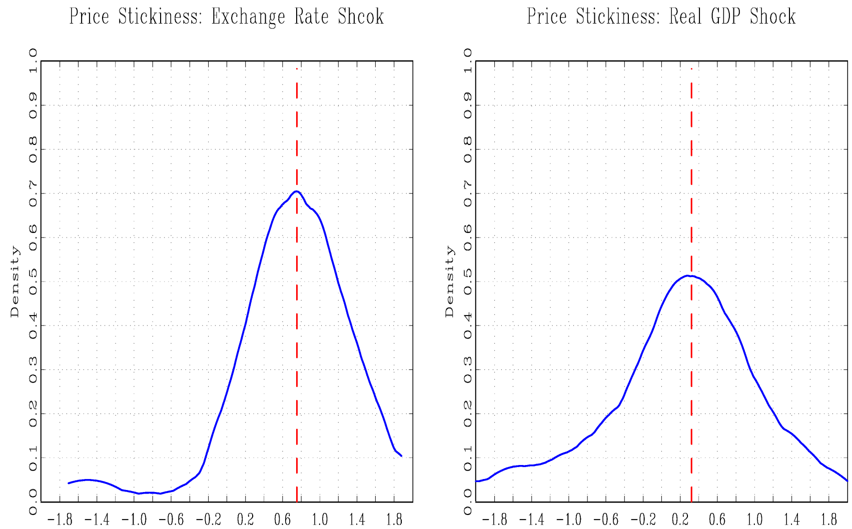
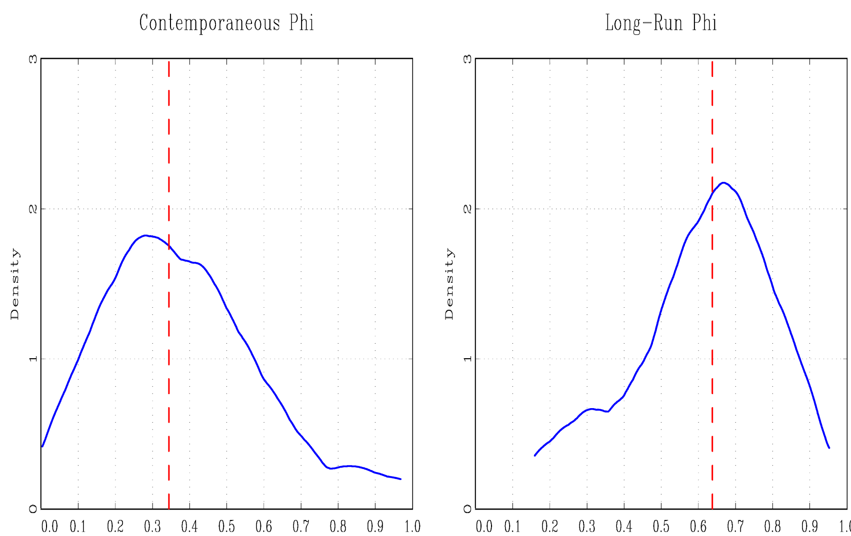


Figure 6. Continued

(c) Price Stickiness Measure



(d) Relative Dynamic Elasticity



Note: The point estimate distribution is solid line. We use the Epanechnikov kernel to estimate distributions. The vertical dashed line is the median value of the point estimate.

Appendix

Table A1. IMF Codes of the World Commodity Prices

ID	IMF Code	Commodity	ID	IMF Code	Commodity
1	PBARL	Barley	26	PCOFFORB	Coffee, Robust
2	PGNUTS	Groundnuts (Peanuts)	27	PTEA	Tea
3	PMAIZMT	Maize (Corn)	28	PLOGORE	Soft Logs
4	PRICENPQ	Rice	29	PLOGSK	Hard Logs
5	PSMEA	Soybean Meal	30	PSAWMAL	Hard Sawnwood
6	PSOYB	Soybeans	31	PSAWORE	Soft Sawnwood
7	PWHEAMT	Wheat	32	PCOTTIND	Cotton
8	PROIL	Rapeseed	33	PWOOLC	Wool, Coarse
9	POLVOIL	Olive Oil	34	PWOOLF	Wool, Fine
10	PPOIL	Palm Oil	35	PRUBB	Rubber
11	PSOIL	Soybean Oil	36	PHIDE	Hides
12	PSUNO	Sunflower Oil	37	PALUM	Aluminum
13	PBEEF	Beef	38	PCOPP	Copper
14	PLAMB	Lamb	39	PIORECR	Iron Ore
15	PPORK	Swine (Pork)	40	PLEAD	Lead
16	PPOULT	Poultry (Chicken)	41	PNICK	Nickel
17	PFISH	Fishmeal	42	PTIN	Tin
18	PSALM	Fish (Salmon)	43	PURAN	Uranium
19	PSHRI	Shrimp	44	PZINC	Zinc
20	PBANSOP	Bananas	45	PCOALAU	Coal
21	PORANG	Oranges	46	POILAPSP	Crude Oil
22	PSUGAISA	Sugar, Free Market	47	POILBRE	Oil, Brent
23	PSUGAUSA	Sugar, USA Import Price	48	POILDUB	Oil, Dubai
24	PCOCO	Cocoa Beans	49	POILWTI	Oil, West Texas Intermediate
25	PCOFFOTM	Coffee, Arabica			

Note: All commodity prices are denominated in the US dollar and are obtained from the IMF website. Observations are from 1980:I to 2013:IV. We transformed monthly data to quarterly frequency data by taking end of period values.

Table A2. Contemporaneous Dynamic Elasticity with respect to the Exchange Rate

$$\eta_e^p(0) = \frac{\psi_e^p(0)}{\psi_e^e(0)},\ \psi_e^p(0) = \rho_e^p(0),\ \psi_e^e(0) = \rho_e^e(0)$$

ID	IMF Code	$\eta_e^p(0)$	5%	50%	95%	ID	IMF Code	$\eta_e^p(0)$	5%	50%	95%
1	PBARL	-0.699	-1.297	-0.749	-0.202	26	PCOFFORB	-0.705	-1.296	-0.709	-0.071
2	PGNUTS	-0.658	-1.381	-0.714	-0.021	27	PTEA	-0.834	-1.387	-0.832	-0.317
3	PMAIZMT	-0.210	-0.717	-0.256	0.268	28	PLOGORE	-0.111	-0.429	-0.116	0.183
4	PRICENPQ	-0.116	-0.597	-0.148	0.334	29	PLOGSK	-0.910	-1.349	-0.903	-0.491
5	PSMEA	-0.709	-1.235	-0.724	-0.274	30	PSAWMAL	-0.716	-1.082	-0.697	-0.348
6	PSOYB	-0.637	-1.122	-0.653	-0.215	31	PSAWORE	0.307	0.037	0.303	0.570
7	PWHEAMT	-0.721	-1.245	-0.722	-0.296	32	PCOTTIND	-0.329	-0.764	-0.349	0.108
8	PROIL	-0.928	-1.489	-0.944	-0.393	33	PWOOLC	-0.674	-1.104	-0.692	-0.251
9	POLVOIL	-1.156	-1.481	-1.161	-0.873	34	PWOOLF	-0.518	-0.956	-0.537	-0.099
10	PPOIL	-0.653	-1.304	-0.692	-0.031	35	PRUBB	-1.217	-1.773	-1.206	-0.736
11	PSOIL	-0.453	-1.000	-0.482	-0.006	36	PHIDE	-0.230	-0.809	-0.207	0.314
12	PSUNO	-0.392	-1.061	-0.412	0.186	37	PALUM	-1.226	-1.663	-1.233	-0.719
13	PBEEF	-0.044	-0.298	-0.05	0.169	38	PCOPP	-1.668	-2.286	-1.666	-1.105
14	PLAMB	-0.877	-1.165	-0.886	-0.595	39	PIORECR	0.175	-0.258	0.153	0.539
15	PPORK	0.449	-0.297	0.468	1.184	40	PLEAD	-1.170	-1.867	-1.201	-0.508
16	PPOULT	0.108	-0.073	0.103	0.269	41	PNICK	-1.045	-1.822	-1.057	-0.235
17	PFISH	-0.582	-0.908	-0.586	-0.225	42	PTIN	-0.54	-1.147	-0.573	0.014
18	PSALM	-1.227	-1.592	-1.248	-0.858	43	PURAN	-0.123	-0.567	-0.144	0.380
19	PSHRI	-0.136	-0.451	-0.149	0.146	44	PZINC	-0.753	-1.414	-0.802	-0.181
20	PBANSOP	0.832	-0.203	0.776	1.712	45	PCOALAU	-0.500	-0.900	-0.520	-0.122
21	PORANG	-0.364	-1.345	-0.387	0.579	46	POILAPSP	-1.036	-1.972	-1.055	-0.200
22	PSUGAISA	-1.255	-2.007	-1.277	-0.544	47	POILBRE	-1.165	-2.114	-1.190	-0.336
23	PSUGAUSA	-0.308	-0.554	-0.312	-0.077	48	POILDUB	-0.998	-1.949	-1.016	-0.112
24	PCOCO	-0.709	-1.106	-0.724	-0.301	49	POILWTI	-0.954	-1.906	-0.952	-0.101
25	PCOFFOTM	-0.406	-1.104	-0.398	0.266	Mean: -0.588, Median: -0.658					

Note: p% denotes the p^{th}percentile obtained from 500 nonparametric bootstrap simulations. 50% is the median elasticity estimate. 5% and 95% constitutes the 90% nonparametric confidence band.

Table A3. Long-Run Dynamic Elasticity with respect to the Exchange Rate

$$\eta_e^p(\infty) = \frac{\psi_e^p(\infty)}{\psi_e^e(\infty)},\ \psi_e^p(\infty) = \sum_{s=0}^{\infty} \rho_e^p(s),\ \psi_e^e(\infty) = \sum_{s=0}^{\infty} \rho_e^e(s)$$

ID	IMF Code	$\eta_e^p(\infty)$	5%	50%	95%	ID	IMF Code	$\eta_e^p(\infty)$	5%	50%	95%
1	PBARL	-1.584	-2.592	-1.569	-0.790	26	PCOFFORB	-1.345	-2.253	-1.385	-0.419
2	PGNUTS	-2.123	-3.407	-2.129	-1.006	27	PTEA	-0.655	-1.643	-0.667	0.175
3	PMAIZMT	-1.231	-2.192	-1.231	-0.368	28	PLOGORE	-0.151	-0.683	-0.135	0.362
4	PRICENPQ	-1.609	-2.434	-1.629	-0.823	29	PLOGSK	-0.912	-1.726	-0.904	-0.158
5	PSMEA	-1.220	-2.053	-1.229	-0.398	30	PSAWMAL	-0.939	-1.611	-0.943	-0.310
6	PSOYB	-1.278	-2.148	-1.306	-0.561	31	PSAWORE	-0.016	-0.326	-0.016	0.336
7	PWHEAMT	-1.078	-1.972	-1.070	-0.382	32	PCOTTIND	-0.790	-1.685	-0.824	0.165
8	PROIL	-1.034	-2.064	-1.076	-0.043	33	PWOOLC	-1.004	-1.671	-1.004	-0.335
9	POLVOIL	-1.125	-1.776	-1.147	-0.478	34	PWOOLF	-1.003	-1.795	-1.024	-0.193
10	PPOIL	-0.667	-1.894	-0.704	0.469	35	PRUBB	-1.610	-2.312	-1.622	-0.961
11	PSOIL	-0.905	-1.877	-0.934	-0.037	36	PHIDE	-0.586	-1.288	-0.551	0.043
12	PSUNO	-1.620	-2.999	-1.695	-0.441	37	PALUM	-1.515	-2.149	-1.518	-0.933
13	PBEEF	-0.205	-0.565	-0.231	0.181	38	PCOPP	-1.562	-2.479	-1.501	-0.665
14	PLAMB	-1.008	-1.563	-1.014	-0.479	39	PIORECR	-0.652	-1.370	-0.660	0.006
15	PPORK	-0.044	-1.003	-0.011	0.925	40	PLEAD	-1.157	-2.330	-1.120	0.119
16	PPOULT	-0.168	-0.432	-0.167	0.071	41	PNICK	-1.570	-2.873	-1.605	-0.416
17	PFISH	-0.475	-1.286	-0.454	0.347	42	PTIN	-0.681	-1.893	-0.723	0.313
18	PSALM	-0.796	-1.271	-0.797	-0.219	43	PURAN	-1.057	-2.140	-1.028	0.111
19	PSHRI	-0.240	-0.850	-0.278	0.345	44	PZINC	-0.577	-1.717	-0.594	0.581
20	PBANSOP	-0.374	-1.172	-0.365	0.381	45	PCOALAU	-1.967	-3.035	-1.949	-0.983
21	PORANG	-0.449	-1.309	-0.462	0.470	46	POILAPSP	-0.909	-2.054	-0.880	0.094
22	PSUGAISA	-1.705	-2.845	-1.672	-0.405	47	POILBRE	-0.994	-2.234	-0.945	0.084
23	PSUGAUSA	-0.440	-0.996	-0.444	0.115	48	POILDUB	-0.864	-2.035	-0.840	0.128
24	PCOCO	0.018	-0.796	-0.018	0.878	49	POILWTI	-0.862	-2.038	-0.873	0.162
25	PCOFFOTM	-1.145	-2.231	-1.194	-0.064	Mean: -0.936, Median: -0.939					

Note: p% denotes the p^{th}percentile obtained from 500 nonparametric bootstrap simulations. 50% is the median elasticity estimate. 5% and 95% constitutes the 90% nonparametric confidence band. Long-run responses are obtained by taking the 40^{th}period ahead response function estimate.

Table A4. Contemporaneous Dynamic Elasticity with respect to the Real GDP

$$\eta_y^p(0) = \frac{\psi_y^p(0)}{\psi_y^y(0)},\ \psi_y^p(0) = \rho_y^p(0),\ \psi_y^y(0) = \rho_y^y(0)$$

ID	IMF Code	$\eta_y^p(0)$	5%	50%	95%	ID	IMF Code	$\eta_y^p(0)$	5%	50%	95%
1	PBARL	1.105	-1.149	1.102	3.950	26	PCOFFORB	0.475	-1.689	0.302	2.845
2	PGNUTS	3.346	0.953	3.431	6.058	27	PTEA	-0.643	-3.188	-0.677	1.781
3	PMAIZMT	0.276	-1.465	0.239	2.106	28	PLOGORE	-0.234	-1.815	-0.191	0.996
4	PRICENPQ	-0.113	-3.863	-0.188	2.240	29	PLOGSK	-1.707	-4.216	-1.497	1.067
5	PSMEA	0.195	-1.782	0.251	3.042	30	PSAWMAL	-1.509	-4.219	-1.266	1.582
6	PSOYB	0.952	-0.938	0.973	3.333	31	PSAWORE	-0.018	-1.609	-0.022	1.113
7	PWHEAMT	-0.052	-1.899	-0.160	2.210	32	PCOTTIND	-1.155	-3.169	-1.071	1.523
8	PROIL	3.662	1.229	3.711	6.302	33	PWOOLC	1.350	-0.235	1.424	3.495
9	POLVOIL	-1.635	-3.258	-1.673	-0.342	34	PWOOLF	3.409	1.022	3.309	5.311
10	PPOIL	0.802	-2.18	0.786	5.297	35	PRUBB	2.311	-0.163	2.257	6.545
11	PSOIL	1.281	-0.897	1.314	4.122	36	PHIDE	3.712	1.292	3.769	7.172
12	PSUNO	1.144	-2.583	0.968	5.530	37	PALUM	2.731	-0.747	2.475	5.245
13	PBEEF	1.069	0.010	1.034	2.133	38	PCOPP	0.894	-1.943	0.865	4.835
14	PLAMB	0.646	-0.461	0.677	1.738	39	PIORECR	-1.049	-3.333	-0.943	1.539
15	PPORK	1.043	-2.087	0.944	4.153	40	PLEAD	3.000	0.678	3.092	6.337
16	PPOULT	-0.142	-1.052	-0.147	0.610	41	PNICK	5.009	-0.364	4.642	9.667
17	PFISH	1.053	-0.296	0.975	2.890	42	PTIN	1.020	-0.895	1.146	3.473
18	PSALM	0.054	-1.519	0.174	2.247	43	PURAN	0.773	-1.327	0.838	3.798
19	PSHRI	-0.286	-2.299	-0.238	1.006	44	PZINC	2.849	0.208	2.858	6.467
20	PBANSOP	-2.759	-7.729	-3.074	1.410	45	PCOALAU	2.725	0.880	2.669	5.695
21	PORANG	-0.663	-4.584	-0.907	3.999	46	POILAPSP	1.778	-1.894	1.820	7.053
22	PSUGAISA	-0.827	-4.166	-0.766	2.476	47	POILBRE	1.524	-2.187	1.609	6.931
23	PSUGAUSA	-0.422	-1.624	-0.468	0.665	48	POILDUB	1.746	-2.052	1.793	7.252
24	PCOCO	-1.020	-2.662	-1.041	1.020	49	POILWTI	2.173	-1.505	2.208	7.286
25	PCOFFOTM	1.936	-0.763	1.717	4.959	Mean: 0.853, Median: 0.894					

Note: p% denotes the p^{th}percentile obtained from 500 nonparametric bootstrap simulations. 50% is the median elasticity estimate. 5% and 95% constitutes the 90% nonparametric confidence band.

Table A5. Long-Run Dynamic Elasticity with respect to the Real GDP

$$\eta_y^p(\infty) = \frac{\psi_y^p(\infty)}{\psi_y^y(\infty)},\ \psi_y^p(\infty) = \sum_{s=0}^{\infty} \rho_y^p(s),\ \psi_y^y(\infty) = \sum_{s=0}^{\infty} \rho_y^y(s)$$

ID	IMF Code	$\eta_y^p(\infty)$	5%	50%	95%	ID	IMF Code	$\eta_y^p(\infty)$	5%	50%	95%
1	PBARL	0.826	-0.356	0.840	1.988	26	PCOFFORB	-0.115	-1.595	-0.046	1.486
2	PGNUTS	1.200	-0.613	1.226	2.708	27	PTEA	-0.413	-1.474	-0.352	0.736
3	PMAIZMT	0.951	-0.219	0.939	2.175	28	PLOGORE	0.093	-0.670	0.061	0.752
4	PRICENPQ	0.720	-0.761	0.726	1.820	29	PLOGSK	-0.219	-1.498	-0.139	1.047
5	PSMEA	0.200	-1.089	0.255	1.552	30	PSAWMAL	-0.314	-1.645	-0.308	1.012
6	PSOYB	0.463	-0.687	0.434	1.645	31	PSAWORE	-0.063	-0.616	-0.063	0.487
7	PWHEAMT	1.466	0.373	1.542	2.645	32	PCOTTIND	-0.871	-2.602	-0.874	0.725
8	PROIL	0.742	-0.736	0.771	2.161	33	PWOOLC	-0.234	-1.468	-0.129	0.938
9	POLVOIL	-0.757	-1.913	-0.777	0.222	34	PWOOLF	0.290	-1.199	0.283	1.332
10	PPOIL	-0.873	-3.098	-0.837	1.215	35	PRUBB	-0.980	-2.565	-0.903	0.493
11	PSOIL	0.355	-1.077	0.285	1.674	36	PHIDE	-0.329	-1.348	-0.267	0.790
12	PSUNO	0.951	-0.892	0.929	2.623	37	PALUM	-0.426	-2.005	-0.429	0.623
13	PBEEF	0.177	-0.370	0.168	0.706	38	PCOPP	0.354	-1.175	0.382	1.672
14	PLAMB	0.248	-0.555	0.255	1.081	39	PIORECR	-0.134	-1.166	-0.085	0.926
15	PPORK	0.032	-1.497	-0.019	1.440	40	PLEAD	0.706	-1.305	0.770	2.553
16	PPOULT	0.384	0.007	0.381	0.755	41	PNICK	0.451	-2.082	0.429	2.199
17	PFISH	-0.663	-2.014	-0.650	0.572	42	PTIN	1.005	-0.221	1.030	2.401
18	PSALM	-0.352	-1.279	-0.336	0.508	43	PURAN	0.149	-1.686	0.143	1.907
19	PSHRI	0.308	-0.636	0.313	1.147	44	PZINC	0.418	-1.485	0.434	1.851
20	PBANSOP	0.906	-0.404	0.893	1.982	45	PCOALAU	1.921	0.697	1.958	3.276
21	PORANG	0.160	-1.010	0.173	1.551	46	POILAPSP	0.636	-0.911	0.637	2.254
22	PSUGAISA	0.768	-1.172	0.756	2.537	47	POILBRE	0.722	-0.813	0.740	2.384
23	PSUGAUSA	-0.212	-1.166	-0.241	0.595	48	POILDUB	0.559	-0.993	0.538	2.251
24	PCOCO	-0.944	-2.182	-0.930	0.342	49	POILWTI	0.755	-0.673	0.753	2.283
25	PCOFFOTM	0.116	-1.615	0.174	1.810	Mean: 0.227, Median: 0.248					

Note: p% denotes the p^{th}percentile obtained from 500 nonparametric bootstrap simulations. 50% is the median elasticity estimate. 5% and 95% constitutes the 90% nonparametric confidence band. Long-run responses are obtained by taking the 40^{th}period ahead response function estimate.

Table A6. Contemporaneous Contribution of the Exchange Rate Shock Relative to the Real GDP Shock

$$\phi(0) = \frac{|\eta_e^p(0)|}{|\eta_e^p(0)|+|\eta_y^p(0)|}$$

ID	IMF Code	$\phi(0)$	5%	50%	95%	ID	IMF Code	$\phi(0)$	5%	50%	95%
1	PBARL	0.387	0.111	0.356	0.871	26	PCOFFORB	0.598	0.096	0.411	0.871
2	PGNUTS	0.164	0.022	0.165	0.505	27	PTEA	0.565	0.156	0.444	0.922
3	PMAIZMT	0.432	0.020	0.282	0.819	28	PLOGORE	0.322	0.022	0.215	0.735
4	PRICENPQ	0.508	0.016	0.147	0.620	29	PLOGSK	0.348	0.148	0.352	0.828
5	PSMEA	0.785	0.143	0.433	0.861	30	PSAWMAL	0.322	0.135	0.317	0.840
6	PSOYB	0.401	0.116	0.361	0.866	31	PSAWORE	0.945	0.080	0.346	0.819
7	PWHEAMT	0.933	0.183	0.488	0.897	32	PCOTTIND	0.222	0.033	0.218	0.723
8	PROIL	0.202	0.071	0.201	0.468	33	PWOOLC	0.333	0.120	0.318	0.789
9	POLVOIL	0.414	0.244	0.407	0.777	34	PWOOLF	0.132	0.033	0.137	0.361
10	PPOIL	0.449	0.056	0.292	0.828	35	PRUBB	0.345	0.166	0.349	0.830
11	PSOIL	0.261	0.040	0.245	0.710	36	PHIDE	0.058	0.005	0.070	0.186
12	PSUNO	0.255	0.019	0.188	0.767	37	PALUM	0.310	0.164	0.329	0.738
13	PBEEF	0.039	0.007	0.094	0.407	38	PCOPP	0.651	0.257	0.563	0.921
14	PLAMB	0.576	0.318	0.563	0.912	39	PIORECR	0.143	0.010	0.148	0.701
15	PPORK	0.301	0.021	0.238	0.797	40	PLEAD	0.281	0.125	0.271	0.600
16	PPOULT	0.433	0.029	0.246	0.831	41	PNICK	0.173	0.047	0.189	0.650
17	PFISH	0.356	0.132	0.354	0.835	42	PTIN	0.346	0.051	0.297	0.807
18	PSALM	0.958	0.315	0.597	0.945	43	PURAN	0.137	0.019	0.169	0.708
19	PSHRI	0.323	0.017	0.202	0.791	44	PZINC	0.209	0.068	0.205	0.612
20	PBANSOP	0.232	0.032	0.200	0.735	45	PCOALAU	0.155	0.047	0.156	0.366
21	PORANG	0.354	0.016	0.209	0.766	46	POILAPSP	0.368	0.073	0.325	0.858
22	PSUGAISA	0.603	0.178	0.483	0.916	47	POILBRE	0.433	0.094	0.361	0.877
23	PSUGAUSA	0.422	0.100	0.352	0.898	48	POILDUB	0.364	0.063	0.318	0.846
24	PCOCO	0.410	0.170	0.380	0.859	49	POILWTI	0.305	0.054	0.280	0.832
25	PCOFFOTM	0.173	0.027	0.201	0.680	Mean: 0.376, Median: 0.346					

Note: p% denotes the p^{th}percentile obtained from 500 nonparametric bootstrap simulations. 50% is the median elasticity estimate. 5% and 95% constitutes the 90% nonparametric confidence band.

Table A7. Long-Run Contribution of the Exchange Rate Shock Relative to the Real GDP Shock

$$\phi(\infty) = \frac{|\eta_e^p(\infty)|}{|\eta_e^p(\infty)|+|\eta_y^p(\infty)|}$$

ID	IMF Code	$\phi(\infty)$	5%	50%	95%	ID	IMF Code	$\phi(\infty)$	5%	50%	95%
1	PBARL	0.657	0.421	0.654	0.942	26	PCOFFORB	0.921	0.246	0.693	0.944
2	PGNUTS	0.639	0.385	0.622	0.918	27	PTEA	0.613	0.062	0.573	0.952
3	PMAIZMT	0.564	0.308	0.570	0.891	28	PLOGORE	0.620	0.054	0.425	0.894
4	PRICENPQ	0.691	0.432	0.665	0.950	29	PLOGSK	0.806	0.195	0.619	0.955
5	PSMEA	0.859	0.339	0.686	0.949	30	PSAWMAL	0.749	0.234	0.622	0.936
6	PSOYB	0.734	0.412	0.678	0.963	31	PSAWORE	0.203	0.038	0.390	0.898
7	PWHEAMT	0.424	0.200	0.425	0.691	32	PCOTTIND	0.476	0.076	0.465	0.914
8	PROIL	0.582	0.139	0.562	0.918	33	PWOOLC	0.811	0.276	0.655	0.948
9	POLVOIL	0.598	0.245	0.589	0.943	34	PWOOLF	0.776	0.232	0.645	0.938
10	PPOIL	0.433	0.036	0.412	0.924	35	PRUBB	0.622	0.319	0.628	0.939
11	PSOIL	0.718	0.197	0.600	0.960	36	PHIDE	0.641	0.094	0.559	0.925
12	PSUNO	0.630	0.256	0.603	0.925	37	PALUM	0.781	0.411	0.729	0.961
13	PBEEF	0.537	0.063	0.495	0.887	38	PCOPP	0.815	0.425	0.705	0.966
14	PLAMB	0.802	0.449	0.720	0.971	39	PIORECR	0.829	0.136	0.605	0.950
15	PPORK	0.581	0.052	0.395	0.895	40	PLEAD	0.621	0.146	0.529	0.909
16	PPOULT	0.304	0.049	0.313	0.698	41	PNICK	0.777	0.236	0.638	0.944
17	PFISH	0.417	0.038	0.383	0.912	42	PTIN	0.404	0.057	0.418	0.886
18	PSALM	0.693	0.214	0.661	0.962	43	PURAN	0.877	0.142	0.564	0.936
19	PSHRI	0.437	0.064	0.418	0.901	44	PZINC	0.580	0.078	0.487	0.883
20	PBANSOP	0.293	0.04	0.333	0.814	45	PCOALAU	0.506	0.339	0.504	0.714
21	PORANG	0.737	0.072	0.498	0.914	46	POILAPSP	0.588	0.123	0.521	0.920
22	PSUGAISA	0.690	0.300	0.617	0.953	47	POILBRE	0.579	0.147	0.514	0.929
23	PSUGAUSA	0.674	0.089	0.531	0.930	48	POILDUB	0.607	0.093	0.517	0.885
24	PCOCO	0.018	0.040	0.280	0.779	49	POILWTI	0.533	0.113	0.485	0.928
25	PCOFFOTM	0.908	0.180	0.625	0.946	Mean: 0.619, Median: 0.622					

Note: p% denotes the p^{th}percentile obtained from 500 nonparametric bootstrap simulations. 50% is the median elasticity estimate. 5% and 95% constitutes the 90% nonparametric confidence band. Long-run responses are obtained by taking the 40^{th}period ahead response function estimate.

Table A8. Contemporaneous Dynamic Elasticity with respect to the Exchange Rate: Real Commodity Prices

$$\eta_e^p(0) = \frac{\psi_e^p(0)}{\psi_e^e(0)},\ \psi_e^p(0) = \rho_e^p(0),\ \psi_e^e(0) = \rho_e^e(0)$$

ID	IMF Code	$\eta_e^p(0)$	5%	50%	95%	ID	IMF Code	$\eta_e^p(0)$	5%	50%	95%
1	PBARL	-0.819	-1.389	-0.852	-0.304	26	PCOFFORB	-0.633	-1.214	-0.641	0.023
2	PGNUTS	-0.704	-1.412	-0.733	-0.113	27	PTEA	-0.824	-1.339	-0.816	-0.328
3	PMAIZMT	-0.288	-0.774	-0.321	0.193	28	PLOGORE	-0.047	-0.378	-0.049	0.229
4	PRICENPQ	-0.224	-0.659	-0.233	0.192	29	PLOGSK	-0.779	-1.219	-0.786	-0.350
5	PSMEA	-0.685	-1.179	-0.696	-0.247	30	PSAWMAL	-0.670	-1.026	-0.656	-0.335
6	PSOYB	-0.667	-1.138	-0.676	-0.231	31	PSAWORE	0.322	0.072	0.315	0.592
7	PWHEAMT	-0.770	-1.304	-0.752	-0.328	32	PCOTTIND	-0.359	-0.810	-0.389	0.140
8	PROIL	-0.933	-1.495	-0.945	-0.426	33	PWOOLC	-0.644	-1.059	-0.666	-0.216
9	POLVOIL	-1.126	-1.448	-1.133	-0.832	34	PWOOLF	-0.592	-1.010	-0.616	-0.173
10	PPOIL	-0.731	-1.340	-0.751	-0.164	35	PRUBB	-1.395	-2.081	-1.366	-0.799
11	PSOIL	-0.531	-1.072	-0.555	-0.073	36	PHIDE	-0.405	-1.077	-0.378	0.242
12	PSUNO	-0.468	-1.118	-0.481	0.093	37	PALUM	-1.223	-1.678	-1.226	-0.719
13	PBEEF	-0.042	-0.282	-0.048	0.178	38	PCOPP	-1.728	-2.383	-1.705	-1.065
14	PLAMB	-0.819	-1.081	-0.821	-0.554	39	PIORECR	0.228	-0.241	0.214	0.612
15	PPORK	0.354	-0.318	0.358	1.044	40	PLEAD	-1.088	-1.796	-1.106	-0.416
16	PPOULT	0.120	-0.060	0.114	0.274	41	PNICK	-1.055	-1.818	-1.048	-0.277
17	PFISH	-0.509	-0.832	-0.515	-0.151	42	PTIN	-0.556	-1.171	-0.579	0.024
18	PSALM	-1.195	-1.549	-1.221	-0.857	43	PURAN	0.003	-0.445	-0.015	0.491
19	PSHRI	-0.047	-0.359	-0.060	0.229	44	PZINC	-0.755	-1.419	-0.793	-0.180
20	PBANSOP	0.699	-0.319	0.645	1.497	45	PCOALAU	-0.693	-1.194	-0.695	-0.236
21	PORANG	-0.447	-1.355	-0.462	0.483	46	POILAPSP	-1.451	-2.370	-1.450	-0.593
22	PSUGAISA	-1.080	-1.781	-1.105	-0.403	47	POILBRE	-1.587	-2.493	-1.565	-0.724
23	PSUGAUSA	-0.274	-0.498	-0.278	-0.048	48	POILDUB	-1.409	-2.406	-1.383	-0.547
24	PCOCO	-0.666	-1.050	-0.686	-0.302	49	POILWTI	-1.341	-2.289	-1.336	-0.481
25	PCOFFOTM	-0.428	-1.136	-0.427	0.255	Mean: -0.632, Median:-0.667					

Note: We divided nominal commodity prices by the US consumer price index to get real commodity prices, because nominal commodity prices are denominated in US dollars. p% denotes the p^{th}percentile obtained from 500 nonparametric bootstrap simulations. 50% is the median elasticity estimate. 5% and 95% constitutes the 90% nonparametric confidence band.

Table A9. Long-Run Dynamic Elasticity with respect to the Exchange Rate: Real Commodity Prices

$$\eta_e^p(\infty) = \frac{\psi_e^p(\infty)}{\psi_e^e(\infty)},\ \psi_e^p(\infty) = \sum_{s=0}^{\infty} \rho_e^p(s),\ \psi_e^e(\infty) = \sum_{s=0}^{\infty} \rho_e^e(s)$$

ID	IMF Code	$\eta_e^p(\infty)$	5%	50%	95%	ID	IMF Code	$\eta_e^p(\infty)$	5%	50%	95%
1	PBARL	-1.527	-2.481	-1.523	-0.719	26	PCOFFORB	-1.190	-2.145	-1.225	-0.282
2	PGNUTS	-2.082	-3.301	-2.103	-1.012	27	PTEA	-0.635	-1.595	-0.654	0.175
3	PMAIZMT	-1.168	-2.104	-1.187	-0.365	28	PLOGORE	-0.158	-0.658	-0.131	0.330
4	PRICENPQ	-1.600	-2.348	-1.607	-0.845	29	PLOGSK	-0.796	-1.593	-0.812	-0.012
5	PSMEA	-1.006	-1.863	-1.010	-0.195	30	PSAWMAL	-0.871	-1.532	-0.850	-0.262
6	PSOYB	-1.118	-1.929	-1.128	-0.376	31	PSAWORE	0.021	-0.309	0.019	0.383
7	PWHEAMT	-1.031	-1.928	-1.027	-0.309	32	PCOTTIND	-0.629	-1.508	-0.692	0.284
8	PROIL	-0.935	-1.939	-0.955	0.054	33	PWOOLC	-0.796	-1.481	-0.794	-0.084
9	POLVOIL	-1.047	-1.730	-1.050	-0.426	34	PWOOLF	-0.950	-1.713	-0.961	-0.219
10	PPOIL	-0.497	-1.699	-0.518	0.660	35	PRUBB	-1.508	-2.176	-1.500	-0.827
11	PSOIL	-0.786	-1.722	-0.810	0.074	36	PHIDE	-0.614	-1.290	-0.577	0.060
12	PSUNO	-1.660	-2.985	-1.728	-0.462	37	PALUM	-1.361	-1.997	-1.363	-0.748
13	PBEEF	-0.125	-0.496	-0.143	0.258	38	PCOPP	-1.445	-2.370	-1.406	-0.521
14	PLAMB	-0.898	-1.453	-0.880	-0.385	39	PIORECR	-0.563	-1.286	-0.559	0.127
15	PPORK	-0.113	-0.986	-0.092	0.841	40	PLEAD	-0.794	-1.950	-0.768	0.525
16	PPOULT	-0.090	-0.365	-0.088	0.161	41	PNICK	-1.317	-2.590	-1.331	-0.162
17	PFISH	-0.274	-1.033	-0.268	0.572	42	PTIN	-0.462	-1.660	-0.493	0.614
18	PSALM	-0.617	-1.148	-0.606	-0.027	43	PURAN	-0.739	-1.839	-0.751	0.463
19	PSHRI	-0.162	-0.762	-0.203	0.432	44	PZINC	-0.424	-1.491	-0.437	0.706
20	PBANSOP	-0.378	-1.167	-0.360	0.382	45	PCOALAU	-2.094	-3.174	-2.074	-1.146
21	PORANG	-0.442	-1.273	-0.449	0.491	46	POILAPSP	-1.076	-2.179	-1.054	-0.011
22	PSUGAISA	-1.308	-2.487	-1.268	-0.050	47	POILBRE	-1.173	-2.329	-1.135	-0.106
23	PSUGAUSA	-0.253	-0.801	-0.250	0.288	48	POILDUB	-1.033	-2.148	-0.998	0.026
24	PCOCO	0.182	-0.674	0.163	1.064	49	POILWTI	-1.006	-2.183	-0.974	-0.038
25	PCOFFOTM	-1.084	-2.207	-1.139	0.047	Mean: -0.850, Median:-0.871					

Note: We divided nominal commodity prices by the US consumer price index to get real commodity prices, because nominal commodity prices are denominated in US dollars. p% denotes the p^{th}percentile obtained from 500 nonparametric bootstrap simulations. 50% is the median elasticity estimate. 5% and 95% constitutes the 90% nonparametric confidence band. Long-run responses are obtained by taking the 40^{th}period ahead response function estimate.

Table A10. Contemporaneous Dynamic Elasticity with respect to the Real GDP: Real Commodity Prices

$$\eta_y^p(0) = \frac{\psi_y^p(0)}{\psi_y^y(0)},\ \psi_y^p(0) = \rho_y^p(0),\ \psi_y^y(0) = \rho_y^y(0)$$

ID	IMF Code	$\eta_y^p(0)$	5%	50%	95%	ID	IMF Code	$\eta_y^p(0)$	5%	50%	95%
1	PBARL	1.057	-1.066	1.075	3.714	26	PCOFFORB	0.461	-1.719	0.282	2.840
2	PGNUTS	3.266	0.878	3.330	6.065	27	PTEA	-0.799	-3.342	-0.860	1.416
3	PMAIZMT	0.248	-1.486	0.218	2.099	28	PLOGORE	-0.323	-1.985	-0.262	0.943
4	PRICENPQ	-0.178	-3.911	-0.266	2.264	29	PLOGSK	-1.696	-4.311	-1.513	1.151
5	PSMEA	0.251	-1.617	0.264	3.111	30	PSAWMAL	-1.570	-4.173	-1.278	1.33
6	PSOYB	0.996	-0.779	1.022	3.391	31	PSAWORE	-0.042	-1.632	-0.036	1.156
7	PWHEAMT	-0.115	-1.815	-0.171	1.964	32	PCOTTIND	-1.084	-2.993	-1.047	1.567
8	PROIL	3.614	1.328	3.710	6.227	33	PWOOLC	1.310	-0.247	1.395	3.350
9	POLVOIL	-1.752	-3.389	-1.780	-0.510	34	PWOOLF	3.357	0.852	3.304	5.229
10	PPOIL	0.827	-1.953	0.804	5.135	35	PRUBB	2.127	-0.357	2.109	5.998
11	PSOIL	1.308	-0.721	1.365	3.956	36	PHIDE	3.604	1.331	3.703	6.935
12	PSUNO	1.098	-2.445	0.948	5.218	37	PALUM	2.454	-0.859	2.229	4.995
13	PBEEF	1.079	-0.010	1.033	2.197	38	PCOPP	0.750	-1.940	0.695	4.378
14	PLAMB	0.624	-0.419	0.654	1.651	39	PIORECR	-1.095	-3.402	-0.988	1.528
15	PPORK	0.985	-2.007	0.890	3.990	40	PLEAD	2.985	0.844	3.054	6.183
16	PPOULT	-0.084	-0.942	-0.111	0.662	41	PNICK	4.994	-0.458	4.655	9.698
17	PFISH	1.034	-0.377	0.947	2.865	42	PTIN	1.059	-0.761	1.172	3.403
18	PSALM	0.038	-1.559	0.124	2.251	43	PURAN	0.855	-1.272	0.942	3.899
19	PSHRI	-0.338	-2.415	-0.305	0.963	44	PZINC	2.804	0.255	2.804	6.346
20	PBANSOP	-2.770	-8.002	-3.091	1.439	45	PCOALAU	2.600	0.881	2.579	5.265
21	PORANG	-0.762	-4.687	-0.914	3.771	46	POILAPSP	1.499	-1.900	1.531	6.288
22	PSUGAISA	-0.791	-4.233	-0.740	2.438	47	POILBRE	1.230	-2.242	1.312	6.188
23	PSUGAUSA	-0.413	-1.584	-0.449	0.621	48	POILDUB	1.467	-2.199	1.551	6.472
24	PCOCO	-1.037	-2.611	-1.077	0.912	49	POILWTI	1.948	-1.316	1.954	6.542
25	PCOFFOTM	1.857	-0.887	1.675	4.943	Mean: 0.795, Median: 0.855					

Note: We divided nominal commodity prices by the US consumer price index to get real commodity prices, because nominal commodity prices are denominated in US dollars. $p\%$ denotes the p^{th} percentile obtained from 500 nonparametric bootstrap simulations. 50% is the median elasticity estimate. 5% and 95% constitutes the 90% nonparametric confidence band.

Table A11. Long-Run Dynamic Elasticity with respect to the Real GDP: Real Commodity Prices

$$\eta_y^p(\infty) = \frac{\psi_y^p(\infty)}{\psi_y^y(\infty)},\ \psi_y^p(\infty) = \sum_{s=0}^{\infty} \rho_y^p(s),\ \psi_y^y(\infty) = \sum_{s=0}^{\infty} \rho_y^y(s)$$

ID	IMF Code	$\eta_y^p(\infty)$	5%	50%	95%	ID	IMF Code	$\eta_y^p(\infty)$	5%	50%	95%
1	PBARL	0.817	-0.303	0.837	1.96	26	PCOFFORB	-0.128	-1.592	-0.041	1.459
2	PGNUTS	1.177	-0.653	1.145	2.694	27	PTEA	-0.468	-1.542	-0.388	0.612
3	PMAIZMT	0.939	-0.243	0.918	2.144	28	PLOGORE	0.035	-0.698	0.003	0.695
4	PRICENPQ	0.696	-0.828	0.714	1.772	29	PLOGSK	-0.220	-1.530	-0.158	1.053
5	PSMEA	0.222	-1.141	0.249	1.571	30	PSAWMAL	-0.341	-1.685	-0.339	0.971
6	PSOYB	0.479	-0.682	0.439	1.639	31	PSAWORE	-0.096	-0.666	-0.089	0.456
7	PWHEAMT	1.449	0.421	1.502	2.545	32	PCOTTIND	-0.831	-2.537	-0.843	0.652
8	PROIL	0.716	-0.729	0.724	2.106	33	PWOOLC	-0.249	-1.466	-0.153	0.972
9	POLVOIL	-0.811	-1.954	-0.819	0.144	34	PWOOLF	0.265	-1.216	0.257	1.302
10	PPOIL	-0.859	-3.030	-0.857	1.137	35	PRUBB	-1.043	-2.682	-1.003	0.440
11	PSOIL	0.366	-1.049	0.280	1.619	36	PHIDE	-0.382	-1.414	-0.322	0.688
12	PSUNO	0.942	-0.817	0.914	2.697	37	PALUM	-0.552	-2.127	-0.607	0.563
13	PBEEF	0.160	-0.386	0.154	0.703	38	PCOPP	0.272	-1.227	0.280	1.561
14	PLAMB	0.229	-0.592	0.226	1.082	39	PIORECR	-0.170	-1.184	-0.116	0.872
15	PPORK	-0.006	-1.525	-0.037	1.392	40	PLEAD	0.721	-1.201	0.782	2.527
16	PPOULT	0.379	-0.021	0.375	0.781	41	PNICK	0.425	-2.275	0.352	2.219
17	PFISH	-0.703	-2.096	-0.709	0.566	42	PTIN	1.021	-0.233	1.039	2.383
18	PSALM	-0.353	-1.305	-0.338	0.450	43	PURAN	0.187	-1.643	0.201	1.904
19	PSHRI	0.268	-0.671	0.258	1.115	44	PZINC	0.390	-1.444	0.409	1.807
20	PBANSOP	0.884	-0.364	0.851	1.955	45	PCOALAU	1.881	0.701	1.926	3.174
21	PORANG	0.126	-1.037	0.142	1.469	46	POILAPSP	0.576	-0.949	0.549	2.160
22	PSUGAISA	0.803	-1.238	0.795	2.529	47	POILBRE	0.659	-0.902	0.680	2.298
23	PSUGAUSA	-0.197	-1.185	-0.232	0.639	48	POILDUB	0.501	-0.972	0.483	2.123
24	PCOCO	-0.964	-2.176	-0.952	0.332	49	POILWTI	0.702	-0.708	0.680	2.184
25	PCOFFOTM	0.078	-1.621	0.118	1.827	Mean: 0.204, Median: 0.229					

Note: We divided nominal commodity prices by the US consumer price index to get real commodity prices, because nominal commodity prices are denominated in US dollars. $p\%$ denotes the p^{th}percentile obtained from 500 nonparametric bootstrap simulations. 50% is the median elasticity estimate. 5% and 95% constitutes the 90% nonparametric confidence band. Long-run responses are obtained by taking the 40^{th}period ahead response function estimate.

Table A12. Contemporaneous Contribution of the Exchange Rate Shock Relative to the Real GDP Shock: Real Commodity Prices

$$\phi(0) = \frac{\left|\eta_e^p(0)\right|}{\left|\eta_e^p(0)\right|+\left|\eta_y^p(0)\right|}$$

ID	IMF Code	$\phi(0)$	5%	50%	95%	ID	IMF Code	$\phi(0)$	5%	50%	95%
1	PBARL	0.437	0.142	0.398	0.853	26	PCOFFORB	0.579	0.076	0.383	0.896
2	PGNUTS	0.177	0.028	0.175	0.529	27	PTEA	0.508	0.153	0.420	0.894
3	PMAIZMT	0.537	0.037	0.310	0.869	28	PLOGORE	0.128	0.013	0.178	0.706
4	PRICENPQ	0.557	0.026	0.177	0.700	29	PLOGSK	0.315	0.116	0.318	0.826
5	PSMEA	0.732	0.148	0.427	0.898	30	PSAWMAL	0.299	0.122	0.298	0.820
6	PSOYB	0.401	0.129	0.379	0.857	31	PSAWORE	0.884	0.093	0.357	0.850
7	PWHEAMT	0.870	0.189	0.519	0.925	32	PCOTTIND	0.249	0.037	0.238	0.789
8	PROIL	0.205	0.080	0.203	0.455	33	PWOOLC	0.329	0.110	0.313	0.823
9	POLVOIL	0.391	0.231	0.386	0.686	34	PWOOLF	0.150	0.043	0.158	0.379
10	PPOIL	0.469	0.086	0.333	0.824	35	PRUBB	0.396	0.199	0.394	0.820
11	PSOIL	0.289	0.061	0.273	0.801	36	PHIDE	0.101	0.010	0.099	0.253
12	PSUNO	0.299	0.026	0.228	0.819	37	PALUM	0.333	0.161	0.348	0.809
13	PBEEF	0.037	0.009	0.087	0.409	38	PCOPP	0.697	0.282	0.567	0.943
14	PLAMB	0.568	0.303	0.547	0.908	39	PIORECR	0.172	0.014	0.168	0.729
15	PPORK	0.265	0.027	0.215	0.787	40	PLEAD	0.267	0.111	0.256	0.555
16	PPOULT	0.590	0.026	0.273	0.806	41	PNICK	0.174	0.044	0.189	0.653
17	PFISH	0.330	0.097	0.329	0.836	42	PTIN	0.344	0.051	0.304	0.818
18	PSALM	0.969	0.302	0.605	0.945	43	PURAN	0.003	0.015	0.145	0.605
19	PSHRI	0.121	0.015	0.147	0.720	44	PZINC	0.212	0.065	0.206	0.596
20	PBANSOP	0.201	0.022	0.181	0.716	45	PCOALAU	0.210	0.077	0.210	0.431
21	PORANG	0.370	0.023	0.211	0.784	46	POILAPSP	0.492	0.143	0.427	0.903
22	PSUGAISA	0.577	0.145	0.453	0.914	47	POILBRE	0.564	0.173	0.468	0.910
23	PSUGAUSA	0.399	0.073	0.330	0.822	48	POILDUB	0.490	0.128	0.414	0.905
24	PCOCO	0.391	0.162	0.364	0.866	49	POILWTI	0.408	0.130	0.378	0.874
25	PCOFFOTM	0.187	0.026	0.203	0.737		Mean: 0.381, Median: 0.344				

Note: We divided nominal commodity prices by the US consumer price index to get real commodity prices, because nominal commodity prices are denominated in US dollars. $p\%$ denotes the p^{th}percentile obtained from 500 nonparametric bootstrap simulations. 50% is the median elasticity estimate. 5% and 95% constitutes the 90% nonparametric confidence band.

Table A13. Long-Run Contribution of the Exchange Rate Shock Relative to the Real GDP Shock: Real Commodity Prices

$$\phi(\infty) = \frac{\left|\eta_e^p(\infty)\right|}{\left|\eta_e^p(\infty)\right| + \left|\eta_y^p(\infty)\right|}$$

ID	IMF Code	$\phi(\infty)$	5%	50%	95%	ID	IMF Code	$\phi(\infty)$	5%	50%	95%
1	PBARL	0.651	0.416	0.656	0.937	26	PCOFFORB	0.903	0.189	0.667	0.949
2	PGNUTS	0.639	0.391	0.622	0.932	27	PTEA	0.576	0.064	0.556	0.947
3	PMAIZMT	0.554	0.288	0.555	0.908	28	PLOGORE	0.816	0.047	0.431	0.912
4	PRICENPQ	0.697	0.440	0.666	0.958	29	PLOGSK	0.783	0.130	0.583	0.937
5	PSMEA	0.819	0.239	0.645	0.957	30	PSAWMAL	0.719	0.202	0.593	0.943
6	PSOYB	0.700	0.348	0.649	0.954	31	PSAWORE	0.181	0.042	0.371	0.916
7	PWHEAMT	0.416	0.176	0.413	0.674	32	PCOTTIND	0.431	0.058	0.425	0.888
8	PROIL	0.566	0.129	0.532	0.898	33	PWOOLC	0.762	0.161	0.611	0.955
9	POLVOIL	0.564	0.213	0.551	0.938	34	PWOOLF	0.782	0.244	0.626	0.931
10	PPOIL	0.366	0.043	0.379	0.898	35	PRUBB	0.591	0.297	0.595	0.938
11	PSOIL	0.683	0.147	0.573	0.948	36	PHIDE	0.617	0.102	0.561	0.931
12	PSUNO	0.638	0.275	0.604	0.938	37	PALUM	0.711	0.349	0.671	0.945
13	PBEEF	0.439	0.058	0.433	0.868	38	PCOPP	0.842	0.356	0.689	0.953
14	PLAMB	0.797	0.415	0.705	0.955	39	PIORECR	0.768	0.115	0.557	0.930
15	PPORK	0.953	0.037	0.392	0.887	40	PLEAD	0.524	0.074	0.455	0.897
16	PPOULT	0.191	0.040	0.255	0.671	41	PNICK	0.756	0.183	0.590	0.917
17	PFISH	0.281	0.039	0.325	0.886	42	PTIN	0.312	0.050	0.374	0.801
18	PSALM	0.636	0.123	0.597	0.937	43	PURAN	0.798	0.102	0.488	0.898
19	PSHRI	0.376	0.072	0.421	0.870	44	PZINC	0.521	0.060	0.460	0.901
20	PBANSOP	0.299	0.036	0.332	0.810	45	PCOALAU	0.527	0.361	0.522	0.738
21	PORANG	0.778	0.059	0.511	0.925	46	POILAPSP	0.651	0.163	0.577	0.920
22	PSUGAISA	0.619	0.189	0.540	0.933	47	POILBRE	0.640	0.193	0.574	0.935
23	PSUGAUSA	0.562	0.074	0.447	0.906	48	POILDUB	0.673	0.137	0.570	0.902
24	PCOCO	0.159	0.030	0.289	0.755	49	POILWTI	0.589	0.158	0.544	0.923
25	PCOFFOTM	0.933	0.165	0.615	0.949	Mean: 0.608, Median: 0.638					

Note: We divided nominal commodity prices by the US consumer price index to get real commodity prices, because nominal commodity prices are denominated in US dollars. $p\%$ denotes the p^{th}percentile obtained from 500 nonparametric bootstrap simulations. 50% is the median elasticity estimate. 5% and 95% constitutes the 90% nonparametric confidence band. Long-run responses are obtained by taking the 40^{th}period ahead response function estimate.