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What Drives Commodity Prices?

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Abstract

This paper examines common forces driving the prices of 51 highly tradable commodities. We demonstrate that highly persistent movements of these prices are mostly due to the first common component, which is closely related to the US nominal exchange rate. In particular, our simple factor-based model outperforms the random walk model in out-of-sample forecast for the US exchange rate. The second common factor and de-factored idiosyncratic components are consistent with stationarity, implying short-lived deviations from the equilibrium price dynamics. In concert, these results provide an intriguing resolution to the apparent inconsistency arising from stable markets with nonstationary prices.

Keywords: Commodity Prices; US Nominal Exchange Rate; Panel Analysis of Nonstationarity in Idiosyncratic and Common Components; Cross-Section Dependence; Out-of-Sample Forecast
JEL Classification: C53, F31

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1 Introduction

International commodity prices, both individually and as a group, exhibit dynamic behavior that is at once intriguing and anomalous. These prices are established in world markets that equate the supply of the product with demand for it. Dynamic stability of equilibria in these markets suggests that time series data on these prices should exhibit some sort of stationary (mean reverting) behavior. Yet empirical time series analyses (unit root tests) of international commodity prices typically reveal them to be, both individually and collectively, highly persistent or even nonstationary. What accounts for this apparent dichotomy between theory and evidence? We address this question by investigating what factors affect commodity prices and then proposing a rationale for how these factors reconcile the dichotomy.

We are not the first to observe this inconsistency between economic theory and unit root test results on commodity prices. Wang and Tomek (2007) note that price theory suggests that agricultural commodity prices should be stationary in their levels. Kellard and Wohar (2006) point out that the Prebisch-Singer hypothesis implies that commodity prices should be trend stationary. They claim that conventional unit root tests are inappropriate due to their low power and report some evidence of nonlinear stationarity.[1] Balagtas and Holt (2009) examine the nonlinearity in commodity prices using the family of

[1]One related literature is empirical work on the validity of the law of one price (LOP) in commodity markets. Since seminal work of Isard (1977), some (among others, Ardeni 1989, Engel and Rogers 2001, Parsley and Wei 2001, and Goldberg and Verboven 2005) find evidence against the LOP, while others (for instance, Goodwin 1992, Michael *et al*. 1994, Obsfeld and Taylor 1997, Lo and Zivot 2001, and Sarno *et al*. 2004), find evidence in favor of the LOP. We focus only on highly tradable commodity prices in the world market, therefore, price convergence across international markets is not our major concern.

smooth transition autoregressive models. They report virtually no evidence in support of the Prebisch-Singer hypothesis for most commodity prices they examine. Enders and Holt (2012) note a mean-shifting pattern in some commodity price dynamics during the recent boom, which implies that such inconsistency may be due to low power of linear unit root tests.

Our approach differs from these studies in that we accept the finding of nonstationarity of commodity prices and attempt to isolate its source. Our premise is that if this nonstationary effect can be factored out, then the correspondingly filtered commodity prices will be consistent with economic theory.

An array of studies argue that dynamics of commodity prices may result from the nature of production and storage of commodities as well as the costs of arbitrage over time (Holt and Craig 2006, Larson 1964, Mundlak and Huang 1996). Recent research of Goodwin, Holt, and Prestemon (2011) notes that nonlinearity in price dynamics for North American oriented strand board markets are induced by unobservable transaction costs. Alternative to the foregoing literature, an array of recent work consider the information content of commodity prices and other macroeconomic variables. For example, Babula, Ruppel, and Bessleer (1995) evaluate the cointegration between the real exchange rate, real corn prices, export sales and export shipments, suggesting no existence of cointegration but the role of the exchange rate appear to be moderate in the post-1985 period. Gospodinov and Ng (2010) report strong evidence of pass-through of commodity price swings to final goods prices.

However, we investigate the possibility that the US nominal exchange rate is a leading candidate for explaining a nonstationary component of international commodity prices even in a linear model framework. The prices of most internationally traded commodities are denominated in dollars, and the US nominal exchange rate, whether the $/£, the $/¥, or the dollar relative to some trade weighted index of currencies, is known to be nonstationary. The behavioral link is simple: If a product's price is stated in US dollars, a depreciation of the dollar should lead to an increase in the price of the product to maintain the same *world* price.[2] Consequently, the dynamic behavior of commodity prices ought to, at least in part, mirror the behavior of the US exchange rate and thus inherit its nonstationarity. Note that this effect should be *common* to all international commodity prices.[3] Further note that this argument overall holds for both nominal commodity prices and relative commodity prices, prices deflated by the US Consumer Price Index (CPI). Since aggregate price indices such as the CPI are much less volatile than world commodity prices, the dynamics of relative prices often resemble that of nominal prices.[4]

We cannot address the theory/evidence dichotomy until we determine what factors are responsible for changes in commodity prices. This topic is closely related to an array of recent work that considers the information content of commodity prices and other macroeconomic variables. For example, Chen *et al*. (2010) study the dynamic relation

[2] An alternative explanation is the following. When the US dollar depreciates, that product becomes cheaper in terms of the foreign currency. Thus, its (foreign) demand increases and hence its price rises.

[3] Given the national price of a commodity (p_i^*), the law of one price implies $p_i^* = E \times p_i$, $i = 1, \cdots, N$, where E and p_i denote the US nominal exchange rate (national currency price of the US dollar) and the world price denominated in the US dollar. That is, when the US dollar depreciates, the world price of commodity i should go up.

[4] We also conducted analysis using commodity prices deflated by US Producer Price Index (PPI). We obtain qualitatively similar results, which are available from authors upon request.

between commodity prices and nominal exchange rates of commodity-producing countries' currencies, finding substantial out-of-sample predictive content of the exchange rate for commodity prices, but not in a reverse direction. Their main argument is that nominal exchange rate contains expectations of future price movements of the country's commodity products, which relate directly with its terms of trade (2008, pp. 2-3). Groen and Pesenti (2010) report similar but much weaker evidence for a broad index of commodity prices. Unlike these studies, we are more interested in the predictive content of commodity prices for movements in the US exchange rate.

We begin our inquiry by conducting a factor analysis on a panel of 51 international commodity prices, including fuel and non-fuel commodity prices, from January 1980 to December 2009 and testing the common factors for stationarity. We accomplish both of these objectives jointly by employing the PANIC (Panel Analysis of Nonstationarity in Idiosyncratic and Common Components) procedure recently developed by Bai and Ng (2004). We prefer this method to other so-called second generation panel unit root test, such as Phillips and Sul (2003), Moon and Peron (2004) and Pesaran (2007), because the latter methods assume that the common factors are stationary, which we believe is not true for commodity prices.[5]

Based on this analysis, we are able to identify two common factors for relative commodity prices.[6] The testing results suggest that the first (most important) common

[5]One substantial advantage of using these second generation tests over the first generation panel unit root tests, such as Levin *et al.* (2002), Maddala and Wu (1999), Im *et al.* (2003) is that these tests have good size properties when the data is cross-sectionally dependent. It is well-known that the first generation tests are seriously over-sized in the presence of cross-section dependence.

[6]We also conducted the same analysis for nominal commodity prices and obtained very similar results. All findings with nominal prices are available upon request.

factor is nonstationary, while the second common factor and the idiosyncratic components are both stationary. Graphical evidence suggests that the first common factor is a mirror image of the US nominal trade-weighted exchange rate. An out-of-sample forecasting analysis shows that the exchange rate is predicted statistically significantly better by a model employing the two common factors than by a random walk model, further supporting the inference that the first common factor is measuring the effect of the nominal US exchange rate on commodity prices. The stationarity of the second common component and the idionsyncratic components provides support for the work of Wang and Tomek (2007) and Kellard and Wohar (2006) regarding market stability and stationary prices. Taken together, these results provide a viable rationalization of the theory/evidence dichotomy.

The paper proceeds as follows: In Section 2 we present the PANIC methodology. Section 3 provides data descriptions, the testing procedure we employ to evaluate the relative accuracy of the out-of-sample forecasts arising from the models of the exchange rate,and an analysis of our empirical results. The last section offers our conclusions.

2 The PANIC Framework

We employ the PANIC method by Bai and Ng (2004) described as follows. Let $p_{i,t}$be the naturallogarithm price of a commodity$i$ at time t that obeys the following stochastic process.[7]

[7] All regularity conditions in Bai and Ng (2004, pp.1130-1131) are assumed to be satisfied.

$$p_{i,t} = c_i + \lambda_i' \mathbf{f}_t + e_{i,t} \tag{1}$$

$$(1-L)\,\mathbf{f}_t = \mathbf{A}\,(L)\,\mathbf{u}_t$$

$$(1-\rho_i L) e_{i,t} = B_i(L) \varepsilon_{i,t}$$

where c_i is a fixed effect intercept, $\mathbf{f}_t = [f_1 \dots f_r]'$is a $r \times 1$ vector of (latent) "common" factors of commodity prices, $\lambda_t = [\lambda_{i,1} \dots \lambda_{i,r}]'$ denotes a $r \times 1$ vector of factor loadings for good i, and $e_{i,t}$ is the idiosyncratic error term. $\mathbf{A}(L)$and$B_i(L)$ are lag(L)polynomials. $\mathbf{u}_t$, $\varepsilon_{i,t}$, and $\lambda_i$are mutually independent.

Estimation is carried out by the method of principal components. When $e_{i,t}$ is stationary, the principal component estimators for $\mathbf{f}_t$ and λ_i are consistent irrespective of the order of $\mathbf{f}_t$. When$e_{i,t}$ is integrated, however, the estimator is inconsistent because a regression of $p_{i,t}$ on $\mathbf{f}_t$ is spurious. PANIC avoids this problem by applying the method of principal components to the ***first-differenced*** data.

Rewrite (1) as the following model with differenced variables.

$$\Delta p_{i,t} = c_i + \lambda_i' \Delta \mathbf{f}_t + \Delta e_{i,t} \tag{2}$$

for $t = 2, \dots, T$. Let $\Delta \mathbf{p}_\mathrm{i} = [\Delta p_{\mathrm{i},1} \dots \Delta p_T]'and\Delta \mathbf{p} = [\Delta \mathbf{p}_1 \dots \Delta \mathbf{p}_N]$. After proper normalization[8],the method of principal components for $\Delta \mathbf{p} \Delta \mathbf{p}'$yields estimated factors $\Delta \hat{\mathbf{f}}_t$, the associated factor loadings $\hat{\lambda}_i$, and the residuals $\Delta \hat{e}_{i,t} = \Delta p_{i,1} - \lambda_i' \Delta \mathbf{f}_t$. Re-integrating these, we obtain the following

[8]Normalization is required because the principal components method is not scale invariant.

$$\hat{e}_{i,t} = \sum_{s=2}^{t} \Delta\hat{e}_{i,s} \tag{3}$$

for $i = 1, \dots, N$ and

$$\hat{\mathbf{f}}_t = \sum_{s=2}^{t} \Delta\hat{\mathbf{f}}_s. \tag{4}$$

Theorem 1 of Bai and Ng (2004, p.1134) shows that testing $\hat{e}_{i,t}$ and $\hat{\mathbf{f}}_t$, latent variables that are not directly observable, are the same as if $\hat{e}_{i,t}$ and $\hat{\mathbf{f}}_t$ are observable. Specifically, the ADF test with no deterministic terms can be applied to each $\hat{e}_{i,t}$ and the ADF test with an intercept can be used for $\hat{\mathbf{f}}_t$. When there are more than two nonstationary factors, cointegration-type tests can be used to determine the rank of $\mathbf{A}(1)$ in (2). Finally, Bai andNg (2004) proposed a panel unit root test for idiosyncratic terms as follows

$$P_{\hat{e}} = \frac{-2\sum_{i=1}^{N} \ln p_{\widehat{e_i}} - 2N}{2N^{1/2}} \xrightarrow{d} N(0,1) \tag{5}$$

where$p_{\widehat{e_i}}$is the p-value from the ADF test for $\hat{e}_{i,t}$.

3 Empirical Results

We use monthly observations of 51 commodity prices and the trade-weighted US exchange rate index against a subset of major currencies. The sample period is January 1980 to December 2009. The source of the exchange rate (series ID: TWEXMANL) is the Federal Reserve Bank of St. Louis Economic Research Database (FRED). The commodity prices are obtained from the IMF Primary Commodity Prices data set with an exception of the natural gas price, which comes from the US Energy Information Administration. Table 1 provides detailed explanations. The source of the US CPI data is the Bureau of Labor Statistics, also available on the FRED website.

Table 1 around here

As a preliminary analysis, we implement the ADF test for relative commodity prices (seeTable 2).[9] The test rejects the null of nonstationarity for only 14 out of 51 relative commodity prices at the 5% significance level. We are cautious in interpreting this as an evidence for overall nonstationary, because the ADF test suffers from low power in small samples. Panel unit root tests are one way to address the low power problem of univariate tests. However, first-generation panel unit root tests, among others, Maddala and Wu (1999), Levin *et al.* (2002), and Im *et al*.(2003), are known to be seriously over-sized (reject the null hypothesis too often) when the true data generating process has substantial cross-section dependence.

To see whether this is the case, we employ a cross-section dependence test by Pesaran (2004),

$$CD = \left(\frac{2T}{N(N-1)}\right)^{1/2} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{i,j}\right) \xrightarrow{d} N(0,1) \tag{6}$$

where $\hat{\rho}_{i,j}$ is the pair-wise correlation coefficients from the residuals of the ADF regressions. The test rejects the null of no cross-section dependence at any conventional

[9]We choose the number of lag by the general-to-specific rule as recommended by Ng and Perron (1995). We used maximum 6 lags combined with the 10% significance level.

significance level (see Table 2), which implies that first-generation panel tests are not proper tools for our purpose.[10]

Table 2 around here

We next implement PANIC for the commodity prices. We first use $PC(r)$ and $IC(r)$ criteria suggested by Bai and Ng (2002) to determine the number of common factors. All criteria except $PC_3(r)$ choose two factors ($r = 2$, see Figure 1).[11]

Applying the method of principal components as described in previous section, we obtained the estimates for common factors $(\hat{\mathbf{f}}_t)$, factor loadings $(\hat{\lambda}_i)$, and idiosyncratic components $(\hat{e}_{i,t})$. We evaluate the importance of common factors for dynamics of the commodity prices relative to idiosyncratic components by

$$rv_i^k = \frac{\sigma\left(\hat{\lambda}_i \hat{f}_t^k\right)}{\sigma\left(\hat{e}_{i,t}\right)}, k = 1, \dots, r \tag{7}$$

Where $\sigma(\cdot)$ denotes the standard deviation. As can be seen in Figure 2, dynamics of individual commodity prices is substantially governed by the first common factor. For many prices, rv_i^k is greater than one, which means that the first factor is more important than idiosyncratic components for those prices. The second common factor also plays an important role for some commodities such as crude oil prices. Similar evidence can be found in factor loading estimates (Figure 3).

[10] All results including individual correlation coefficients used in constructing the CD test statistic are available upon request.

[11] For detailed explanations, see Bai and Ng (2002, Sections 4-5). One important difference from ones in time series analysis is that the penalty function depends on the cross-section dimension as well as the time series length and the number of factors.

Figures 1 through 3around here

The PANIC unit root test results are reported in Table 3. The ADF test cannot reject the null of nonstationarityfor the first factor (f_t^1), but can reject the null for the second factor (f_t^2) at the 5% significance level.[12] Since there is one nonstationary factor among two common factors, $rank\ (\mathbf{A}(1)) = 1$, we do not implement cointegration tests. For the *de-factored* (filtered) idiosyncratic components, the ADF test rejects the null for29 out of 51 relative commodity prices. The panel unit root test by (5) rejects the null hypothesis at any common significance level. The results given here provide strong evidence that there is a single nonstationary common factor that drives the persistent movement of commodity prices.

Table 3 around here

Since the factors are latent variables, there is no obvious way of identifying the source of this nonstationarity. However, we note that the estimated first common factor is approximately a mirror image of the US nominal exchange rate (see Figure 4). The exchange rate exhibits two big swings in1980s and from mid 1990s until mid 2000s. We note that the first common factor estimate exhibits similar big swings in opposite

[12] Implementing more powerful tests such as the DF-GLS test resulted in the same inferences. Specifically, the test statistic was -0.948 and -2.394 for the first and second common factor, respectively, which reject the null hypothesis only for the second factor at the 5% significance level.

directions. This may make sense when we recognize most commodities are priced in US dollars. When the US dollar depreciates relative to overall other currencies, nominal commodity prices may rise given the world price, and vice versa. Because aggregate prices such as the CPI tend to exhibit sluggish movements with low volatility, relative commodity prices exhibit upward movements.

The second common factor shows stable fluctuations which may be consistent with stationarity.[13] Figure 5 provides some interesting dynamics of three crude oil prices, that is, Brent, Dubai, and Western Texas Intermediate oil prices. We plot oil prices in panel (a) while de-factored oil prices (idiosyncratic components) are drawn in panel (b). Panel (a) clearly shows extremely persistent (possibly nonstationary) movements of oil prices. De-factored oil prices, however, exhibit much less persistent dynamics.

The economic profession seems to agree on the nonstationarity of nominal exchange rates. If so, and if commodity prices are largely governed by a single nonstationary common factor, it is not unreasonable to suggest that such nonstationarity is inherited from the US nominal exchange rate. The remaining factors and/or idiosyncratic components may reflect changes in world demand and supply conditions, which may fluctuate around the long-run equilibrium in accordance with price theories.

Figures 4 and 5 around here

[13] The second common factor may be closely related to some economic conditions such as the excess demand for certain commodities. We do not investigate it as we focus on the first common factor.

To further investigate the link between commodity prices and the value of the US dollar, we implement out-of-sample forecast exercises based on our factor model, with the random walk model serving as a benchmark.[14] We use a conventional method proposed by Diebold and Mariano (1995) and West (1996) to evaluate the out-of-sample forecast accuracy of these models.

Let s_t denote the natural logarithm US nominal exchange rate. The random walk model of s_t implies

$$s^R_{t+k|t} \;=\; s_t, \tag{8}$$

where $s^R_{t+k|t}$ is the *k*-step ahead forecast by the random walk model given information set at time *t*. The competing model using the two common factors from the commodity price panel is based on the following least squares regression

$$\mathbf{\Delta} s_{t+k} = \; c + \; \beta' \mathbf{\Delta f}_t + \; u_t. \tag{9}$$

Given the least squares coefficient estimate, we construct the *k*-step ahead forecast by the factor model $s^F_{t+k|t}$ by

$$s^F_{t+k|t} \;=\; \sum_{s=1}^{k} \widehat{\mathbf{\Delta} s_{t+s}} + s_t, \tag{10}$$

where $\widehat{\mathbf{\Delta} s_{t+s}}$ is the fitted value from (9) and s_t is the actual data at time *t*. Note that conditional forecasts for the return (differenced) variables for $t+1, \cdots, t+k$ as well as the

[14] Stock and Watson (2002) discussed merits of using factor models to forecast time series variables. Engel, Mark, and West (forthcoming) use factors from a cross-section exchange rate and idiosyncratic components to forecast exchange rates.

current period level variable are iteratively used to get the k-period ahead conditional forecast for the level exchange rate.

The forecast errors from the two models are,

$$\varepsilon^R_{t+k|t} = s_{t+k} - s^R_{t+k|t}, \qquad \varepsilon^F_{t+k|t} = s_{t+k} - s^F_{t+k|t}$$

For the Diebold-Mariano-West test, define the following function.

$$d_t = L(\varepsilon^R_{t+k|t}) - L((\varepsilon^F_{t+k|t}),$$

where $L(\varepsilon^j_{t+k|t}),\ j = R, F$ is a loss function.[15] To test the null of equal predictive accuracy, $H_0{:}Ed_t = 0$, the Diebold-Mariano-West statistic (*DMW*) is defined as

$$DMW = \frac{\bar{d}}{\sqrt{\widehat{Avar}(\bar{d})}} \tag{11}$$

where$\bar{d}$ is the sample mean loss differential,

$$\bar{d} = \frac{1}{T - T_0} \sum_{t=T_o+1}^{T} d_t,$$

$\widehat{Avar}\left(\bar{d}\right)$is the asymptotic variance of $\bar{d}$,

$$\widehat{Avar}\left(\bar{d}\right) = \frac{1}{T - T_0} \sum_{j=-q}^{q} k(j, q)\hat{\Gamma}_j,$$

$k(\cdot)$ denotes a kernel function where $k(\cdot) = 0$, $j > q$, and $\hat{\Gamma}_j$ is thej^{th} autocovariance function estimate.[16] It is known that the DMW statistic is severely under-sized with

[15] We use the conventional squared error loss function, $(\varepsilon^j_t + k|t)^2,\ j = R, F$.

asymptotic critical values when competing models are nested, which is the case here. We use critical values by McCracken (2007) to avoid this size distortion problem.

To further address the possibility that the first common factor measures the effect of the exchange rate on commodity prices, we report out-of-sample forecast exercise results in Table 4. We carried out forecasting recursively by sequentially adding one additional observation from 180 initial observations toward 360 total observations for forecast horizons ranging k= 1, 2, 3, 4. We re-estimate factors for each recursive sample. First, the ratios of the root mean square prediction error of the random walk model to the factor model were greater than one for all k, that is, the factor model outperformed the benchmark random walk model. Second, the *DMW* statistics with McCracken's (2007) critical values rejects the null of equal predictability for k = 1, 4 at the 5% significance level and for k = 3 at the 10% level when estimated factors from nominal prices are used. Using factors from relative prices, we obtain even stronger evidence of forecast predictability.[17,18]

Finally, we implement a robustness analysis to see if our results depend on the location of split points. It is known that out-of-sample forecast performance may depend on how a given data set is divided into estimation and evaluation periods. To see whether our results are robust to this choice of split points, we repeated estimations of the ratio of the root mean squared prediction error (*RRMSPE*) of the random walk hypothesis to the

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[16] Following Andrews and Monahan (1992), we use the quadratic spectral kernel with automatic bandwidth selection for our analysis.

[17] We also implemented similar exercise using a rolling window scheme instead of the recursive method. For $k = 1$, we consistently obtained evidence in favor of our factor model approach. For longer horizon, we find mixed evidence. All results are available upon request.

[18] As a robustness check, we replaced the first common factor by the IMF spot index for our forecast exercises using the available spot index data from 1992M1 to 2009M12. Our factor approach outperforms the IMF spot index for $k = 1, 3, 4$. All results are available upon request.

common factor models for an array of alternative possible sizes of the estimation period relative to the evaluation period. That is, we estimated the *RRMSPE* from our benchmark split point (sp) $sp = 0.5$ to $sp = 0.89$, which corresponds to 320 months for the *initial* estimation periods. Results with one and two factor models are reported in Figure 6, which shows that our findings are quite robust.[19] In all cases, RRMSPEs are greater than 1, implying that our factor models consistently outperform the random walk model.

Table 4 around here

Figure 6 around here

4 Concluding Remarks

In this paper, we pose the question, "What drives commodity prices?" We began by noting a dichotomy between the implications of economic theory concerning the dynamic behavior of commodity prices and the implications of empirical tests of that behavior: stable commodity market equilibria should imply some form of stationary (mean reverting) commodity price behavior over time, but unit root tests on the behavior of commodity prices typically find evidence of nonstationarity. To investigate this dichotomy, we undertook a careful analysis of what factors play dominant roles in determining the dynamics of highly tradable commodity prices. Employing the PANIC method of Bai and

[19] This issue is discussed in, among others, Hansen and Timmermann (2012) and Rossi and Inoue (2011). We thank an anonymous referee who suggested this robustness analysis.

Ng (2004), we identified two important common factors from 51 world relative commodity prices.

The first common factor explains the largest proportion of the variation in the panel of prices. It was found to be nonstationary, and there is theoretical, graphical, and out of sample forecasting evidence that it is closely related to the nominal US exchange rate. The result that our simple two-factor model significantly outperforms a random walk in forecasting the exchange rate is itself of interests, because the profession has recognized that the random walk model consistently outperforms economic models for forecasting the exchange rate since the work of Meese and Rogoff (1983).

One is tempted to suggest that this factor measures the effect of the exchange rate on our panel of commodity prices. But perhaps a more appropriate inference is that this factor and exchange rates share information content; factors that have a predictable effect on the exchange rate will have a correspondingly predictable effect on commodity prices.

The second common factor and the idiosyncratic components of each series were found to be stationary. Results for these components are consistent with equilibrium price dynamics – short-lived deviations that quickly revert back to equilibrium. Thus, when the effects of the exchange rate, or at the minimum the first common factor, are filtered out of the panel of commodity prices, the remaining factors affecting commodity prices exhibit exactly the type of dynamic behavior that theory would suggest.

Taken together these two factors explain what drives commodity prices. Further, the results provide a viable rationale for the theory/evidence dichotomy of international commodity prices noted above.

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Table 1. Commodity Price Data Description

Category	ID	Commodity	IMF Code
Metals	1	Aluminum, LME standard grade, minimum purity, CIF UK	PALUM
	2	Copper, LME, grade A cathodes, CIF Europe	PCOPP
	3	Iron Ore Carajas	PIORECR
	4	Lead, LME, 99.97 percent pure, CIF European	PLEAD
	5	Nickel, LME, melting grade, CIF N Europe	PNICK
	6	Tin, LME, standard grade, CIF European	PTIN
	7	Zinc, LME, high grade, CIF UK	PZINC
	8	Uranium, NUEXCO, Restricted Price, US$ per pound	PURAN
Fuels	9	Coal thermal for export, Australia	PCOALAU
	10	Oil, Average of U.K. Brent, Dubai, and West Texas Intermediate	POILAPSP
	11	Oil, UK Brent, light blend 38 API, fob U.K.	POILBRE
	12	Oil, Dubai, medium, Fateh 32 API, fob Dubai	POILDUB
	13	Oil, West Texas Intermediate, 40 API, Midland Texas	POILWTI
	14	Natural Gas, BEA	
Food	15	Bananas, avg of Chiquita, Del Monte, Dole, US Gulf delivery	PBANSOP
	16	Barley, Canadian Western No. 1 Spot	PBARL
	17	Beef, Australia/New Zealand frozen, U.S. import price	PBEEF
	18	Cocoa, ICO price, CIF U.S. & European ports	PCOCO
	19	Coconut Oil, Philippines/Indonesia, CIF Rotterdam	PROIL
	20	Fishmeal, 64/65 percent, any orig, CIF Rotterdam	PFISH
	21	Groundnut, US runners, CIF European	PGNUTS
	22	Lamb, New Zealand, PL frozen, London price	PLAMB
	23	Maize, U.S. number 2 yellow, fob Gulf of Mexico	PMAIZMT
	24	Olive Oil, less that 1.5% FFA	POLVOIL
	25	Orange Brazilian, CIF France	PORANG
	26	Palm Oil, Malaysia and Indonesian, CIF NW Europe	PPOIL
	27	Hogs, 51-52% lean, 170-191 lbs, IL, IN, OH, MI, KY	PPORK
	28	Chicken, Ready-to-cook, whole, iced, FOB Georgia Docks	PPOULT
	29	Rice, 5 percent broken, nominal price quote, fob Bangkok	PRICENPQ
	30	Norwegian Fresh Salmon, farm bred, export price	PSALM
	31	Shrimp, U.S., frozen 26/30 count, wholesale NY	PSHRI
	32	Soybean Meal, 44 percent, CIF Rotterdam	PSMEA
	33	Soybean Oil, Dutch, fob ex-mill	PSOIL
	34	Soybean, U.S., CIF Rotterdam	PSOYB
	35	Sugar, EC import price, CIF European	PSUGAEEC
	36	Sugar, International Sugar Agreement price	PSUGAISA
	37	Sugar, US, import price contract number 14 CIF	PSUGAUSA
	38	Sunflower Oil, any origin, ex-tank Rotterdam	PSUNO
	39	Wheat, U.S. number 1 HRW, fob Gulf of Mexico	PWHEAMT
Beverages	40	Coffee, Other Milds, El Salvdor and Guatemala, ex-dock New York	PCOFFOTM
	41	Coffee, Robusta, Uganda and Cote dIvoire, ex-dock New York	PCOFFROB
	42	Tea, From July 1998,Kenya auctions, Best Pekoe Fannings. Prior, London auctions, CIF U.K. warehouses	PTEA
Raw Materials	43	Cotton, Liverpool Index A, CIF Liverpool	PCOTTIND

	44	Wool Coarse, 23 micron, AWEX	PWOOLC
	45	Wool Fine, 19 micron, AWEX	PWOOLF
Industrial Inputs	46	Hides, US, Chicago, fob Shipping Point	PHIDE
	47	Log, soft, export from U.S. PaCIFic coast	PLOGORE
	48	Log, hard, Sarawak, import price Japan	PLOGSK
	49	Rubber, Malaysian, fob Malaysia and Singapore	PRUBB
	50	Sawnwood, dark red meranti, select quality	PSAWMAL
	51	Sawnwood, average of softwoods, U.S. West coast	PSAWORE

Note: All data is obtained from IMF website with an exception of natural gas (ID#14). The US wellhead natural gas data is obtained from the US Energy Information Administration.

Table 2. Augmented Dickey-Fuller Test and Cross-Section Dependence Test Results: Relative Commodity Prices

ID	*ADF*	*p*-value	ID	*ADF*	*p*-value	ID	*ADF*	*p*-value
1	-3.569*	0.006	18	-2.689	0.071	35	-2.492	0.108
2	-2.087	0.237	19	-2.807	0.053	36	-3.274*	0.014
3	-0.969	0.763	20	-2.232	0.189	37	-2.946*	0.035
4	-1.843	0.351	21	-3.226*	0.016	38	-3.200*	0.017
5	-2.663	0.075	22	-3.805*	0.002	39	-2.706	0.067
6	-2.501	0.108	23	-2.636	0.080	40	-2.360	0.141
7	-2.740	0.063	24	-2.669	0.074	41	-2.035	0.262
8	-1.879	0.334	25	-3.751*	0.003	42	-3.036*	0.028
9	-2.410	0.133	26	-3.231*	0.016	43	-2.445	0.116
10	-1.864	0.343	27	-1.493	0.536	44	-2.590	0.088
11	-1.952	0.294	28	-5.692*	0.000	45	-2.364	0.141
12	-1.766	0.391	29	-2.540	0.097	46	-2.487	0.108
13	-2.080	0.246	30	-2.090	0.237	47	-1.735	0.407
14	-2.284	0.165	31	-0.709	0.843	48	-2.876*	0.043
15	-3.813*	0.002	32	-2.915*	0.040	49	-2.631	0.081
16	-3.870*	0.002	33	-2.705	0.068	50	-2.336	0.149
17	-2.146	0.213	34	-2.688	0.071	51	-2.237	0.181

CD Statistic: 48.313*, *p*-value: 0.000

Note: i) *ADF* denotes the augmented Dickey-Fuller t-statistic with an intercept with the null of nonstationarity. ii) Superscript * refers the case when the null hypothesis is rejected at the 5% significance level. iii) *CD* statistic is a cross-section dependence test statistic by Pesaran (2004) with the null hypothesisof no cross-section dependence. iv) Each commodity price is deflated by the US consumer price index to obtain the relative price.

Table 3. PANIC Test Results: Relative Commodity Prices

Idiosyncratic Components

ID	*ADF*	*p*-value	ID	*ADF*	*p*-value	ID	*ADF*	*p*-value
1	-2.089*	0.032	18	-0.978	0.294	35	-1.311	0.173
2	-2.890*	0.004	19	-2.865*	0.004	36	-1.518	0.124
3	-0.798	0.367	20	-0.990	0.294	37	-3.429*	0.001
4	-1.396	0.157	21	-4.626*	0.000	38	-4.648*	0.000
5	-1.928*	0.048	22	-2.335*	0.018	39	-3.385*	0.001
6	-1.224	0.205	23	-2.233*	0.023	40	-2.078*	0.033
7	-2.201*	0.025	24	-1.658	0.091	41	-1.773	0.070
8	-0.807	0.367	25	-8.250*	0.000	42	-2.259*	0.022
9	-3.090*	0.002	26	-3.282*	0.001	43	-3.578*	0.001
10	-1.910*	0.050	27	-3.560*	0.001	44	-1.802	0.066
11	-1.974*	0.043	28	-2.269*	0.021	45	-2.316*	0.019
12	-2.062*	0.035	29	-1.114	0.246	46	-1.536	0.116
13	-2.197*	0.025	30	-2.038*	0.037	47	-1.666	0.090
14	-1.761	0.072	31	-1.868	0.056	48	-2.095*	0.031
15	-3.870*	0.000	32	-2.293*	0.020	49	-1.528	0.116
16	-1.071	0.262	33	-1.357	0.165	50	-2.214*	0.024
17	-1.170	0.221	34	-1.471	0.133	51	-1.671	0.089

Panel Test Statistics: 19.497*, *p*-value: 0.000

Common Factor Components

ADF (Factor 1): -1.887, *p*-value; 0.326
ADF (Factor 2): -2.912*, *p*-value: 0.040

Note: i) *ADF* denotes the augmented Dickey-Fuller t-statistic with no deterministic terms (idiosyncratic components) and with an intercept (common factors) with the null hypothesis of nonstationarity. ii) Superscript * refers the case when the null hypothesis is rejected at the 5% significance level. iii) Each commodity price is deflated by the US consumer price index to obtain the relative price.

Table 4. Out-of-Sample Forecast Performance: Relative Commodity Price Factors

	2 Factor Model			*1 Factor Model*	
K	*RRMSPE*	*DMW*	*k*	*RRMSPE*	*DMW*
1	1.0169	0.9804**	1	1.0173	1.3267***
2	1.0062	0.5834*	2	1.0041	0.6093*
3	1.0082	0.7753**	3	1.0050	0.8723**
4	1.0167	1.3815***	4	1.0085	1.0619**

Note: i) Out-of-sample forecasting was recursively implemented by sequentially adding one additionalobservation from 180 initial observations toward 360 total observations. ii) *k* denotes the forecast horizon. iii) *RRMSPE* denotes the ratio of the root mean squared prediction error of the random walk hypothesisto the common factor model. iv) *DMW* denotes the test statistics of Diebold and Mariano (1995) andWest (1996). v) *, **, and ** denote rejection of the null hypothesis of equal predictability at the 10%,5%, and 1% significance levels, respectively. Critical values were obtained from McCracken (2007). vi)Eachcommodity price is deflated by the US consumer price index to obtain the relative price. vi) 1 factor model denotes the case when only the first common factor is utilized.

Figure 1. Number of Factors Estimation: Relative Commodity Prices

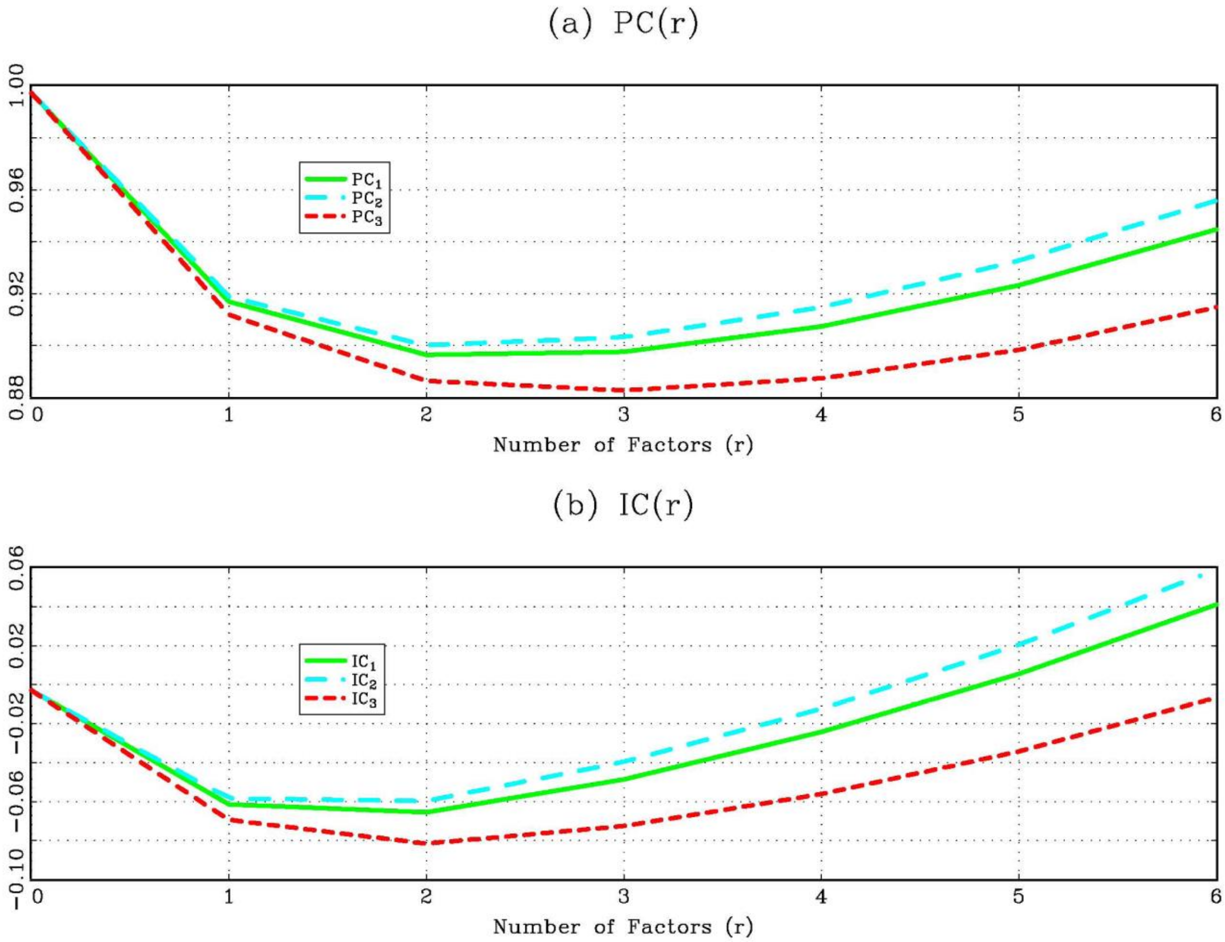


Figure 2. Relative Importance of Common Factors: Commodity Prices

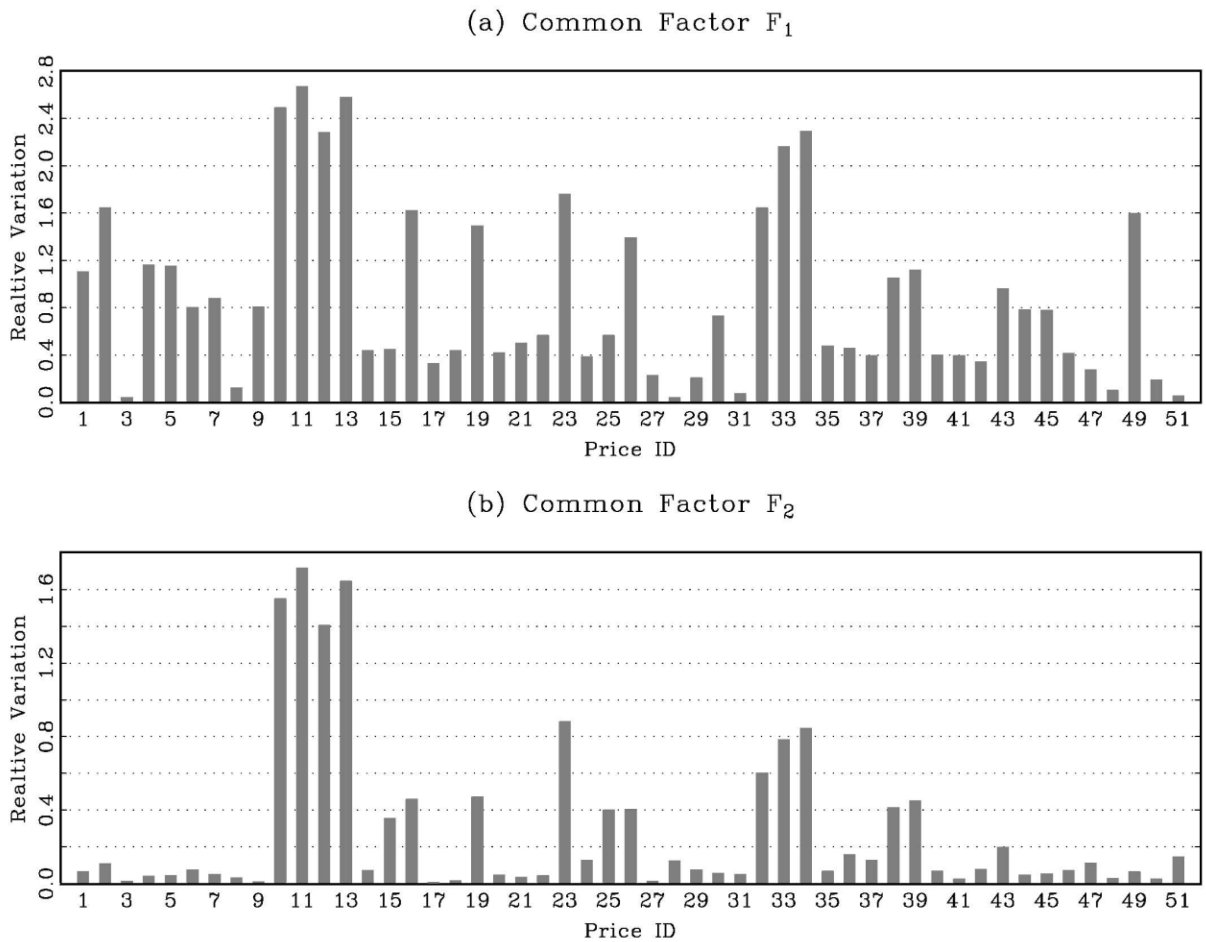


Figure 3. Factor Loadings Estimates: Commodity Prices

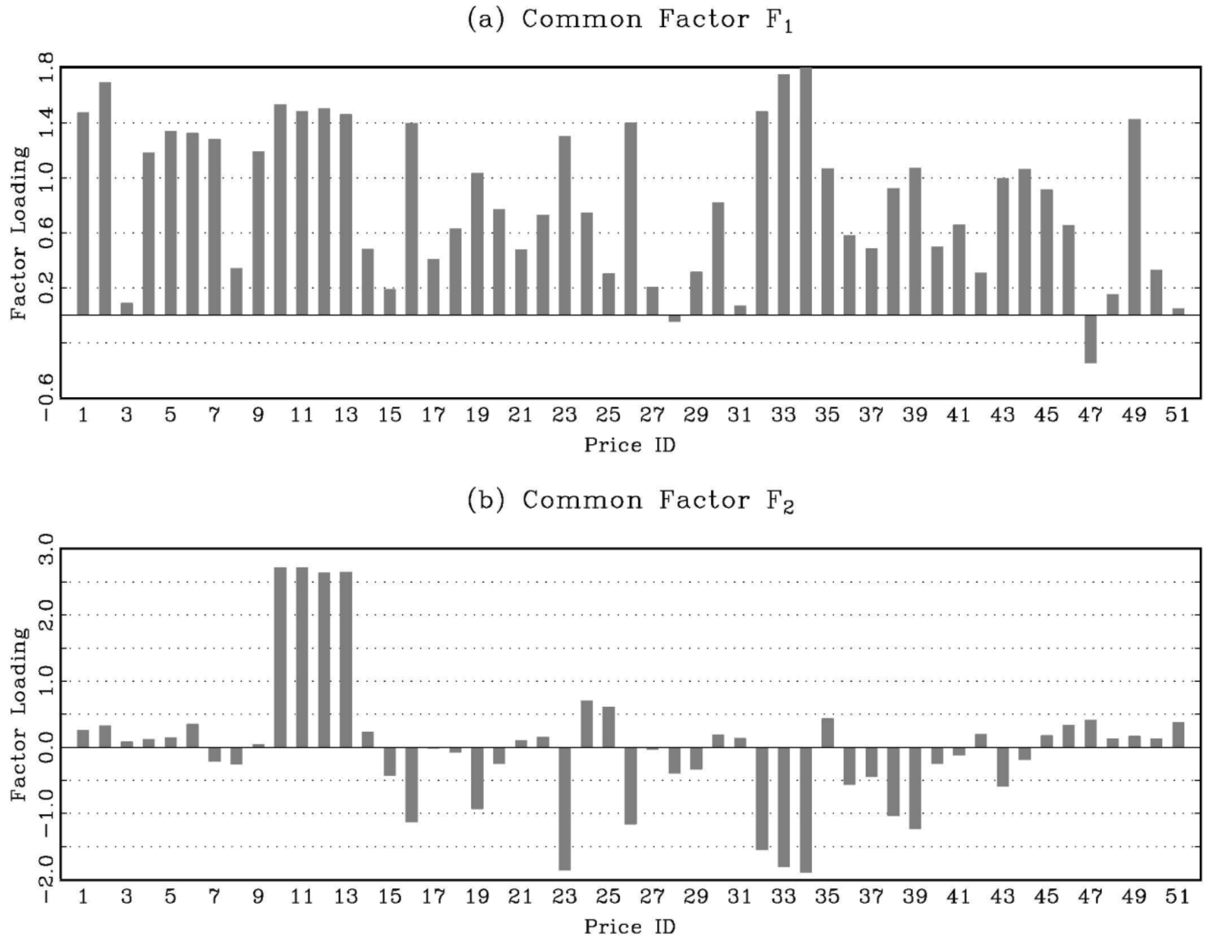


Figure 4. U.S. Exchange Rates vs. Common Factor Estimates

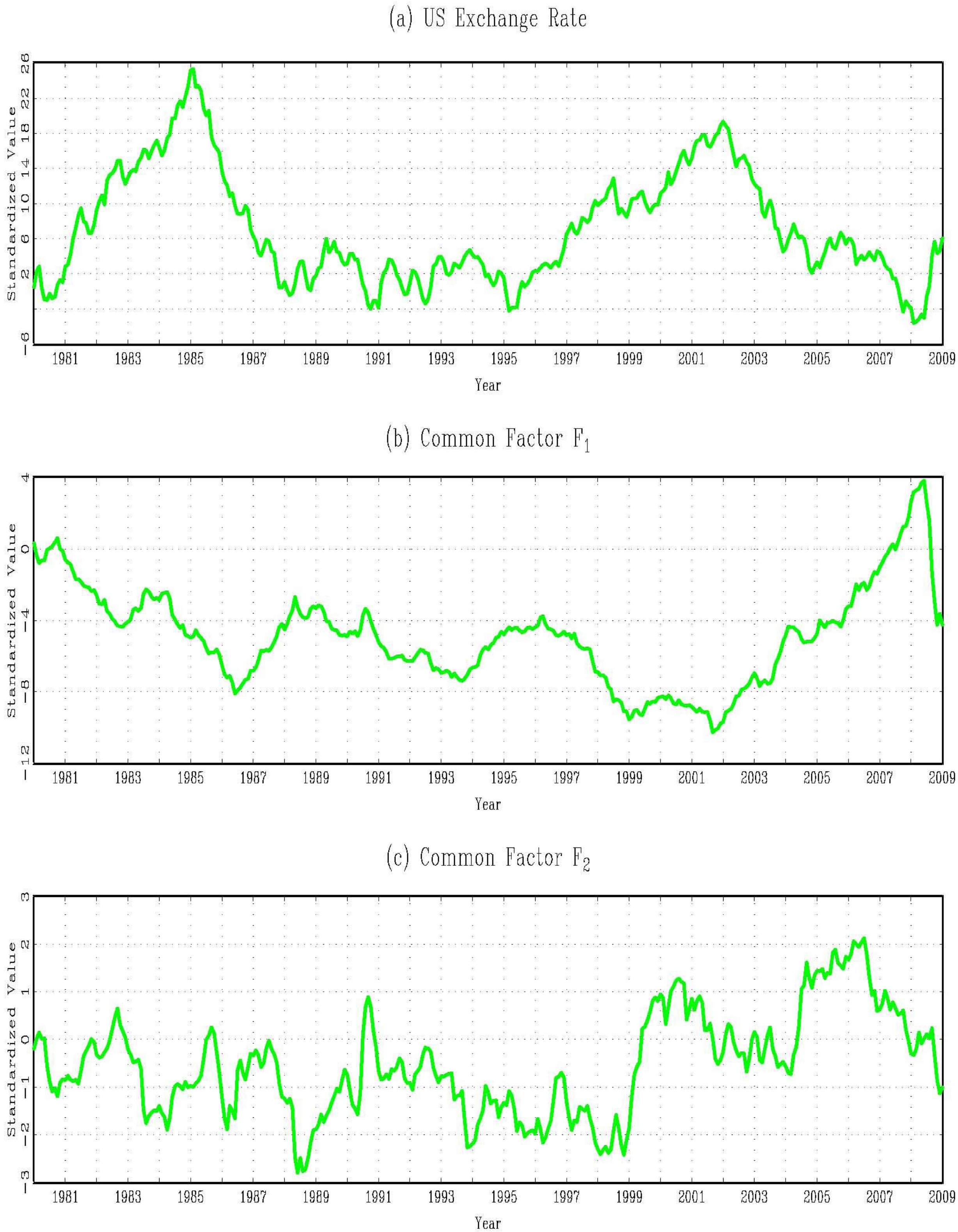
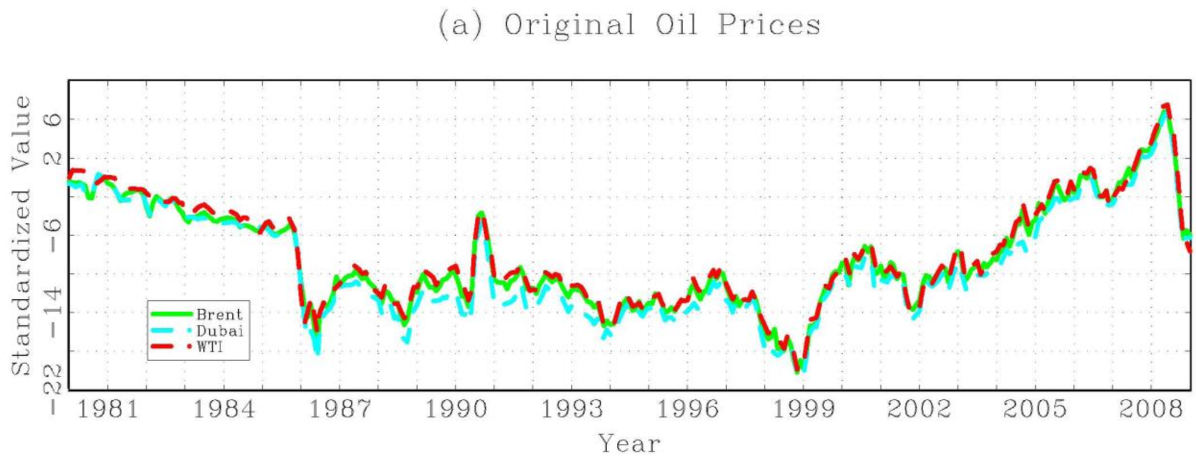


Figure 5. Crude Oil Prices



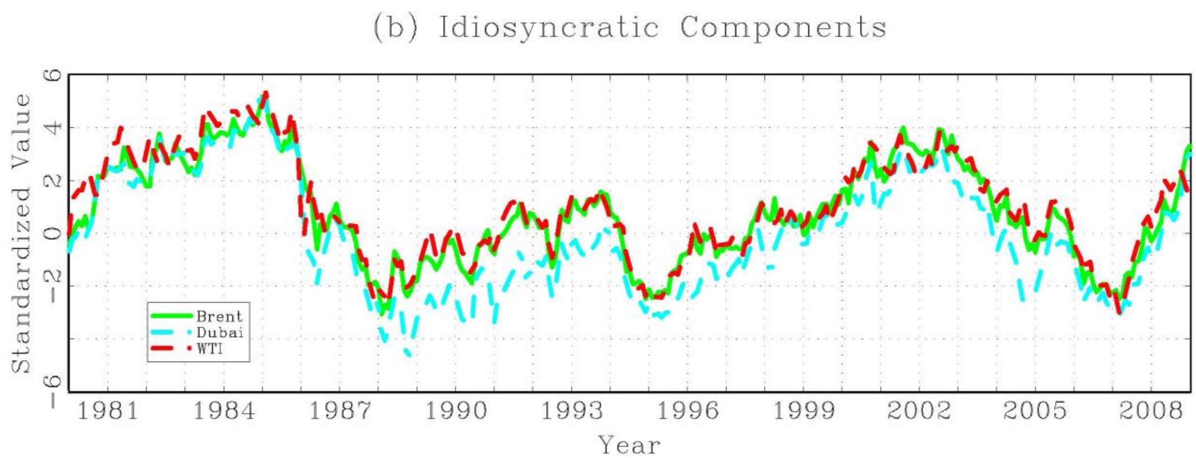
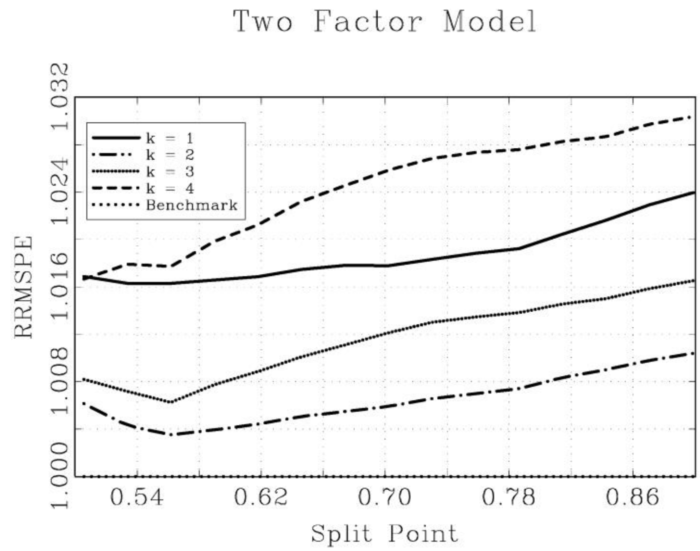
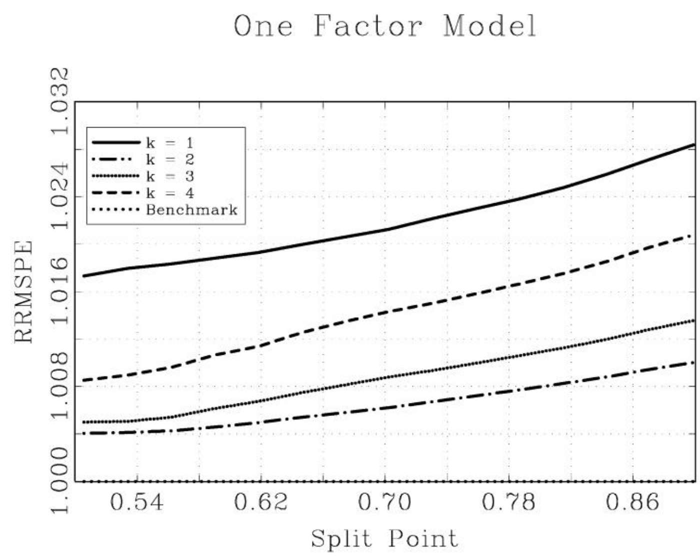


Figure 6. RRMSPE Estimations over Different Split Points





Note: i) Out-of-sample forecasting was recursively implemented by sequentially adding one additional observation from initial split points (180, 200, 220, …, 320). ii) Split point on the *x*-axis, $sp \in [0,1]$, denotes the relative size of the estimation period to the evaluation period. iii) k denotes the forecast horizon. iv) *RRMSPE* denotes the ratio of the root mean squared prediction error of the random walk hypothesis to the common factor model.