FORECASTING THE SPOT PRICES OF VARIOUS COFFEE TYPES USING LINEAR AND NON-LINEAR ERROR CORRECTION MODELS

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ABSTRACT

This paper estimates linear and non-linear error correction models for the spot prices of four different coffee types. In line with economic priors, we find some evidence that when prices are too high, they move back to equilibrium more slowly than when they are too low. This may reflect the fact that, in the short run, it is easier for countries to restrict the supply of coffee in order to raise prices, rather than increase supply in order to reduce them. Further, there is some evidence that adjustment is faster when deviations from the equilibrium level get larger. Our forecasting analysis suggests that asymmetric and non-linear error correction models offer weak evidence of improved forecasting performance relative to the random walk model.

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I. Introduction

The exports of many developing countries are often concentrated on a relatively small number of primary commodities, whose international prices are highly volatile. Indeed, primary commodities, unlike manufactures, usually have low supply and demand price elasticities (in absolute value), so that a given shift in one of the curves causes a much larger change in prices compared with the case where the elasticities are larger in absolute value. Dealing with large fluctuations in commodity prices certainly represents a challenge from a policy perspective, as the mismanagement of commodity booms and slumps (i.e. sharp price rises or falls over a relatively short period of time) may constitute a significant source of macroeconomic instability.

Among agricultural commodities, coffee is the major source of export revenue for low- and middle-income countries (Varangis *et al*., 1995). It is difficult to speak of an international coffee market in the strict sense of the term, since there are two important species of coffee that can be distinguished, namely Arabica (which accounts for more than 70% of the world coffee production) and Robusta. The best-known varieties of the former are Unwashed Arabicas (mainly coffee from Brazil, thereafter UA), Colombian Mild Arabicas (mainly coffee from Colombia, thereafter COL), and Other Mild Arabicas (mainly coffee from other Latin American countries, thereafter OM), whereas Robusta coffee (thereafter ROB) is mainly grown in African countries and Southeast Asia.

In an earlier study, Vogelvang (1992) investigated the existence of long-run relationships among the spot prices of the four types of coffee discussed above, traded in the New York market. This was done using quarterly data over the period 1960-1982. More recently, Otero and Milas (2001) re-examined the relationships among coffee prices based on an extended sample period up to 1998, also allowing for the possibility of non-linear adjustment back to equilibrium in the short-run behaviour of the four coffee prices. In the case of the coffee market, the adoption of a non-linear framework to study price behaviour can be motivated by the fact that relative price increases in periods of a boom seem higher than relative price decreases in periods of a slump. In addition, there have been periods of time when the market operated under conditions of international agreements, which restricted exports, and periods of time when the market operated freely. Therefore, the behaviour of coffee prices may differ from one period to another.

The purpose of this paper is to perform an evaluation of the forecast performance of multivariate non-linear and linear error correction models of the spot prices of the four coffee types discussed above. Forecasting variations in the price of coffee is particularly important for countries that rely on exports of this commodity as a source of foreign exchange. At the macroeconomic level, accurate information about future coffee prices can help policymakers devise measures to smooth out the impact of such price fluctuations on the economy. Unforeseen booms or misconceptions about their duration can certainly complicate macroeconomic management. In some developing countries, for example, temporary commodity booms have been thought to be permanent, and so they have been typically accompanied by overspending booms that are fuelled not only by higher incomes, but also by the increased indebtedness that results from the country's improved access to international borrowing.[1]

Our forecasting modelling exercise uses multivariate non-linear error correction models, which have been found to provide an appropriate framework for studying the behaviour of several macroeconomic time series; see e.g. Anderson (1997), and van Dijk and Franses

[1] The problems arising from commodity booms have been widely discussed in the development economics literature, and are often known as "Dutch disease". This term refers to the fact that during the 1960s, Dutch manufacturing suffered from the appreciation of the real exchange rate that followed the discovery of natural gas in the North Sea. On the theoretical aspects of the Dutch disease literature see e.g. Corden and Neary (1982) and Neary and van Wijnbergen (1986). Varangis *et al*. (1995) focus on the management of commodity price volatility from the perspective of developing countries, examining and contrasting government policies and their effects.

(2000) for two recent applications of these models to the modelling of interest rates in the US and the Netherlands, respectively. Non-linear models are flexible as they allow us to examine the asymmetric effects of positive and negative deviations from equilibrium as well as the differential effects of small and large discrepancies. Despite these interesting properties associated with non-linear models, the question that needs to be answered is how successful they are for forecasting coffee prices (or the prices of other commodities). Examining the behaviour of four commodities that are important for many African economies (that is, cocoa, coffee, copper and cotton), Deaton (1992) found that neither linear univariate time series models, nor more elaborate structural models are very useful for predicting their prices. Our paper thus examines whether multivariate non-linear error correction models yield useful out-of-sample coffee price forecasts.

Our main results are summarised as follows. First, markets for different types of coffee are highly integrated as the long-run relationships among coffee prices are found to affect all different coffee types. Second, in line with economic reasoning, there is evidence that when prices are too high, they move back to equilibrium more slowly than when they are too low. Further, there is some evidence that adjustment is faster when deviations from the equilibrium level get larger. Third, asymmetric and non-linear models offer improved forecasting performance relative to the random walk model primarily for the case of Colombian Milds but not for the other coffee types. However, this should not deter us from employing non-linear models in empirical modelling. Economic priors suggest that non-linear models may be successful within the estimation sample. On the other hand, their (relatively) weak out-of-sample forecasting performance may be due to the fact that non-linearity is not present in the forecast period. Alternatively, introducing different non-linear structure in coffee price models could improve their forecasting performance.

The paper is organised as follows. Section II estimates the long-run relationships among the prices of different coffee types. Section III tests for asymmetric and non-linear adjustment in the behaviour of the coffee prices and discusses their out-of-sample forecasting performance. Finally, section IV offers some concluding remarks.

II. Long-run estimates of coffee price models

We have p = 4 variables, $y_t = [P^{UA}, P^{OM}, P^{ROB}, P^{COL}]'$, where P^{UA}, P^{OM}, P^{ROB} and P^{COL} are the logs of the spot prices of the different coffee types in the New York market. We use quarterly data from 1962(1) to 2001(1). The coffee prices are taken from the International Coffee Organisation (ICO).[2] In our empirical work, we carry out our estimations over the period 1962(1)-1996(1), reserving the last five years of data for out-of-sample forecasting tests. Estimations are done in PcFiml 9.0 (Hendry and Doornik, 1997) and Eviews 4.0 (Quantitative Micro Software, 2001). In Johansen's (1988, 1995) notation, we write a p-dimensional Vector Error Correction Model (VECM) as:

$$\Delta y_t = \sum_{i=1}^{k-1} \Gamma_i \Delta y_{t-i} + \Pi y_{t-1} + \mu + \varepsilon_t, t = 1, \ldots, T \tag{1}$$

where Δ is the first difference operator, y_t is the set of $I(1)$ variables discussed above, $\varepsilon_t \sim niid(0, \Sigma)$, μ is a drift parameter, and Π is a (p x p) matrix of the form $\Pi = \alpha\beta'$, where α and β are (p x r) matrices of full rank, with β containing the r cointegrating vectors and α carrying the corresponding loadings in each of the r vectors.

Figure 1 plots the levels and the first differences of the four coffee price series. Preliminary analysis of the data using the Augmented Dickey-Fuller (ADF) tests suggested that all series are $I(1)$ without drift when considered in levels. Applying the Johansen (1988, 1995) cointegrating approach to find the number of cointegrating vectors and using a lag length of

[2] We would like to thank Ben Vogelvang for providing us with the pre 1983 dataset.

k = 4 in the linear VAR,[3] the following vectors were identified:

$$P^{COL} = \underset{(0.056)}{0.304}\, P^{UA} + \underset{(0.062)}{0.672}\, P^{OM} + \underset{(0.052)}{0.183} \qquad (2)$$

and

$$P^{ROB} = P^{UA} \underset{(0.024)}{- 0.247} \qquad (3)$$

where standard errors are given in parentheses.[4] The first vector involves P^{COL}, P^{UA} and P^{OM}. The estimated positive intercept supports the price differential of Colombian over the other Arabica coffee types (Colombian is regarded as a higher quality coffee). The second vector involves P^{ROB} and P^{UA}. Here, the negative intercept proxies the quality premium of Unwashed Arabica over Robusta, since the latter is a lower quality of all four coffees. In the next section, we discuss linear and non-linear specifications of the error correction equations that will be used for forecasting analysis.

III. Short-run estimates of coffee price models

III.1. *In sample estimates*

OLS estimates of the error correction models are reported in the first panel of Table 1. To save space, we report only the estimated coefficients associated with the error correction terms.

[3] We also allowed for three zero/one dummy variables. The first two (denoted by $d1$ and $d2$) capture moderate and grave frosts or droughts in the coffee areas, respectively, with information taken from ICO's web page, *www.ico.org*. In particular, $d1$ takes the value of 1 in the third quarter of the years 1962, 1963, 1969, 1972, 1978, 1984, 1985; 1 in the second quarter of the years 1967, 1979; 1 in 1985(4) and 1986(1); and 0 otherwise, whereas $d2$ takes the value of 1 in the third quarter of the years 1966, 1975, 1981, 1994; 1 in the second quarter of the year 1994; and 0 otherwise. The third dummy (denoted by $d893$) captures the collapse of the international coffee agreement in July 1989. Detailed cointegration results are available on request.

[4] For exact identification we imposed a unit coefficient on P^{COL} and a zero coefficient on P^{ROB} in the first vector and a unit coefficient on P^{ROB} and a zero coefficient on P^{OM} in the second one. The unit coefficient on P^{UA} and long-run exclusion of P^{COL} were tested in the second vector, producing a $\chi^2(2) = 0.635$ (p-value = 0.728).

These are denoted by $CV1_{t-1}$ and $CV2_{t-1}$ and are given by equations (2) and (3), respectively. The other significant regressors appear in the notes of Table 1. The results show significant feedbacks from both disequilibrium errors in the ΔP^{UA} and ΔP^{OM} equations. In addition, $CV1_{t-1}$ affects significantly ΔP^{ROB}, whereas $CV2_{t-1}$ affects significantly ΔP^{COL}. A battery of diagnostic tests suggests some non-linear structure in the residuals of the estimated models. We postpone their discussion for the following section where we also provide evidence that a significant part of this non-linearity is captured by our asymmetric and non-linear specifications.

The literature on non-linearities in the behaviour of error correction models is now rich (see e.g. Granger and Lee, 1989; Granger and Teräsvirta, 1993; Escribano and Granger, 1998; Escribano and Pfann, 1998; and Escribano and Aparicio, 1999, among others). For instance, Granger and Lee (1989) partition the error correction term into its positive and negative components, and feed them back into the short-run dynamic equations, whereas Escribano and Granger (1998) and Escribano and Aparicio (1999) use a cubic error correction term. This type of non-linear adjustment allows for a faster adjustment when deviations from the equilibrium level get larger.

The second and third panel of Table 1 report the asymmetric and non-linear error correction equations, respectively. First, as in Granger and Lee (1989), we take the deviations of $CV1$ and $CV2$ around their mean values, and partition them into their positive and negative components (denoted by CV_j^+ and CV_j^-, j = 1,2, respectively). The results in the second panel of Table 1 indicate that the speed of adjustment varies depending on whether prices are above or below their equilibrium. For all equations, there is evidence that when prices are too high, they move back to equilibrium more slowly than when they are too low. This reflects the fact that, in the short run, it is easier for countries to restrict supply in order to raise prices, rather than increase supply in order to reduce them.

In the spirit of Escribano and Granger (1998) and Escribano and Aparicio (1999) we also allow for CV_j^2 and CV_j^3 (j = 1,2, respectively) to enter the short-run equations. Our results in the last panel of Table 1 show some rather weak evidence that adjustment is faster when deviations from the equilibrium level get larger.

III.2. *In sample diagnostic checking*

Next we discuss some diagnostic checks which can be used to evaluate our estimated models. As can be seen from Table 1, the asymmetric and non-linear error correction models seem to capture some of the normality and heteroscedasticity failures that are present in the linear coffee price equations. As a further check for the adequacy of our asymmetric and non-linear models, we examine their ability to capture all non-linear features of the first differences of the four coffee prices. This is done by applying three fairly general tests for remaining non-linearity to the residuals of the estimated models, namely the well-known Brock, Dechert and Sheinkman (1996, thereafter BDS) test, the bicovariance test due to Hinich (1996), and the Tsay (1986) test for quadratic serial dependence. In all cases, the null hypothesis of linearity is tested against an unspecified alternative. Ashley and Patterson (2001) offer a complete discussion of this group of tests. Taking into account that our sample size is small and that a single non-linearity test can only detect or fail to detect non-linearity, the application of a battery of non-linearity tests can provide valuable non-linear identification information on a given time series. That said, Ashley and Patterson (2001, p. 20) point out, in line with previous literature, that “the BDS test is the best test of this group for use as a non-linearity screening test”. The tests were estimated using The Non-linear Toolkit by Patterson and Ashley (2000) and *BDS Stats* 8.21 by Brock, Dechert and Scheinkman (1996). Due to our small sample size, we follow Ashley and Patterson (2001) in computing the bootstrapped significance levels as well as those based on asymptotic theory.

For each of the four coffee price series, the tests are applied to the residuals of four different models that will be used for forecasting analysis in the next section, that is, a random walk model (i.e. a model where the only explanatory variable is the intercept term) and the linear, asymmetric and non-linear models of Table 1. Results are reported in Table 2. In the case of UA, the random walk and the non-linear specification are doing better than the other two models. On the other hand, there is strong evidence to suggest that the residuals of the non-linear and the asymmetric models for COL are *i.i.d.*, that is, both models seem to be able to capture most of the non-linearities, therefore providing a good in-sample fit. In the case of OM, the non-linear specification produces higher BDS asymptotic *p*-values, thus providing evidence to suggest that the residuals of this model are *i.i.d.* At the same time, both the linear and the asymmetric model give much higher *p*-values than the random walk model. Last, the non-linear and the asymmetric models for ROB do not fail to capture the important non-linearities in the data generating process. [5]

The results from the Bicovariance and the Tsay test (see Table 3), are somewhat different from the BDS results, suggesting that non-linearity is not present in the residuals of the linear equations for COL, OM, and ROB, respectively. However, they also suggest that compared to random walk models, the asymmetric model for COL and the non-linear and asymmetric models for OM succeed in capturing non-linearities.

III.3. *Out of sample forecasting performance*

In order to assess the usefulness of our linear and non-linear error correction models, dynamic out-of-sample forecasts of the first differences of the four coffee prices are computed. These are compared with the forecasts of random walk coffee price models. Forecasting accuracy is evaluated using Mean Absolute Error (MAE) and Mean Square Error

[5] Bootstrapped BDS *p*-values are almost identical to the asymptotic *p*-values and for this reason not reported here.

(MSE) criteria. Further, in order to assess the accuracy of the linear and non-linear models relative to the random walk models we employ the modified version of the Diebold and Mariano (1995) test as proposed by Harvey *et al*. (1997). Following Diebold and Mariano (1995), the time t loss associated with a forecast (say i) is an arbitrary function of the realisation and prediction, $g(y_t, \hat{y}_{it})$. The loss function is a direct function of the forecast error, that is, $g(y_t, \hat{y}_{it}) = g(e_{it})$. The null hypothesis of equal forecast accuracy for two competing forecasts is $E[g(e_{it})] = E[g(e_{jt})]$, or $E[d_t] = 0$, where $d_t \equiv [g(e_{it}) - g(e_{jt})]$ is the loss differential (i.e. the difference between absolute or square forecast errors). Thus, the "equal accuracy" null hypothesis is equivalent to the null hypothesis that the population mean of the loss-differential series is 0. Let $\bar{d} = \frac{1}{T}\sum_{t=1}^{T}[g(e_{it}) - g(e_{jt})]$ denote the sample mean loss differential (over T forecasts), and let $g(e_{it})$ be is a general function of forecast errors (e.g. MAE or MSE). Then, $\sqrt{T}(\bar{d} - \mu) \xrightarrow{d} N(0, 2\pi f_d(0))$, where $N(.)$ refers to the normal distribution. The Diebold and Mariano (1995) test is given by:

$$DM = \frac{\bar{d}}{\sqrt{\frac{2\pi \hat{f}_d(0)}{T}}} \xrightarrow{d} N(0,1) \tag{4}$$

where $\hat{f}_d(0)$ is a consistent estimate of the spectral density of the loss differential at frequency 0.[6] To counteract the tendency of the DM test statistic to reject the null too often when it is true, Harvey *et al*. (1997) propose a modified Diebold-Mariano test statistic:

$$DM^* = \left[\frac{T + 1 - 2h + T^{-1}h(h-1)}{T}\right]^{1/2} DM \xrightarrow{d} t_{(T-1)} \tag{5}$$

where DM is the original Diebold and Mariano (1995) test statistic for h-steps ahead forecasts

[6] In order to provide a consistent estimate of the spectral density, the appropriate truncation lag is chosen by examining the loss differential autocorrelation functions (see e.g. the discussion in Diebold and Mariano, 1995).

and $t_{(T-1)}$ refers to Student's t distribution with $(T - 1)$ degrees of freedom.

Tables 4 and 5 report MAE and MSE criteria for the different versions of the coffee price models. The statistical significance of the forecasting performance of the linear, asymmetric, and non-linear error correction models relative to random walk models, respectively, is examined using modified DM^* tests. We examine the forecasting performance of the different models over a forecast horizon of $h = 1, 2, 3$ and 4 quarters ahead, respectively. According to our results, the asymmetric and non-linear error correction models offer improved forecasting performance relative to the random walk model primarily for the case of Colombian Milds. For all other coffee types, our linear, asymmetric and non-linear models cannot beat the random walk model. One possible explanation may have to do with what our results in section III.2 suggested; although our asymmetric and non-linear models are quite successful for Colombian Milds, there seems to be some remaining non-linear structure in the residuals of the asymmetric and non-linear models of all other three coffee prices. Therefore, introducing different non-linear structures could possibly improve the forecasting performance of the coffee price models.[7] Furthermore, although non-linearities might be present and significant in our models, the latter may fail to produce *ex ante* forecast improvement; in other words, statistical significance does not imply economic significance (see e.g. Diebold and Nason, 1990). Therefore, the puzzle remains unsolved in the sense that in-sample non-linearities are not useful out-of-sample (see e.g. the discussion in Ramsey, 1996). Another possible explanation for the relatively poor forecasting performance of the non-linear models is that non-linearity is not present in the forecast period (see e.g. the discussion in van Dijk *et al*., 2000).

[7] That said, the infinite set of non-linear models makes determination of a good approximation to the data generating process a difficult task.

IV. Concluding remarks

This paper has examined the price relationships between different types of coffees both in a linear and a non-linear environment. Using price data for Unwashed Arabicas (i.e. coffee from Brazil), Colombian Mild Arabicas (i.e. coffee from Colombia) Other Mild Arabicas (i.e. coffee from other Latin American countries) and Robusta coffee (i.e. coffee from Africa and Southeast Asia), we identified two cointegrating relationships affecting the short-run dynamics of the four coffee prices. Our estimates of the asymmetric and non-linear error correction models provided evidence that when the coffee prices are too high, they move back to equilibrium more slowly than when they are too low. At the same time, there is some evidence that adjustment is faster when deviations from the equilibrium level get larger.

Finally, our results suggested that non-linear error correction models offer very weak evidence of improved forecasting performance relative to the random walk model. However, this should not deter us from using non-linear models in empirical modelling. Economic priors suggest that non-linear models may be successful within the estimation sample. On the other hand, their (relatively) weak out-of-sample forecasting performance may be due to the fact that non-linearity does not show up in the forecast period. Alternatively, specifying different non-linear structures could possibly improve the forecasting performance of the coffee price models. It is notable that commenting on Ericsson *et al.*'s (1998) UK money demand model, Teräsvirta (1998) pointed out that non-linear models with quadratic and cubic error correction terms, are first-order approximations to smooth transition regressions (STR; see e.g. Granger and Teräsvirta, 1993), where the transition mechanism is driven by the disequilibrium error. Building on that comment, Teräsvirta and Eliasson (2001) estimated smooth transition error correction models using alternative transition variables. It is our intention to address coffee price models in the context of smooth transition models in future research.

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Table 1. Error correction models

Variable	ΔP^{UA}		ΔP^{COL}		ΔP^{OM}		ΔP^{ROB}	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
				Linear adjustment				
$CV1_{t-1}$	0.760	0.237			0.622	0.267	0.708	0.217
$CV2_{t-1}$	0.329	0.082	0.120	0.067	0.152	0.081		
F *ar*	1.148	[0.338]	0.568	[0.687]	0.601	[0.663]	0.394	[0.813]
χ^2 *nor*	11.466	[0.003]	11.577	[0.003]	3.525	[0.172]	4.844	[0.089]
F *arch*	2.373	[0.057]	0.327	[0.859]	0.924	[0.453]	2.118	[0.083]
F *het*	2.186	[0.007]	1.850	[0.027]	1.368	[0.148]	1.490	[0.099]
σ	0.119		0.100		0.115		0.110	
				Asymmetric adjustment				
$CV1^{+}_{t-1}$	0.248	0.428			0.280	0.438	0.121	0.393
$CV1^{-}_{t-1}$	1.036	0.366			0.920	0.381	1.119	0.315
$CV2^{+}_{t-1}$	0.184	0.162	0.035	0.135	0.220	0.158		
$CV2^{-}_{t-1}$	0.427	0.150	0.190	0.118	0.072	0.148		
F *ar*	1.370	[0.249]	0.345	[0.847]	0.704	[0.591]	0.374	[0.827]
χ^2 *nor*	7.723	[0.021]	11.265	[0.004]	3.332	[0.189]	6.221	[0.045]
F *arch*	2.694	[0.035]	0.426	[0.790]	1.295	[0.276]	2.230	[0.070]
F *het*	1.747	[0.033]	1.729	[0.039]	1.225	[0.237]	1.417	[0.124]
σ	0.118		0.100		0.114		0.108	
				Non-linear adjustment				
$CV1_{t-1}$	0.499	0.377			0.685	0.383	0.982	0.346
$CV1^{2}_{t-1}$	-3.093	2.209			-1.971	2.192	-4.117	1.963
$CV1^{3}_{t-1}$	-2.033	22.590			-18.987	22.900	-28.955	21.142
$CV2_{t-1}$	0.085	0.127	0.057	0.105	0.013	0.127		
$CV2^{2}_{t-1}$	0.155	0.482	-0.138	0.407	0.494	0.480		
$CV2^{3}_{t-1}$	3.332	1.614	0.723	1.350	2.503	1.601		
F *ar*	0.906	[0.463]	0.391	[0.815]	0.618	[0.651]	0.255	[0.906]
χ^2 *nor*	7.806	[0.020]	12.590	[0.002]	5.732	[0.057]	6.621	[0.037]
F *arch*	1.639	[0.170]	0.371	[0.829]	0.792	[0.533]	2.327	[0.061]
F *het*	1.521	[0.079]	1.565	[0.072]	1.038	[0.432]	1.322	[0.173]
σ	0.116		0.100		0.114		0.108	

Notes: S.E. are standard errors. σ is the regression standard error. F *ar* is the LM F-test for serial correlation of up to fourth order. F *arch* is the fourth order ARCH F-test. χ^2 *nor* is a Chi-square test for normality. F *het* is an F test for heteroscedasticity. Numbers in [•] are the *p*-values of the test statistics.

ΔP_t^{UA} includes $\Delta P^{UA}_{\{-1,-3\}}$, $\Delta P^{COL}_{\{-1\}}$, $\Delta P^{OM}_{\{-1,-2\}}$, $\Delta P^{ROB}_{\{-2\}}$, *d*1, *d*2, *d*893 and a constant.

ΔP_t^{COL} includes $\Delta P^{UA}_{\{-3\}}$, $\Delta P^{COL}_{\{-1,-2\}}$, $\Delta P^{OM}_{\{-1,-2,-3\}}$, $\Delta P^{ROB}_{\{-2\}}$, *d*1, *d*2, *d*893 and a constant.

ΔP_t^{OM} includes $\Delta P^{UA}_{\{-1,-2,-3\}}$, $\Delta P^{COL}_{\{-1,-2\}}$, $\Delta P^{OM}_{\{-1,-2\}}$, $\Delta P^{ROB}_{\{-2\}}$, *d*1, *d*2, *d*893 and a constant.

ΔP_t^{ROB} includes $\Delta P^{UA}_{\{-3\}}$, $\Delta P^{COL}_{\{-1\}}$, $\Delta P^{OM}_{\{-1,-2,-3\}}$, $\Delta P^{ROB}_{\{-1,-2,-3\}}$, *d*1, *d*2, *d*893 and a constant.

Table 2. Linearity tests on the residuals, BDS tests

Unwashed Arabica (UA)

m	Random Walk			Linear ECM			Non-Linear ECM			Asymmetric ECM		
	$\varepsilon =$			$\varepsilon =$			$\varepsilon =$			$\varepsilon =$		
	0.065	0.131	0.261	0.085	0.171	0.340	0.086	0.173	0.349	0.090	0.180	0.357
2	0.000	0.033	0.351	0.069	0.026	0.020	0.039	0.110	0.436	0.003	0.003	0.010
3	0.000	0.011	0.229	0.005	0.004	0.010	0.003	0.009	0.181	0.000	0.000	0.002
4	0.000	0.002	0.283	0.002	0.000	0.005	0.000	0.001	0.118	0.000	0.000	0.001
5	0.000	0.001	0.178	0.001	0.000	0.001	0.000	0.000	0.029	0.000	0.000	0.000
6	0.000	0.000	0.178	0.001	0.000	0.001	0.000	0.000	0.013	0.000	0.000	0.000

Colombian Milds (COL)

m	Random Walk			Linear ECM			Non-Linear ECM			Asymmetric ECM		
	$\varepsilon =$			$\varepsilon =$			$\varepsilon =$			$\varepsilon =$		
	0.062	0.124	0.247	0.083	0.167	0.336	0.082	0.166	0.334	0.083	0.167	0.335
2	0.000	0.027	0.718	0.215	0.375	0.902	0.377	0.584	0.725	0.342	0.553	0.863
3	0.000	0.012	0.842	0.014	0.063	0.858	0.005	0.143	0.866	0.007	0.147	0.442
4	0.000	0.004	0.514	0.031	0.026	0.729	0.001	0.091	0.947	0.004	0.088	0.731
5	0.000	0.001	0.300	0.007	0.005	0.569	0.000	0.027	0.745	0.000	0.025	0.517
6	0.000	0.000	0.199	0.012	0.003	0.426	0.000	0.028	0.573	0.000	0.020	0.368

Other Milds (OM)

m	Random Walk			Linear ECM			Non-Linear ECM			Asymmetric ECM		
	$\varepsilon =$			$\varepsilon =$			$\varepsilon =$			$\varepsilon =$		
	0.063	0.128	0.257	0.096	0.192	0.384	0.092	0.184	0.368	0.095	0.190	0.382
2	0.000	0.036	0.255	0.243	0.180	0.847	0.141	0.163	0.937	0.026	0.057	0.849
3	0.000	0.027	0.200	0.001	0.007	0.931	0.001	0.019	0.982	0.000	0.002	0.681
4	0.000	0.008	0.077	0.000	0.003	0.749	0.001	0.015	0.678	0.000	0.001	0.400
5	0.000	0.000	0.033	0.002	0.000	0.524	0.001	0.006	0.499	0.000	0.000	0.249
6	0.000	0.000	0.019	0.006	0.000	0.338	0.001	0.002	0.380	0.000	0.000	0.150

Robusta (ROB)

m	Random Walk			Linear ECM			Non-Linear ECM			Asymmetric ECM		
	$\varepsilon =$			$\varepsilon =$			$\varepsilon =$			$\varepsilon =$		
	0.071	0.141	0.280	0.081	0.162	0.323	0.076	0.153	0.307	0.078	0.158	0.318
2	0.069	0.052	0.061	0.392	0.473	0.550	0.354	0.865	0.744	0.323	0.661	0.803
3	0.005	0.047	0.031	0.326	0.708	0.687	0.157	0.568	0.825	0.215	0.738	0.677
4	0.000	0.004	0.005	0.029	0.162	0.817	0.024	0.239	0.463	0.009	0.252	0.239
5	0.000	0.000	0.002	0.000	0.007	0.304	0.031	0.060	0.145	0.000	0.034	0.060
6	0.000	0.000	0.002	0.000	0.000	0.125	0.000	0.008	0.057	0.000	0.001	0.018

Notes: The BDS test statistic tests the null hypothesis that a series is *i.i.d.* against the alternative of realisation from an unspecified non-linear process. m is the embedding dimension and ε equals $0.5\sigma_u$, $1.0\sigma_u$ and $2.0\sigma_u$, respectively, where σ_u is the standard deviation of the residuals. Given that the choices of m and ε are crucial for the power of the test, we report the results for different plausible values of m and ε as suggested by Brock, Hsieh and LeBaron (1991). Only p-values are reported.

Table 3. Linearity tests on the residuals, Bicovariance and Tsay's test

Coffee type	Model	Bootstrap Bicovariance $l = 7$	Bootstrap Tsay $k = 5$	Asymptotic Theory Bicovariance $l = 7$	Asymptotic Theory Tsay $k = 5$
UA	Random Walk	0.011	0.024	0.000	0.016
UA	Linear ECM	0.039	0.004	0.014	0.003
UA	Non-Linear ECM	0.010	0.003	0.001	0.002
UA	Asymmetric ECM	0.016	0.002	0.003	0.001
COL	Random Walk	0.016	0.053	0.001	0.039
COL	Linear ECM	0.321	0.783	0.582	0.870
COL	Non-Linear ECM	0.055	0.316	0.021	0.336
COL	Asymmetric ECM	0.690	0.997	1.000	1.000
OM	Random Walk	0.019	0.403	0.001	0.460
OM	Linear ECM	0.760	0.983	1.000	1.000
OM	Non-Linear ECM	0.866	0.947	1.000	1.000
OM	Asymmetric ECM	0.869	0.939	1.000	1.000
ROB	Random Walk	0.027	0.165	0.005	0.186
ROB	Linear ECM	0.884	0.712	1.000	0.936
ROB	Non-Linear ECM	0.161	0.350	0.206	0.390
ROB	Asymmetric ECM	0.197	0.426	0.273	0.478

Notes: The Tsay (1986) test explicitly looks for quadratic serial dependence in the data and follows the F-distribution. Under the null hypothesis that a time series is a serially *i.i.d.* process, the Bicovariance test (Hinich, 1996), follows asymptotically the χ^2 distribution. Following Ashley and Patterson (2001), both the bootstrap and the asymptotic theory p-values are reported and we set $k = 5$ and $l = 7$, where k refers to the number of column vectors which contain all possible cross-products of the estimated residuals and $l = T^{0.4}$ where T is the sample size. Only p-values are reported.

Table 4. Forecast evaluation for the spot prices of various coffee types
Mean Absolute Error (MAE)

h	Random Walk	Linear ECM		Asymmetric ECM		Non-linear ECM	
				Unwashed Arabica (UA)			
1	0.140	0.120	[0.160]	0.119	[0.139]	0.145	[0.569]
2	0.144	0.146	[0.526]	0.133	[0.248]	0.174	[0.773]
3	0.140	0.139	[0.491]	0.129	[0.099]	0.191	[0.755]
4	0.147	0.150	[1.000]	0.131	[0.000]	0.222	[0.792]
				Colombian Milds (COL)			
1	0.126	0.096	[0.027]	0.095	[0.023]	0.093	[0.027]
2	0.130	0.110	[0.135]	0.113	[0.106]	0.095	[0.024]
3	0.135	0.119	[0.213]	0.124	[0.200]	0.106	[0.000]
4	0.140	0.115	[0.210]	0.116	[0.100]	0.115	[0.000]
				Other Milds (OM)			
1	0.132	0.133	[0.529]	0.134	[0.577]	0.119	[0.201]
2	0.136	0.155	[0.750]	0.155	[0.807]	0.121	[0.170]
3	0.140	0.156	[0.662]	0.153	[0.701]	0.143	[1.000]
4	0.147	0.152	[0.532]	0.135	[0.374]	0.168	[0.734]
				Robusta (ROB)			
1	0.098	0.110	[0.788]	0.092	[0.314]	0.095	[0.420]
2	0.100	0.151	[0.963]	0.129	[0.960]	0.116	[0.914]
3	0.097	0.146	[0.903]	0.119	[0.922]	0.110	[0.896]
4	0.095	0.150	[0.816]	0.116	[0.742]	0.112	[0.968]

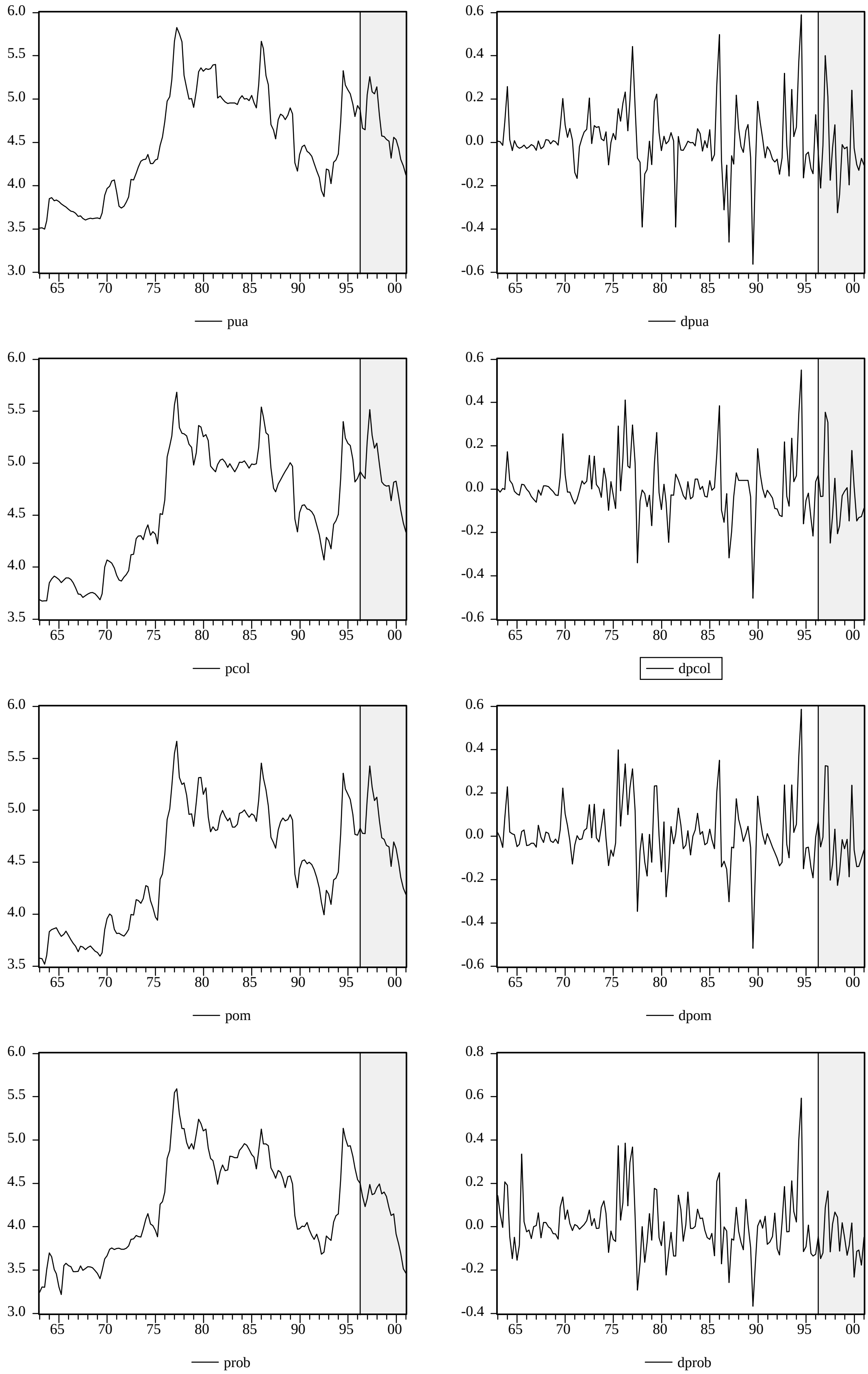
Notes: The forecasting period runs from 1996(2) to 2001(1). *h* = Forecast horizon. Figures in [•] contain the *p*-values for the forecast comparison statistic *DM**of Diebold and Mariano (1995), as modified by Harvey *et al*. (1997), against the one-sided alternative that the MAPE of the linear (asymmetric, non-linear) error correction model is less than the MAPE of the random walk model.

Table 5. Forecast evaluation for the spot prices of various coffee types
Mean Squared Error (MSE)

h	Random Walk	Linear ECM		Asymmetric ECM		Non-linear ECM	
				Unwashed Arabica (UA)			
1	0.031	0.023	[0.135]	0.023	[0.109]	0.033	[0.583]
2	0.032	0.034	[0.553]	0.030	[0.340]	0.049	[0.825]
3	0.031	0.033	[0.575]	0.029	[0.358]	0.069	[0.830]
4	0.033	0.034	[0.538]	0.028	[0.218]	0.089	[0.819]
				Colombian Milds (COL)			
1	0.025	0.017	[0.021]	0.017	[0.009]	0.016	[0.013]
2	0.026	0.021	[0.129]	0.022	[0.091]	0.018	[0.000]
3	0.028	0.022	[0.158]	0.024	[0.152]	0.022	[0.000]
4	0.029	0.021	[0.187]	0.021	[0.090]	0.025	[0.255]
				Other Milds (OM)			
1	0.026	0.025	[0.403]	0.025	[0.405]	0.022	[0.156]
2	0.027	0.036	[0.776]	0.034	[0.798]	0.025	[0.270]
3	0.028	0.038	[0.727]	0.032	[0.657]	0.033	[1.000]
4	0.030	0.035	[0.593]	0.025	[0.365]	0.041	[0.737]
				Robusta (ROB)			
1	0.014	0.019	[0.888]	0.014	[0.556]	0.015	[0.675]
2	0.014	0.033	[0.943]	0.022	[0.927]	0.019	[0.960]
3	0.013	0.032	[0.890]	0.020	[0.865]	0.017	[0.939]
4	0.013	0.037	[0.826]	0.021	[0.782]	0.018	[0.902]

Notes: The forecasting period runs from 1996(2) to 2001(1). *h* = Forecast horizon. Figures in [•] contain the *p*-values for the forecast comparison statistic *DM** of Diebold and Mariano (1995), as modified by Harvey *et al*. (1997), against the one-sided alternative that the MSPE of the linear (asymmetric, non-linear) error correction model is less than the MSPE of the random walk model.

Figure 1. Coffee prices - Levels and first differences



Note: Observations in the shadowed area are used for forecast comparison.