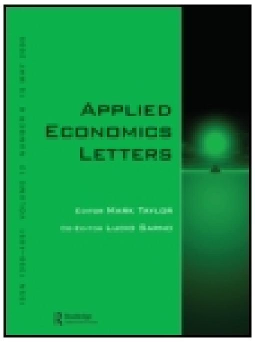

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Explaining stationary variables with non-stationary regressors

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When variables included in an OLS regression are stationary, conventional statistical measures such as t-statistics and R^2's – in addition to *a priori* information from economic theory – are the standard indicators used to assess the performance of the hypothesized model. However, if the variables under consideration are non-stationary, such conventional measures no longer have the usual interpretation. With recent developments in time-series analysis, namely cointegration, researchers are able to deal with models containing non-stationary variables effectively. A standard cointegration model, however, requires all variables included in the regression to be of the same order of integration. In this paper we consider a regression in which the dependent variable is integrated of order zero, $I(0)$, while the explanatory variables are integrated of order one, $I(1)$. Conventional statistical measures are inapplicable because the regressors are not stationary. On the other hand, cointegration statistics are inapplicable because the variables are not of the same order of integration. This letter proposes a methodology on how to evaluate the performance of such a model.

INTRODUCTION

When variables included in an OLS regression are stationary, conventional statistical measures such as t-statistics and R^2's – in addition to *a priori* information from economic theory – are the standard indicators used to assess the performance of the hypothesized model. However, if the variables under consideration are non-stationary, such conventional measures no longer have the usual interpretation. With recent developments in time-series analysis, namely cointegration, researchers are able to deal with models containing non-stationary variables effectively (Engle and Granger, 1987). A standard cointegration model, however, requires that all variables included in the regression are of the same order of integration.[1] In this paper we consider a regression in which the dependent variable is integrated of order zero $I(0)$, while the explanatory variables are integrated of order one, $I(1)$. Conventional statistical measures are inapplicable because the regressors are not stationary. On the other hand, cointegration statistics are inapplicable because the variables are not of the same order of integration. Hence, it is reasonable to be ask how can one evaluate the performance of such a model.

Pagan and Wickens (1989) offer an intuitive answer to this question. In particular, they write: 'The disturbance will also be $I(1)$ if the dependent variable is $I(0)$ and there is only one $I(1)$ regressor; to achieve an $I(0)$ disturbance there must be at least two $I(1)$ regressors. The reason for all of these claims is straightforward and is a matter of "integration or growth accounting", i.e. the left- and right-hand sides of the equation must have the same order of integration or trend' (p. 1002). Recently, Banerjee *et al.* (1993), referring to this type of model as unbalanced regression write: 'The mere fact that a regression is unbalanced may not be a matter of concern; for example, ADF statistics are computed from models that, in

[1] Intuitively, a series is said to be stationary or integrated of order zero denoted as $I(0)$ if its mean and variance exist. If the series needs to be differenced once to become $I(0)$ it is called integrated of order one, $I(1)$. Two or more $I(1)$ series, a non-trivial combination of which is $I(0)$ are said to be cointegrated (Engle and Granger, 1987).

this terminology, are unbalanced. They are nonetheless valid tools for inference as long as the correct critical values are used' (p. 166).

Therefore, a natural way to proceed would be to examine the stationarity properties of the error term as in the typical cointegration regression. An $I(0)$ error term would indicate a model performing in a satisfactory manner. However, this may not be necessarily the case. To illustrate, consider the following OLS regression:

$$Y_t = \mu + \beta_1 X_{1t} + \beta_2 X_{2t} + \epsilon_t \tag{1}$$

where Y_t is $I(0)$ while X_{1t} and X_{2t} are processes; μ, β_1 and β_2 are parameters to be estimated; ϵ_t denotes the error term. Suppose that ϵ_t is stationary. Is it a result of co-movement between X_{1t} and X_{2t}? Not necessarily, since, if the regressors have no explanatory power at all the parameter estimates will not differ from zero. Hence, the resulting error term will simply inherit the stationarity properties of the dependent variable. To see this, take the extreme case where the slope parameters of Equation 1 are zero, i.e. $\beta_1 = \beta_2 = 0$. In such case, the error term will be equal to the dependent variable minus its mean (i.e. $\epsilon_t = Y_t - \mu$), which in turn implies that ϵ_t and Y_t will share the same stationarity properties.[2]

Therefore, stationarity of the disturbance term may be the outcome of *either* of the following two conditions.

Condition I: Stationary ϵ_t being the outcome of 'good' model where the growth of X_{1t} fully accounts for the growth of X_{2t} (in Pagan and Wickens sense).
Condition II: Stationary ϵ_t being the outcome of a 'bad' model, where it only reflects the stationarity properties of the dependent variable (as in the above extreme case).

In turn, this raises the following question of how we can distinguish models consistent with Condition I from models consistent with Condition II?

This paper offers the following answer. In addition to examining the properties of the disturbance term, the stationarity properties of the predicted value of the dependent variable are to be examined. If the model performs satisfactorily, it is at least expected that the observed Y_t will share the same stationarity properties with the predicted Y_t. In particular, if the observed Y_t is stationary (or trend stationary), then the predicted Y_t must be stationary (or trend stationary). As an additional test the variances of the observed and predicted Y_t will be compared. Again, it is expected that the variances will be equal.

To further illustrate the point, the next section sets up a simple two-stage least squares metal supply model, examines the stationarity properties of the variables under consideration and discusses the results. Section III tests the model according to the new criteria proposed above. The last section concludes the paper.

II. A SIMPLE METAL SUPPLY MODEL

This section develops a metal export supply model within a two-stage least squares framework: in the first stage a price determination equation is specified (acting as instrumental regression) while in the second stage the supply equation is specified. The motivation behind such structure lies on the assumption that exports of metals and prices may be correlated at time t and therefore some instruments must be used.[3] In what follows a brief description of the factors influencing metal prices is offered.

On the supply side it is expected that the higher the level of stocks the lower the price of the metal in question. Also, the inclusion of time trend is supposed to capture possible technological change effects. On the demand side, it is assumed that industrial production induces an outward shift of the demand for metals which in turn leads to higher prices.

Given that a major part of transactions of metals is made in US dollars, it is deemed appropriate to include the rate of appreciation of the US dollar against the other currencies in the set of explanatory variables. Gilbert (1989), for example, argued that the appreciation of the US dollar in the first half of the 1980s against the other developed currencies appears to have forced greater than proportionate depreciations of developing countries currencies, consequential falls in real wages, and thus greater than proportionate reductions in dollar commodity prices.

The treatment of inflation receives special attention. Deflating prices assumes a one-to-one correspondence between changes in the general price level and changes in metal prices. However, as Houthakker (1975) has argued, the imposition of the homogeneity restriction between inflation and commodity prices might not be an appropriate specification as commodity prices may overreact to inflationary pressures. Therefore, rather than deflating prices, the weighted consumer price index of the OECD countries is included in the set of explanatory variables. Lastly, interest rates and the price of crude oil are also included in the price equation. It is expected that high interest rates depress metal prices while high crude oil prices lead to higher metal prices.

[2] Hall (1986) considered a model with series of different orders of integration. In particular, the logarithm of wage [$I(2)$] was regressed on the logarithm of $CPI[I(2)]$ and on the logarithms of productivity, unemployment rate, and hours worked [all $I(1)$]. The difference between the logarithms of wage rate and CPI was $I(1)$, thus making the regression a legitimate cointegration relationship.
[3] Admittedly, the introduction of such a simplistic model does not capture the realities of the complex interplay of the metal market. For example, a model accounting for the demand side as well as the (possible) endogeneity of exchange rates would be more appropriate. However, the structure introduced here shares the merit of keeping the model tractable while focusing on its econometric characteristics.

In view of the above, the metal price determination equation takes the following form:

$$\ln(P_t) = \mu + \beta_0 Trend + \beta_1 \ln(CPIIC_t) + \beta_2 \ln(SDRUS_t) + \beta_3 \ln(IQ_t) + \beta_4 \ln(STOCK_t) + \beta_5 \ln(INTR_t) + \beta_6 \ln(POIL_t) + \epsilon_t \quad (2)$$

where μ, β_1, β_2, β_3, β_4, β_5 and β_6 are parameters to be estimated while ϵ_t denotes the error term. The remaining notation is as follows: P_t = spot price of the metal (expressed in US$); $CPIIC_t$ = consumer price index of OECD countries (acts as deflator); $SDRUS_t$ = special drawing rights (spot rate, number US$ per SDR); IQ_t = industrial production index in OECD countries; $STOCK_t$ = stocks of metal (held by the metal exchange): $INTR_t$ = one plus the US three-month Treasury bill rate; $POIL_t$ = spot price of crude oil (Saudi Arabia light).

Quarterly data for tin, iron, copper, bauxite and lead were obtained. The series cover the period from 1971: 4 to 1988: 4 – a total of 79 observations – and represent spot rates expressed in US$. With the exception of stocks which were obtained from the *Metal Statistics*, all other series, including the ones to be used in the second stage, were obtained from the *International Financial Statistics*.

Table 1 reports results regarding the order of integration of the variables included in Equation 2.[4] The first three columns refer to levels while the last three columns refer to first differences. With the exception of the price of iron (5% level of significance) none of the other price series is $I(0)$. Differencing them once, however, induces stationarity, therefore concluding that all price series are $I(1)$.[5] Furthermore, none of the explanatory variables was $I(0)$; difference them once however induced stationarity, thus confirming the fact that all series in Equation 2 are $I(0)$. We also tested for trend stationarity; however, no such evidence was found (results of trend stationarity tests are not reported here).

Next, we estimated Equation 2. Results (reported in Table 2) indicate that all five equations exhibited satisfactory performance in terms of expected signs. In particular, the coefficient of *CPIIC* is positive and in three cases exceeds unity. With the exception of the parameter estimate of industrial production for bauxite which was negative, both *SDRUS* and industrial production for the rest of the metals have had a positive effect on prices as expected. Stocks, for the metals with available data, negatively affected prices, though the estimated coefficient for lead was insignificant. The last four columns of Table 2 report cointegration statistics. With the exception of tin (DF test) all statistics indicate that the disturbance term of all price equations is stationary at the 1% level of significance, hence establishing the validity of relationship in Equation 2.

Table 1. *Stationarity tests: price determination equation*

	Levels w/o trend			First differences		
	DF	ADF	PP	DF	ADF	PP
$\ln(P^T)$	−2.17	−2.14	−2.21	−6.77**	−4.55**	−6.81**
$\ln(P^I)$	−2.97*	−2.94*	−3.04*	−7.64**	−3.82**	−7.76**
$\ln(P^C)$	−2.20	−2.30	−2.36	−6.74**	−5.77**	−6.84**
$\ln(P^B)$	−2.85	−2.62	−2.79	−7.53**	−3.86**	−7.76**
$\ln(P^L)$	−2.36	−2.17	−2.58	−6.15**	−4.98**	−6.31**
$\ln(STOCK^C)$	−1.89	−1.98	−2.14	−7.29**	−3.99**	−7.43**
$\ln(STOCK^L)$	−2.27	−2.53	−2.52	−6.87**	−4.81**	−6.68**
$\ln(P^{OIL})$	−1.34	−1.43	−1.47	−5.45**	−4.47**	−5.38**
$\ln(IQ)$	−0.49	−0.50	−0.81	−3.75**	−3.76**	−3.84**
$\ln(CPIIC)$	−2.97*	−2.21	−2.39	−4.92**	−3.08*	−5.08**
$\ln(INTR)$	−1.79	−1.59	−1.97	−6.85**	−6.62**	−6.96**
$\ln(SDRUS)$	−1.28	−1.41	−1.61	−7.10**	−3.81**	−7.25**

Notes: superscripts denote commodities: T = Tin; I = Iron Ore; C = Copper; B = Bauxite; L = Lead; OIL = crude oil. The critical values are: −2.93 (5%) and −3.58 (1%) (Fuller, t_μ statistic, Table 8.5.2). One asterisk (*) denotes rejection of the null hypothesis at the 5% level of significance while two asterisks (**) denote rejection of the null hypothesis at the 1% level of significance.

[4] The following three procedures were employed to determine the order of integration: (1) Dickey-Fuller (DF), (2) augmented Dickey-Fuller (ADF), and (3) Phillips-Perron (PP) Let z_t denote the series under consideration. The DF test is based on the regression $\Delta z_t = \mu + \beta z_{t-1} + \epsilon_t$, where Δ denotes the difference operator (i.e. $\Delta z_t = z_t - z_{t-1}$) while μ and β are parameters to be estimated. A negative and significantly different from zero value of β indicates that z_t is $I(0)$ (Fuller, 1976; Dickey and Fuller, 1981). The ADF test accounts for the possibility that ϵ_t is not white noise; it is based on the following regression: $\Delta z_t = \mu + \beta z_{t-1} + lags(\Delta z_t) + \epsilon_t$. Again, a negative and significantly different from zero value of β indicates that z_t is $I(0)$. The PP test is similar to the ADF one. Their difference lies on the treatment of any 'nuisance' serial correlation aside from that generated by the hypothesized unit root (Phillips and Perron, 1988). To identify the presence of one unit root we test the following: $H_0 : z_t$ is not $I(0)$ against $H_1 : z_t$ is $I(0)$.

[5] Because of the non-availability of data on stocks, this series was not included in the tin, iron ore, and bauxite price equations.

Table 2. *Regression result: price determination equation*

	Tin	Iron	Copper	Bauxite	Lead
μ	−26.72@	1.22	−4.69	−14.5@	−18.2@
	(−6.06)	(0.47)	(−1.49)	(−5.76)	(−4.06)
Trend	−0.11@	−0.01	−0.03@	−0.08@	−0.05@
	(−7.30)	(−0.80)	(−2.24)	(−8.55)	(−3.25)
$\ln(CPIIC_t)$	4.74@	0.71	0.82	4.92@	1.23
	(6.12)	(1.47)	(1.33)	(10.2)	(1.47)
$\ln(SDRUS_t)$	0.73@	0.33@	0.34	1.27@	2.49
	(3.10)	(2.34)	(1.78)	(9.72)	(10.4)
$\ln(IQ_t)$	3.52@	−0.28	1.42@	0.29	3.76@
	(5.77)	(−0.75)	(3.65)	(0.84)	(5.18)
$\ln(STOCK_t)$			−0.09@		−0.03
			(−3.49)		(−0.64)
$\ln(INTR_t)$	−2.16	−1.25	−1.19	−0.94	1.72
	(−1.73)	(−1.64)	(−1.12)	(−1.30)	(1.33)
$\ln(POIL_t)$	0.30@	0.17@	0.25@	−0.04	0.22@
	(4.22)	(3.90)	(5.03)	(−1.06)	(3.26)
R^2	0.91	0.85	0.84	0.97	0.88
DW	0.82**	0.84**	1.11**	1.14**	1.07**
DF	−3.84*	−4.24**	−4.69**	−5.19**	−4.87**
ADF	−3.89**	−4.06**	−4.76**	−4.05**	−4.86**
PP	−3.89**	−4.28**	−4.79**	−5.30**	−4.88**

Notes: The dependent variable is $\ln(P_t)$. The numbers in parentheses denote t-values. The critical, values for the cointegration tests are: (DF = −4.07, ADF and PP = −3.77) (1%), (DF = −3.37, ADF and PP = −3.17) (5%). One asterisk (*) denotes rejection of the null hypothesis of no cointegration at the 5% level of significance while two asterisks (**) denote rejection at the 1% level of significance; @ denotes a parameter estimate significant at the 5 % level.

In the second stage, the supply of exports is expressed as a function of the real world price of metals (predicted from the first stage and then deflated) and the real bilateral exchange rate between the country in question and the USA:

$$\ln(X_t) = \mu + \beta_0 Trend_t + \beta_1 \ln(\hat{p}_t/CPIIC_t) + \beta_2 \ln(R_t) + \epsilon_t \tag{3}$$

where R_t denotes the real exchange rate (i.e. $R_t = EXRATE_t{}^*CPIIC_t/CPI_t$); X_t is volume of exports of the metal in question; CPI_t is the exporting country's consumer price index; and $EXRATE_t$ denotes the bilateral spot exchange rate between the exporting country and the USA, number of domestic currency units per US$.[6] The following nine country/metal pairs were examined: Bolivia/tin, Brazil/iron, Chile/copper, Guyana/bauxite, Jamaica/bauxite, Peru/iron, Peru/lead, Peru/copper and Venezuela/iron.

The first five rows of Table 3, Panel A, report stationarity results regarding prices. All three tests indicated that prices are $I(1)$ at the 1% level of significance (a result which was expected given the strong evidence of cointegration in the first stage).[7] The second variable examined was the real exchange rate (last seven rows of Panel A, Table 3). With the exception of Bolivia and Peru (DF and PP tests), real exchange rate was found to be $I(1)$, a conclusion was supported by all three tests (1% level). Notice that neither prices nor exchange rates presented any evidence of trend stationarity. Finally, if one excludes the Peru/iron and Peru/lead exports which were trend stationary, all other exports presented strong evidence in favour of stationarity, a result which holds at the 1% level of significance (Panel A, Table 3).

Table 4 reports regression results regarding the supply equation. With the exception of three cases, both price and exchange rate coefficients are positive as expected from theory (upward-sloping supply schedule).[8] Furthermore, all models provided overwhelming evidence of a stationary disturbance, a result supported by all three tests (1% level of significance). Based on this finding, one would conclude that the models performed in a satisfactory manner and therefore interpret the elasticities accordingly.

III. TWO ALTERNATIVE INDICATORS

Are the results presented in Table 4 to be trusted? Alternatively, is the finding of a stationary residual a result of Condition I or Condition 11? Consider the Peru/iron case.

[6] Apart for the requirement that at least two $I(1)$ explanatory variables are needed when the dependent variable is $I(0)$, the fact that we did not impose the homogeneity condition is consistent with the hypothesis that domestic costs may not be fully denominated into foreign currency terms.

[7] Such results (i.e. that predicted prices are stationary) could have been reversed only if nominal metal prices and *CPIIC* were cointegrated with the cointegration parameter being unity.

[8] However, a negative sign may be justified on the grounds of a backward bending supply of metals (Chang, 1987; Gilbert, 1989).

Table 3. *Stationarity tests: supply equation*

	Levels w/o Trend DF	ADF	PP	First differences DF	ADF	PP
PANEL A:						
$\ln(P^T)$	0.90	−0.36	0.08	−4.32**	−4.56**	−4.33**
$\ln(P^I)$	0.31	0.14	0.56	−7.00**	−8.28**	−7.05**
$\ln(P^C)$	0.03	−0.52	−0.24	−5.34**	−4.70**	−5.42**
$\ln(P^B)$	−0.68	−1.15	−0.96	−6.95**	−4.55**	−7.18**
$\ln(P^L)$	−0.75	−1.33	−1.23	−5.22**	−4.29**	−5.34**
$\ln(R_O)$	−3.31**	−2.83	−3.18**	−7.21**	−8.03**	−7.74**
$\ln(R_B)$	−1.04	−1.68	−1.60	−5.58**	−4.39**	−5.71**
$\ln(R_C)$	−2.42	−2.14	−2.34	−8.10**	−2.75	−8.49**
$\ln(R_G)$	−1.76	−2.03	−1.94	−7.56**	−6.43**	−7.70**
$\ln(R_J)$	−0.55	−1.30	−0.95	−5.23**	−5.47**	−5.23**
$\ln(R_P)$	−1.69	−1.85	−1.94	−7.18**	−5.70**	−7.35**
$\ln(R_V)$	−1.34	−2.23	−1.58	−5.29**	−6.73**	−5.08**
PANEL B:						
$\ln(X_O^T)$	−2.41	−1.08	−2.08	−4.94**	−3.38**	−5.20**
$\ln(X_B^I)$	−2.86	−2.48	−2.81	−4.54**	−3.94**	−4.53**
$\ln(X_C^C)$	−2.84	−2.03	−2.67	−6.71**	−3.80**	−6.93**
$\ln(X_G^B)$	−3.07*	−2.27	−2.82	−4.65**	−3.57*	−4.81**
$\ln(X_J^B)$	−2.26	−2.19	−2.23	−3.52*	−4.59**	−3.63**
$\ln(X_P^I)$	−8.74**	−5.09**	−9.06**	−8.94**	−7.20**	−9.65**
$\ln(X_P^L)$	−5.08**	−3.04*	−5.35**	−5.15**	−3.09*	−5.46**
$\ln(X_P^C)$	−3.27*	−1.49	−3.23*	−4.42**	−2.81	−4.77**
$\ln(X_V^I)$	−3.05*	−2.75	−2.93*	−3.70**	−3.62**	−3.75**

Notes: The first five rows of Panel A denote the predicted, from the first stage (and deflated by *CPIIC*), price of the commodity. Subscripts denote countries: O = Bolivia; B = Brazil; C = Chile; G = Guyana; J = Jamaica; P = Peru; V = Venezuela. Superscripts are defined in Table 1. The critical values are: −2.93 (5%) and −3.58 (1%) (Fuller, 1976, t_μ statistic, Table 8.5.2). One asterisk (*) denotes rejection of the null hypothesis at the 5 % level of significance while two asterisks (**) denote rejection of the null hypothesis at the 1 % level of significance.

Its R^2 is 0.02, a statistic which is unacceptable by any conventional standards. To that, if one adds the fact that the three slope coefficients exhibited absolute t-values less than unity, the existence of a stationary disturbance term (with cointegration statistics being equal to −8.99, −7.13, and −9.53) is, to say the least, a suspicious finding. Similarly, Peru/lead exhibited an R^2 of 0.16, relatively low t-values, and a stationary error term (with cointegration statistics being equal to −6.32, −4.47 and −6.42). Therefore, at least for these two cases, stationarity of the disturbance term seems to be the outcome of Condition II rather than Condition I.

In what follows we will discuss results pertaining to the stationarity properties of the predicted $\ln(X_t)$ as discussed previously (Panel A of Table 5). In accordance to the argument advanced earlier, stationarity test results reported in Panel A of Table 5 should lead to the same conclusions as the stationarity test results reported in Panel B of Table 3.

Consider the case of Bolivia/tin. While the observed $\ln(X_t)$ was trend stationary (all statistics supported this conclusion at the 1% level of significance), no test gave evidence of trend stationarity of the predicted $\ln(X_t)$ as no statistic was less than −2.00. Guyana/bauxite presented the same pattern: although the observed exports were trend stationary, their predicted counterparts were not. Similar conclusions hold for the Jamaica/bauxite, Peru/iron, Peru/lead, and Peru/copper cases. Exceptions to this trend constitute the cases of Brazil/iron (DF and PP tests at the 5 % level and ADF test at the 1% level), Chile/copper (DF test, 5% level), and Venezuela/iron (DF test, 5% level). Therefore, contrary to expectations, even in cases where *both* conventional *and* cointegration statistics indicate a relatively good model (e.g. Peru/copper), stationarity properties of the predicted $\ln(X_t)$ indicated that the models did not perform in a satisfactory manner.

To further investigate the differences (or similarities for that matter) between the observed and predicted export series, the hypothesis that their sample variances were equal was tested. For the instances where exports were trend stationary, the deterministic trend component was removed from both observed and predicted $\ln(X_t)$. Results are reported in Panel B of Table 5. The first and second column report the variances of the observed and predicted exports while the last column reports the respective ratio. With the exception of Brazil/iron, which exhibited a ratio of 1.15 (not significantly different from unity at the 5 % level), all other ratios far exceeded unity. This latter result

Table 4. *Regression results: supply equation*

	μ	β_0	β_1	β_2	R^2	DW	DF	ADF	PP
Bolivia/	4.71$^{@}$	−0.01$^{@}$	0.35$^{@}$	0.05	0.77	1.45**	−6.11**	−4.54**	−6.30**
tin	(29.7)	(−7.67)	(4.14)	(0.43)					
Brazil/	3.99$^{@}$	0.03$^{@}$	1.58$^{@}$	−0.17	0.76	1.38**	−6.31**	−4.63**	−6.43**
iron	(3.83)	(9.05)	(4.82)	(−1.07)					
Chile/	3.12$^{@}$	0.01$^{@}$	0.18	0.19$^{@}$	0.82	2.19**	−7.82**	−4.63**	−7.95**
copper	(12.8)	(5.18)	(1.92)	(3.06)					
Guyana/	5.05$^{@}$	−0.01$^{@}$	−0.38$^{@}$	0.12	0.63	1.23**	−5.19**	−4.12**	−5.34**
bauxite	(21.5)	(−9.86)	(−3.58)	(0.89)					
Jamaica/	5.40$^{@}$	−0.01$^{@}$	0.56$^{@}$	0.27	0.57	0.74**	−5.18**	−4.04**	−5.30**
bauxite	(12.6)	(−5.30)	(2.03)	(0.87)					
Peru/	5.82$^{@}$	0.01	0.44	0.07	0.02	2.11**	−8.99**	−7.13**	−9.53**
iron	(2.06)	(0.21)	(0.58)	(0.31)					
Peru/	8.10$^{@}$	−0.01$^{@}$	−0.12	0.30$^{@}$	0.16	1.54**	−6.33**	−4.47**	−6.42**
lead	(14.1)	(−2.79)	(−1.63)	(2.73)					
Peru/	14.1$^{@}$	0.02$^{@}$	0.71$^{@}$	0.87$^{@}$	0.63	1.53**	−4.69**	−4.76**	4.79**
copper	(5.97)	(3.63)	(3.20)	(4.50)					
Venezuela/	3.94$^{@}$	−0.02$^{@}$	0.32	1.05$^{@}$	0.46	1.01**	−4.24**	−4.97**	4.70**
iron	(6.44)	(−2.21)	(0.46)	(3.90)					

Notes: The dependent variable is $\ln(X_t)$. @ denotes parameter estimate significant at the 5 % level. The numbers in parentheses denote t-statistics. Critical values along with some other notes are presented in Table 2.

Table 5. *Results of proposed tests*

PANEL A: Stationarity tests: supply equation predicted values

	Levels w/o trend			Levels with trend		
	DF	ADF	PP	DF	ADF	PP
$\ln(X_O^T)$	2.61	1.32	2.16	−1.45	−1.93	−1.55
$\ln(X_B^I)$	−2.35	−3.00*	−2.51	−3.20*	−4.00**	−3.15*
$\ln(X_C^C)$	−1.19	−2.23	−1.16	−2.22	−3.30*	−2.46
$\ln(X_G^B)$	−2.38	−2.29	−2.30	−0.49	−0.97	−0.59
$\ln(X_J^B)$	1.13	1.65	1.58	−1.24	−1.31	−1.04
$\ln(X_P^I)$	−0.25	0.51	0.01	−2.84	−2.89	−2.73
$\ln(X_P^L)$	−1.26	−2.09	−1.78	−1.38	−2.15	−1.93
$\ln(X_P^C)$	−1.83	−1.95	−1.92	−0.94	−1.84	−1.63
$\ln(X_V^I)$	−0.95	−1.35	−1.05	−1.90	−2.92*	−2.19

PANEL B: Variances of observed and predicted $\ln(X_t)$

	Variance of observed $\ln(X_t)$	Variance of predicted $\ln(X_t)$	ratio
$\ln(X_O^T)$	0.051	0.019	2.703
$\ln(X_B^I)$	0.194	0.169	1.150*
$\ln(X_C^C)$	0.013	0.003	4.825
$\ln(X_G^B)$	0.034	0.007	5.161
$\ln(X_J^B)$	0 097	0 009	10.909
$\ln(X_P^I)$	0.167	0.009	17.994
$\ln(X_P^L)$	0.047	0.010	4.555
$\ln(X_P^C)$	0.071	0.027	2.588
$\ln(X_V^I)$	0.164	0.035	4.642

Notes: Panel A: the critical values are: −2.93 (5 %) and −3.58 (1 %) (Fuller, 1976, t_μ statistic, Table 8.5.2). One asterisk (*) denotes rejection of the null hypothesis at the 5 % level of significance while two asterisks (**) denote rejection of the null hypothesis at the 1 % level of significance. Subscripts and superscripts are given in Tables 1 and 3. Panel B: The first column gives the variance of the observed $\ln(X_t)$ while the second column gives the variance of the predicted $\ln(X_t)$. Notice that in both cases the deterministic trend has been removed. The third column gives the ratio of observed over predicted variance of $\ln(X_t)$. One asterisk (*) indicates that the null hypothesis of equal variances cannot be rejected at the 5% level of significance (Brazil/iron case only).

further points to the conclusion that observed and predicted $\ln(X_t)$ have indeed different statistical properties.

IV. CONCLUDING COMMENTS

This paper considered a model in which the dependent variable was stationary while the explanatory variables were non-stationary. A metal export supply equation belonging to the class of unbalanced regressions (in the terminology of Banerjee *et al.*) was specified for nine countries. The finding of a stationary disturbance term, pointed to the conclusion that the model performed in a satisfactory manner. To account for the fact that cointegration statistics could lead to erroneous conclusions two tests were proposed. First, the stationarity properties of the predicted and observed dependent variables were compared. Second, the hypothesis that their sample variances were equal was tested. Results from both tests pointed to the surprising conclusion that only one model performed well. In turn this finding implies that in assessing the performance of models of the type examined here, one should not rely on the stationary properties of the error term alone.

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REFERENCES

Banerjee, A., Dolado, J., Galbraith, J. W. and Hendry, D. F. (1993) *Co-Integration, Error-Correction, and the Econometric Analysis of Non-Stationary Data*, Oxford University Press, New York.

Chang, K. P. H. (1987) The role of developing country debt and currency devaluation in the current commodity slump, *Division Working Paper No 1987–1*, Commodity Studies and Projections Division, *The World Bank*, February.

Dickey D. and Fuller, W. A. (1979) Distribution of the estimators for time series regression with unit roots, *Journal of the American Statistical Association,* **74**, 427–31.

Engle R. F. and Granger, C. W. (1987) Co-integration and error correction: presentation, estimation, and testing; *Econometrica*, **55**, 251–76.

Fuller, W.A. (1976) *Introduction to Statistical Time Series*, John Wiley, New York.

Gilbert, C. L. (1989) The impact of exchange rates and developing country debt on commodity prices, *The Economic Journal*, **99** 773–84.

Hall, S.G. (1986) An application of the Granger and Engle two-step estimation procedure to United Kingdom aggregate wage data Data, *Oxford Bulletin of Economics and Statistics*, **48**, 229–40.

Houthakker, H. S. (1975) Comments and discussion, *Brookings Papers on Economic Activity*, **3**, 718–20.

International Monetary Fund, *International Financial Statistics*, selected issues

Pagan, A. R. and Wickens, M. R. (1989) A survey of some recent econometric methods, *The Economic Journal*, **99**, 962–1025.

Phillips, P. C. B. and Perron, P. (1988) Testing for a unit root in time series regression, *Biometrica*, **65**, 335–46.