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Energy Savings via Foreign Direct Investment? - Empirical evidence from Portugal

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Abstract

This study runs a cointegration analysis on annual data from 1980 to 2007 to investigate the relationship between primary energy consumption, economic growth and net inflows of foreign direct investment with the Engle and Granger method, Stock-Watson dynamic ordinary least squares (DOLS), the bounds testing approach to cointegration and error correction modelling. The empirical results suggest that there is a stable long run linear cointegration relationship between these three variables. While income has a large and positive influence on energy consumption, the results point to a small but negative effect of foreign direct investment (FDI) on energy consumption. As for the short-run relationship among the series, the estimation and inference in the autoregressive distributed lag error correction model (ARDL) further confirm this link. These findings have important policy implications, since the promotion of appropriate structural policies aiming at attracting foreign investment can induce energy conservation without obstructing economic growth.

Keywords: energy consumption, economic growth, foreign direct investment, cointegration

1. Introduction

Since the Kyoto protocol, many countries are tackling global warming and are committing to reduce their energy use and carbon emissions by promoting renewable energy sources and taking major energy efficiency policies initiatives to develop a more independent energy mix, which is currently dominated by imported liquid fossil fuels and natural gas (see Cravinho et al, 2011; Pereira and Pereira, 2010). The increasing attention given to global energy issues and international policies, offers a renewed incentive to research the linkages between the energy sector and economic performance by emphasizing potential energy efficiency gains stemming from Foreign Direct Investment (hereafter FDI), i.e. energy that would be saved as a result of FDI.

The goal of this paper is to extend the strand of literature on energy consumption and economic growth to examine the energy saving technology transfer hypothesis via FDI. This literature (see, *inter alia*, Belloumi, 2009; Ozturk, 2010; Payne, 2010) suggests a causal and positive relationship between energy consumption and economic growth. Additionally, several studies also present statistical evidence with time series analysis that the two variables are cointegrated and find long run solutions or equilibrium relationships from non stationary series (Yuan et al., 2007; Apergis and Payne, 2010).

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The importance of FDI on economic growth is in now well recognized in the empirical literature (see, for example, Dunning, 1993; Barrel and Pain, 1996; De Mello, 1999; Trevino et al., 2002; Basu et al., 2003). A consensus view is reached on the clear positive impact of FDI on overall economic growth in less developed countries, while research that focuses only on developed countries has found ambiguous results (Borzenstein et al., 1998; Nair Reichert et al., 2001). Most of the existing studies (Barrel and Pain, 1997; Blomstrom et al., 1998; Borensztein et al., 1998) focus on the impact of FDI over the productivity and technology transfer in general and up till now the literature is scarce and provides inconclusive direct evidence regarding the impacts of FDI on energy consumption specifically.

The results emerging from this strand of literature are mainly based on empirical evidence from developing countries. Firm- and plant-level analysis has found a negative impact of foreign ownership on the energy intensity of firms (Eskeland and Harrison, 2003; Fisher-Vanden et al., 2004). Cross-sectional aggregation of economic data has revealed that FDI has a reducing impact on energy intensity (Mielnik and Goldemberg, 2002), while macro level panel data models have not been able to confirm a robust energy reducing effect by FDI (Hübler and Keller, 2008). Besides that, Tang (2009) has identified a long run cointegrating relation between electricity consumption, income and FDI and a bilateral direction of causality between these variables.

The first contribution of this paper to this literature is that it empirically investigates the effect of FDI on energy consumption at country level. Energy saving technology transfer could answer the question if more FDI flows to the economy can bring about the technology transfer, which could restrain energy use. Even if such an effect is not obvious to analyze at the aggregate level, research is recommended to identify country specific characteristics that are likely to interact with FDI and therefore put forth an energy reducing effect. It can be helpful to use country specific data in order to analyze whether FDI inflows reduce energy use to provide policymakers a better understanding of the energy use-economic growth-foreign direct investment nexus to assist in the adoption and implementing of key energy efficiency and climate change mitigation measures.

The second contribution is that unlike majority of previous studies, the present study uses a combination of different cointegration regression techniques, considered more appropriate for estimation purpose in case of small samples, such as the Engle and Granger (1987) two-step procedure, Stock and Watson (1983) Dynamic Ordinary Least Squares (DOLS) and the Autoregressive Distributed Lag (ARDL) and error correction model bounds testing approach (Pesaran et al., 2001). By making use of these modeling procedures, this study is capable not only to estimate long run equilibrium relationships amongst variables, i.e., confirm the existence of cointegration, but also to investigate short-run dynamics around equilibrium.

The reminder of this paper is organized as follows. Section 2 contains the description of the data and discussion of different approaches towards establishing cointegration between variables and estimating the long-run relationship, and the subsequent specification of an error correction model representing the short-run adjustment towards equilibrium. Section 3 presents and discusses the empirical results. The paper ends with the main conclusions and policy implications.

2. Data and estimation techniques

The data used in this study are obtained from various sources and relate to the period from 1980 to 2007. Prior to the empirical analysis, all variables are transformed into logarithmic form to reduce heteroscedasticity. Annual data on energy consumption has been gathered from the International Energy Agency. Income data is from World Bank's International Comparison Program database. Foreign direct investment inflows are taken from the Balance of Payments Statistics and International Financial Statistics database and browser on CD-ROM published by the International Monetary Fund.

As the purpose of this paper is to find out whether there is any relationship between FDI and energy consumption, the linear specification for the long run energy consumption function adopts the following form:

$$\ln EC_t = \alpha_1 + \beta_1 \ln GDP_t + \beta_2 \ln FDI_t + \varepsilon_t \quad (1)$$

where α_1 is a constant and ε_t the error term. EC_t is the total primary energy consumption in kg of oil equivalent units. GDP_t is real gross income per capita proxied by gross domestic product converted to 2005 constant international US dollars using purchasing power parity rates. FDI_t refers to the net inflows of foreign direct investment as a percentage of gross domestic product. Primary energy consumption refers to the supply to users without any conversion or transformation of crude energy. The use of energy is occurring on the consumption side of the energy balance in the energy supply sector. The logarithmic model has the advantage that its parameters β_1 and β_1 are elasticities which provide a simple and convenient way to measure the effect of the explanatory variables on the response variable.

This study follows estimation techniques used commonly in time series econometrics. If an Ordinary Least Squares (OLS) regression is estimated, regression models for non-stationary variables give spurious results (Granger and Newbold, 1974). Standard regression proprieties hold only if variables are stationary. Most of economic variables do not satisfy these assumptions, but when combinations of I(1) variables become I(0), or stationary, then OLS estimates are valid. In this case, these variables are cointegrated and they share a long term or common equilibrium relationship. Long run equations can be used to detect the presence of cointegration. Only if the residuals from the cointegrating regression are stationary, a valid long run relationship exists between the variables. On the contrary, if the stationary test indicates I(1), therefore the variables are not cointegrated and we have the case of spurious regression.

To test for the degree of integration of the individual time series, using standard unit root tests on the levels and first differences of variables, this study employs the regression equation for the Augmented Dickey-Fuller test (Dickey and Fuller, 1979). The null hypothesis to be tested is that the series is non-stationary, i.e. has a unit root, against the alternative that it does not. This stationary test uses the lagged dependent variable to overcome the problem of autocorrelation often found in time series data and can be expressed in its most general form as shown in the following equation:

$$\Delta Y_t = \mu_t + \eta_t Y_{t-1} + \sum_{j=1}^{p} \alpha_j \Delta Y_{t-j} + \beta_t \gamma_t + \varepsilon_t \quad (2)$$

where, the " μ " symbol denotes the drift term, " γ" denotes the time trend and "ε" the distributed random error correction term with zero value of mean and constant variance. The correct value for " p ", the largest lag length used, is determined by reference to the Schwartz-Baysian information criteria. Robustness checks are done with the more robust PP test (Phillips and Perron, 1988) for the same function forms to overcome the weakness of the ADF test. The latter are similar to former, but they incorporate an automatic correction to the Dickey Fuller procedure to control for serial correlation when testing for a unit root.

The Engle and Granger (1987) begins with pre-testing the variables for their order of integration and assuring that all of them are I(1). To test for cointegration between two or more non-stationary time series, it simply requires running an OLS regression, saving the residual and then running the ADF test on the residual to assess if the regression produces a stationary error term. The computed ADF statistics are compared with the critical values tabulated in MacKinnon (1991). If test statistics reject the null hypothesis of no cointegration, then the variables are cointegrated, i.e., they do have a long run relationship.

Evidence based on Monte Carlo experiments shows that, when dealing with small sample sizes, the Stock and Watson dynamic OLS method is a more robust single equation method for parameter estimation than OLS as it includes the leads and lags of first differences of the repressors. Apart from correcting for endogeneity and serial correlation effect, the DOLS procedure allows to use cointegrated variables, which are integrated of mixed order. It involves regressing any I(1) variables on other I(1) variables, any I(0) variables and leads and lags of the first differences of I(1) variables. The long run model for total energy consumption can be expressed as follows:

$$\ln EC_t = \alpha_2 + \beta_1 \sum_{i=-m}^{i=m} \varphi_i \Delta \ln GDP_{t-i} + \beta_2 \sum_{i=-n}^{i=n} \phi_i \Delta \ln FDI_{t-i} + \varepsilon_t \tag{3}$$

where α_2 and ε_t are the intercept and error terms respectively. Subscripts m and n are the lengths of leads and lags of the repressors and the parameters β_1 and β_1 of this function are elasticities.

The ARDL bounds testing procedure is an alternative way of assessing the cointegration and to identify the long run relationship between energy consumption and FDI. The merit of this technique is that it can be applied regardless whether underlying regressors are purely I(1) or integrated of order I(0) and performs well on small sample sizes. This means that the pre-testing problems associated with conventional cointegration, which requires that variables are already classified of order I(d) can be overlooked. It is capable of dealing with the likely endogeneity problem of the regressors and as such provides unbiased parameter estimates and valid t-statistics of the long run model (Harris and Sollis, 2003) and therefore is preferred to all other methods to estimate together the long run relationships and the short run dynamic interactions among the variables. The approach involves estimating the conditional error correction version of the ARDL model for energy consumption and is represented by the following equation:

$$\Delta \ln EC_t = \alpha_3 + \delta_1 \ln EC_{t-1} + \delta_2 \ln GDP_{t-1} + \delta_3 \ln FDI_{t-1} + \sum_{i=1}^{n} \delta_{4i} \Delta \ln EC_{t-i}$$

$$+ \sum_{i=0}^{n} \delta_{5i} \Delta \ln GDP_{t-i} + \sum_{i=0}^{n} \delta_{6i} \Delta \ln FDI_{t-i} + \varepsilon_t \qquad (4)$$

where Δ is the first difference operator, EC_t, the dependent variable, and GDP_t, FDI_t are the explanatory variables and ε_t the white noise error term. From the above model δ_1, δ_2 and δ_3, are the long run parameters. Lag selection is selected by a criterion such as Akakie Information Criterion (hereafter AIC). For annual data, Pesaran and Shin (1999) recommend choosing a maximum of 2 lags. The joint significant *F*-test or Wald statistic of the lagged level variables is employed for investigating the existence of a long run behaviour among the variables. The null hypothesis of having no cointegration, H_0: $\delta_1 = \delta_2 = \delta_3 = 0$ is tested against the alternative hypothesis, H1: $\delta_1 \neq \delta_2 \neq \delta_3 \neq 0$. The critical values used are those tabulated by Pesaran et al. (2001) for different numbers of regressors and for the ARDL model with a restricted intercept and no trend. There are two sets of critical values, one upper bound and a lower bound. The former refers to I(1) variables and the latter to I(0) series. If the computed *F*-statistic exceeds the upper bound of the critical values, then the null hypothesis of no cointegration is rejected. If it is less than the lower bounds value, then the null cannot be rejected, but if it falls between the two levels of the bands, the cointegration test becomes inconclusive.

If a long-run relationship is established between the variables, the long run model and the short run dynamics derived from an error correction model are estimated from the following equations respectively:

$$\ln EC_t = \alpha_4 + \sum_{i=1}^{n} \delta_{1i} \ln EC_{t-i} + \sum_{i=0}^{n} \delta_{1i} \ln GDP_{t-i} + \sum_{i=0}^{n} \delta_{1i} \ln FDI_{t-i} + \mu_t \qquad (5)$$

$$\Delta \ln EC_t = \alpha_5 + \sum_{i=1}^{n} \delta_{2i} \Delta \ln EC_{t-i} + \sum_{i=0}^{n} \delta_{2i} \Delta \ln GDP_{t-i} + \sum_{i=0}^{n} \delta_{2i} \Delta \ln FDI_{t-i} + \psi ECM_{t-1} + \vartheta_t \qquad (6)$$

where ψ_t is the coefficient the error correction term ECM_{t-1} defined as

$$ECM_t = \ln EC_t - \alpha_4 - \sum_{i=1}^{n} \delta_{1i} \Delta \ln EC_{t-i} + \sum_{i=0}^{n} \delta_{1i} \Delta \ln GDP_{t-i} + \sum_{i=0}^{n} \delta_{1i} \Delta \ln FDI_{t-i} \qquad (7)$$

The error correction term should have a negative sign and have a statistical significant coefficient. The stability of the relationship between variables is further investigated by means of diagnostic tests on the Error Correction Models (ECM) residuals. Failure of serial correlation, heteroscedasticity and functional form or normality tests implies the model is inadequate. The goodness of fit for the chosen ARDL model is checked through stability tests such as Cumulative Sum of Recursive Residuals (CUSUM) and Cumulative Sum of Square of Recursive Residuals (CUSUMQ) tests.

The OLS approach, while simple to implement, is not without problems. Parameter estimates can be biased, irrespective of the number of integrated covariates, when the number of regressors exceeds two because there can be more than one cointegrating relationship or vector. Being concerned with the robustness of univariate cointegration tests, the existence of only one cointegration relationship is not assumed a priori and further evidence on cointegration is tested for in the Johansen and Juselius (1990) maximum likelihood estimation procedure to test for the presence of multiple cointegrating vectors. The Johansen's multivariate approach to cointegration is a full information technique and consists of estimating the rank of the matrix Π in the following equation:

$$\Delta X_t = \delta + \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-1} + \Pi X_{t-1} + \varepsilon_t \tag{8}$$

where X_t is a column vector of variables that are integrated of order one and ε_t is a nx1 vector of innovations. Γ_i and Π are coefficient matrixes, Δ is a difference operator, p is the lag lenght and δ is a constant. If the coefficient matrix Π has zero rank, no stationary combination can be identified, hence variables X_t are not cointegrated. Thus, if the rank of Π is different from zero, there exist r possible stationary linear combinations and variables are cointegrated. Johansen (1991) proposes two different likelihood ratio tests, which have non-standard asymptotic null distributions, to determine the number of cointegrating vectors, i.e. the trace test and maximum eigenvalue test. The trace test tests the null hypothesis that the cointegration rank is equal to r against the alternative that the cointegration rank is k. The maximum eigenvalue test, on the other hand, tests the null hypothesis of r cointegrating vectors against the alternative hypothesis of $r+1$ cointegrating vectors.

3. Estimation and discussion of results

Before proceeding with any cointegration method, it is important to investigate the order of integration of the variables. Table 1 summarizes the results of the ADF and PP stationary tests for the variables on their level and first difference form. From the table, it is evident that the three variables are not stationary on their levels and this result is justified by both unit root tests with and without trend terms. Moreover, the first differences suggest that all variables are stationary. Therefore, the hypothesis that the time series contain an autoregressive unit root is accepted. The Dickey-Fuller test based on the 10%, 5% and 1% critical values supports the hypothesis that all series contain a unit root. Although, employing the Phillips-Perron test gives different results for the test with an intercept and trend and lowers the level of significance, the main conclusion is qualitatively the same as reported by the Dickey-Fuller tests. Both tests are in favour of the unit root hypothesis in all time series. The combined results of all tests suggest that all the series appear to be I(1) processes, hence integrated of order one.

Since the data appears to be integrated of order one and stationary in first differences, the next step is to estimate long run parameters from equations (1), (3) and (5). Table 2 reports the long run cointegration testing results produced by Engle and Granger, DOLS and ARDL approaches and provides evidence for the existence of one long run cointegration relationship between EC_t, GDP_t and FDI_t in the second column from the left side. Both ADF and PP stationary tests applied on the error term retrieved by simple OLS indicate that the residuals are stationary. Statistics of AIC and SBC, which are -3.51 and -3.24 respectively, are both significant and less than their critical values of -2.97 at 5 percent level and -2.62 at 10 per cent level of significance.

Table 1: Augmented Dickey-Fuller and Philips-Perron stationary tests

	Test with an intercept		Test with an intercept and trend		Test with no intercept or trend	
	Levels	1st differences	Levels	1st differences	Levels	1st differences
ln EC_t	-1.45 (-1.49)	-5.11* (-4.94*)	-0.71 (-0.66)	-5.61* (-5.64*)	3.27 (3.31)	-1.27 (-3.71*)
ln GDP_t	-3.22** (-1.27)	-2.72*** (-2.95***)	-3.34*** (-1.61)	-4.68* (-2.14)	3.60 (2.95)	-1.81*** (-1.67)
ln FDI_t	-3.35** (-3.25**)	-6.25* (-12.75*)	-4.07** (-4.07**)	-6.22* (-16.24*)	-2.75* (-2.65*)	-6.22* (-10.38*)
CV (1%)	-3.69	-3.71	-4.33	-4.35	-2.65	-2.66
CV (5%)	-2.97	-2.98	-3.58	-3.59	-1.95	-1.95
CV (10%)	-2.62	-2.62	-3.22	-3.23	-1.60	-1.61

Note: the asterisks *, ** and *** denote the significance level at 1, 5 and 10 per cent respectively. The optimal lag length for the Augmented Dickey-Fuller unit root test is selected using the Schwartz Information Criteria (SIC), while the bandwidth for the Philips-Perron stationary tests is selected using Newey-West Barlett kernel. All variables are transformed into logarithm form. The maximum lag length is 4 for the ADF test. All tests are conducted including no intercept or trend, only an intercept or both an intercept and linear deterministic trend. The McKinnon critical values reported in the last three rows are for the 1, 5 and 10 per cent levels of significance. The Philips-Perron unit root tests results are presented within the parentheses.

Stock Watson DOLS estimates of the long run parameters with all variables appearing in levels and leads and lags of their first differences are placed into the third column in Table 2. This equation uses up to one leads and lags of the dependent variables. Likewise the OLS estimation model, the adjusted R-squared value of the dynamic regression model is high. This indicates a good-fit situation of the series in both cases.

Having found that there is a long run relationship between the variables with OLS and DOLS, the next step is to confirm the long run relationship using the ARDL approach and estimate its long run coefficients. The ARDL(1,0,0) specification is selected based on Schwarz Bayesian Criterion. The result of the *F*-test for cointegration from the ARDL bound method is reported in the last column in Table 2. The calculated *F*-statistic is 2.81 and not greater than the critical values of the top level of the bound in significance levels 1, 5 and 10 per cent. Proof of long run relation among variables is not established. The computed *F*-statistics fall below the lower bound critical values for the different levels of significance, except at 10 per cent significance level. According to the computed *F*-statistic compared against the Pesaran et al. (2001) lower bound critical value of 2.63, the null hypothesis of no cointegration in lag order one is rejected. The bounds cointegration test is regarded as inconclusive because the *F*-statistic falls into the bounds.

Table 2: Estimated long run coefficients

Dependent variable: ln EC_t	OLS	DOLS	ARDL
Constant	-5.63* (0.44)	-5.56* (0.47)	-5.22* (0.48)
ln GDP_t	1.58* (0.05)	1.58* (0.05)	1.54* (0.05)
ln FDI_t	-0.02*** (0.01)	-0.03*** (0.02)	-0.04** (0.02)
Δ ln GDP_{t-1}		-0.33 (0.33)	
Δ ln GDP_{t+1}		0.001 (0.25)	
Δ ln FDI_{t-1}		-0.009 (0.008)	
Δ ln FDI_{t+1}		-0.002 (0.01)	
Phillips Perron	-3.24**		
Augment Dickey Fuller	-3.51**		
Diagnostic tests			
Adjusted R^2	0.98	0.99	
Durbin Watson statistic	1.23	2.22	
X^2 Serial correlation	2.30 [0.13]	0.58 [0.45]	
X^2 Functional form	0.46 [0.49]	0.22 [0.64]	
X^2 Normality	2.66 [0.26]	2.01 [0.37]	
X^2 Heteroscedasticity	2.79 [0.09]	3.32 [0.07]	

Note: the asterisks *, ** and *** indicate statistically significant at 1, 5 and 10 per cent significance level and figure in parenthesis and brackets are standard error and *p*-values respectively. DOLS long-run variance estimate is done with Barlett kernel. Newey-West fixed bandwidth is set to three. The leads and lag order of the DOLS is set to one on the first differences of the dependent variables. The last column displays the long run coefficients and their asymptotic standard errors based on the estimates of the selected ARDL regression with the maximum order of lag set to 2. The results don't change all that much if lag order is set to 1. The lag length criteria or optimal lag length is obtained with an unrestricted VAR model based on SBC criterion. The upper bound critical value of the F-test for cointegration is 5, 3.87 and 3.35 respectively, at the 1, 5 and 10 per cent level of significance. The critical values of *F*-statistics taken from Pesaran et al. (2001, Table CIii) for lower bound are 4.13, 3.10 and 2.63 respectively, for the same significance levels. Diagnostic tests are the Lagrange multiplier test of residual serial correlation, the Ramsey's RESET test for functional form using the square of the fitted values, the normality test based on a test of skewness and kurtosis of residuals and the heteroscedasticity test based on the regression of squared residuals on squared fitted values. The results show that in the long GDP_t has a significant effect on EC_t and a one per cent increase in this variable leads to 1.54 per cent to 1.58 per cent increase in the dependent variable. FDI_t has also a significant effect on EC_t, meaning that one per cent increase in this variable leads to a 0.02 per cent to 0.04 per cent fall in energy consumption.

Next, the short run dynamics of the variables are examined by estimating the ARDL error correction representation in equation (6). Table 3 reports the short run coefficients of the variables estimated from the selected ARDL(1,0,0) model based on Schwarz Bayesian Criterion. In the short run error correction model, the income coefficient is equal to 1.13. It has the theoretically expected sign and is statistically significant at the 1 per cent level. This value is lower than the long run income elasticity values reported in Table 2 ranging between 1.54 and 1.58. This means that this variable has a significant and sizable effect on the dependent variable. It is also observed, that FDI_t has statistically significant short run and long run parameters, varying between -0.02 and -

0.04, and are inversely related to EC_t. This infers that, this explanatory variable will induce a decrease in energy consumption.

The ECM version of the ARDL model is significant at 1 per cent level with $F(3,22) = 17.61$ and p-value < 0.01, besides de adjusted R-squared which is equal to 0.71. It has a statistically significant lagged error correction coefficient which has a negative sign and is less than unity as expected by theory. The coefficient of ECM_{t-1} indicates how much of the disequilibrium in the short run will be eliminated in the long run. This result implies that the adjustment process to equilibrium is quite fast. Approximately 73 per cent of the previous year's deviations in energy consumption from its equilibrium path are corrected over the following year.

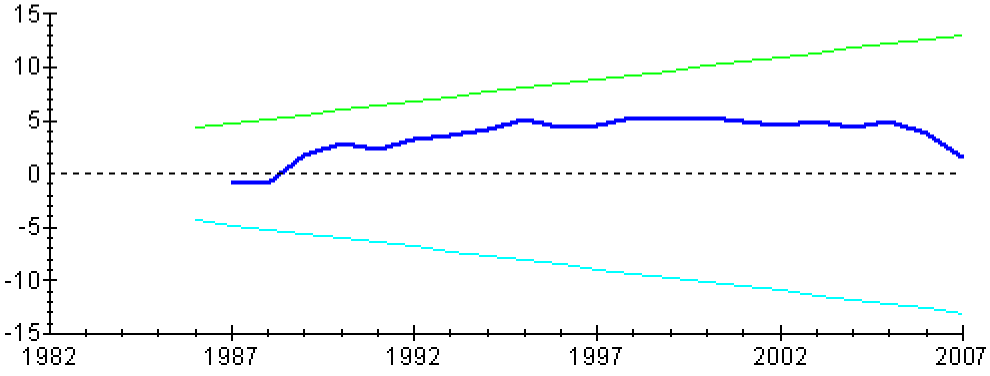
Table 3: Estimated short run error correction model

Dependent variable: $\Delta \ln EC_t$	Coefficient
Constant	-3.83* (0.69)
$\Delta \ln GDP_t$	1.13* (0.17)
$\Delta \ln FDI_t$	-0.03** (0.01)
ECM_{t-1}	-0.73* (0.11)
Diagnostic tests	
F-statistic	F(3, 22) = 17.61 [0.00]
Adjusted R^2	0.71
Durbin Watson statistic	2.01
X^2 Serial correlation	0.41[0.52]
X^2 Functional form	0.73[0.39]
X^2 Normality	1.11 [0.57]
X^2 Heteroscedasticity	0.08 [0.78]

Note: the asterisks *, ** and *** denotes statistically significant at 1, 5 and 10 per cent level. Figures in brackets are p-values and standard errors are in parentheses.

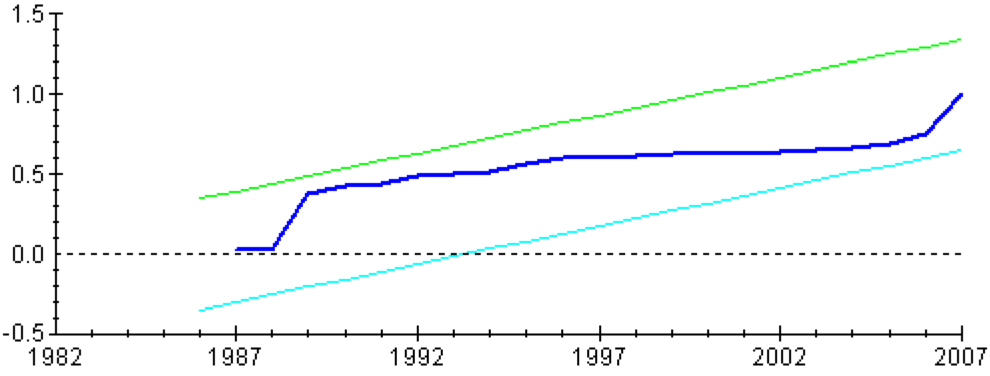
The ECM model passes all diagnostic tests. There is no evidence of serial correlation. The model seems to be well specified with reference to functional form. Diagnostic checking does not detect any significant deviation from a normal distribution and no econometric problem resulting from heteroscedastic residuals. Similar conclusions are reached when comparing the long run estimation test results. Since unstable parameter may cause misspecification issues and ultimately produce biased results, parameter stability tests are performed on the selected ARDL representation of the ECM. Recursive estimation using the cumulative sum (CUSUM) and the cumulative sum of squares (CUSUMSQ) indicate that the parameters remain stable over the sample period. As it is clear from Figure 1 and Figure 2, the plots both the CUSUM and CUSUMSQ of recursive residuals, drawn to check the stability of the long run coefficients together with the short run dynamics, are within the critical bounds of 5 per cent. Graphical inspection indicates that the model's long run coefficients are structurally stable.

Figure 3: Plot of cumulative sum tests for the coefficients stability



The straight lines represent critical bounds at 5% significance level

Figure 4: Plot of cumulative sum of squares tests for the coefficients stability



The straight lines represent critical bounds at 5% significance level

Further evidence on cointegration is found with the Johansen maximum likelihood procedure. Based on the Schwarz Bayesian Criterion, the appropriate number of lags in the VAR system with unrestricted intercept and no trend is set to one. Table 4 indicates that the cointegration likelihood ratio test based on the maximum eigenvalue cannot reject the null hypothesis of no-cointegration because the test statistic is 18.80 and is lower than the critical values of 21.12 and 19.02 at the 5 per cent and 10 percent level of significance respectively. The trace statistic gives opposite results, providing evidence to reject the null of zero cointegrating vectors in favour of one cointegrating vector at 5 per cent and 10 per cent levels of significance. The trace statistic is 32.53 and higher than the critical values of 31.54 and 28.78 at the 5 per cent and 10 per cent levels respectively. On the basis of the results of trace tests, there exists a long run relationship between the variables included in the cointegrated vector and hence evidence for cointegration is found.

Table 4: Johansen and Juselius cointegration tests

Null	Alternative	Eigenvalue	Critical values	
			95%	90%
Maximum eigenvalues				
r = 0	r = 1	18.80	21.12	19.02
r < = 1	r = 2	12.70	14.88	12.98
r < = 2	r = 3	1.03	8.07	6.50
Trace statistic				
r = 0	r > 1	32.53*	31.54	28.78
r < = 1	r = > 2	13.73	17.86	15.75
r < = 2	r = 3	1.03	8.07	6.50

Note: in the maximum likelihood procedure, *r* indicates the number of cointegration relationships. Cointegration tests based on maximal eigenvalue and on trace statistics of the stochastic matrix are compared with the critical values from Johansen and Juselius (1990). The asterisk indicates rejection of the null hypothesis at 95 per cent critical value.

4. Conclusion

This study employs distinctive time series techniques to test for the presence of cointegration and to empirically examine the long run relations and short run dynamics between energy consumption, economic growth and foreign direct investment at the aggregate level. Long- and short-run energy demand elasticities are estimated on Portuguese annual data for 1980-2007. The results from the time series analysis reveal that energy consumption, economic growth and foreign direct investment are cointegrated in the long- and short run. Empirical results show that all the series are integrated of order one and evidence of cointegration is established using the Engle and Granger method. Furthermore, the assumption concerning the existence of a unique cointegration vector is confirmed by the Johansen's multivariate cointegration tests.

Once the presence of cointegration is established, the error correction model, that includes both long run and short run information, is derived from the autoregressive distributed lag model. The estimated coefficient of the equilibrium correction term in the ARDL model is statistically significant, possesses the correct specification, and indicates that the adjustment process by which long run equilibrium is restored after a shock is relatively fast. Altogether, the results of the diagnostic and stability tests, and the high explanatory power of the estimated models, further confirm the robustness of the results.

An equally important finding is the strong impact of economic growth on the consumption of energy. The high income elasticity of demand for total energy consumption in all models suggests that economic growth is accompanied by a major increase in energy consumption. For each percentage point of economic growth, energy consumption increases by approximately one and a half percentage points. This result accords with the positive growth effect on energy use well known and extensively documented in the empirical literature.

The key result arising from the study is that it finds empirical evidence for a robust energy reducing effect of aggregate FDI. Although, the elasticity or responsiveness of energy consumption to changes in FDI is small, the econometric investigation suggests that FDI is statistically significant in determining energy consumption in the long- and in the short run. These findings have important policy implications insofar as energy conservation measures and environmental policies are concerned, since FDI is generally a channel for technology transfer, which contributes to restrain energy use and hence gas house emissions.

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