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Spurious Cointegration: The Engle-Granger Test in the Presence of Structural Breaks

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Abstract

This paper analyses the asymptotic behavior of the Engle-Granger t-test for cointegration when the data include structural breaks, instead of being pure $I(1)$ processes. We find that the test does not possess a limiting distribution, but diverges as the sample size tends to infinity. Calculations involving the asymptotic expression of the t-test, as well as Monte Carlo simulations, reveal that the test can diverge in either direction, making it unreliable as a test for cointegration, when there are neglected breaks in the trend function of the data. Using real data on car sales and murders in the US, we present an empirical illustration of the theoretical results.
Keywords: Spurious cointegration, structural breaks, integrated processes.
JEL Classification:C12, C13, C22.

Resumen

Este documento analiza el comportamiento asintótico de la prueba t de Engle-Granger para cointegración, cuando los datos incluyen cambios estructurales, en vez de ser procesos $I(1)$ puros. Encontramos que la prueba no posee una distribución límite, sino que diverge cuando la muestra tiende a infinito. Cálculos que involucran la expresión asintótica de la prueba t, así como simulaciones Monte Carlo, revelan que la prueba puede divergir en ambas direcciones (hacia más, o menos infinito), haciéndola poco confiable como una prueba de cointegración, cuando existen cambios estructurales en la función de tendencia de los datos. Usando datos reales sobre ventas de vehículos y número de asesinatos en los Estados Unidos, se presenta un ejemplo empírico de los resultados teóricos.
Palabras Clave: Cointegración espuria, cambios estructurales, procesos integrados.

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1 Introduction

Since the seminal contribution of Engle and Granger (1987), many economic theories involving long-run relationships have been analyzed through the concept and techniques of cointegration. These theories include money demand relations, consumption functions, the unbiased forward market hypothesis, purchasing power parity, etc.[4] The basic idea is that even though economic time series may wander in a nonstationary way, there exists the possibility that a linear combination of them could be stationary. If this is the case, then there should be some long-run equilibrium relation tying the individual variables together: this is what Engle and Granger (1987) call cointegration.

Assume that we are interested in testing whether two time series, x_t and y_t, are cointegrated. A preliminary requirement for cointegration is that each series is individually $I(1)$ nonstationary, that is, each has a unit root. If that is the case, cointegration among them would imply that a linear combination will be stationary, that is $I(0)$. The Engle-Granger (EG) test proceeds in two steps. The first step involves the following static OLS regression

$$y_t = \widehat{\alpha} + \widehat{\delta} x_t + \widehat{u}_t \tag{1}$$

which captures any potential long-run relationship among the variables. In the second step the residuals, $\widehat{u}_t$, are used in the following Dickey-Fuller (DF) regression:

$$\Delta \widehat{u}_t = \widehat{\gamma} \widehat{u}_{t-1} + \widehat{\eta}_t \tag{2}$$

If we cannot reject the hypothesis $\gamma = 0$ then there will be a unit root in the residuals, and therefore, the series x_t and y_t will not be cointegrated. On the other hand, when the t-statistic for testing the hypothesis $\gamma = 0$ ($t_{\widehat{\gamma}}$) is smaller than the corresponding critical value, the residuals will be stationary, thus indicating cointegration between y_t and x_t.[5]

As argued above, the EG residual-based DF $t-$test for cointegration assumes that both variables have a unit root. In a related paper, Gonzalo and Lee (1998) study the robustness of this test when the variables deviate from pure $I(1)$ processes. In particular, they find that the test is robust (i.e. suffers almost no size problems) to the following misspecifications: (a) AR roots larger that unity; (b) stochastic AR roots; (c) $I(2)$ processes, and (d) $I(1)$ processes with deterministic linear trends.

[4]See for instance Maddala and Kim (1998), and Enders (2004).

[5]Critical values for this test can be found in Phillips and Oularis (1990) and MacKinnon (1991).

This paper extends Gonzalo and Lee's (1998) results by studying the robustness of the EG cointegration test to nonlinearities in the deterministic trend function of the processes generating y_t and x_t in model (1). The relevance of this analysis stems from the well known difficulty in distinguishing pure $I(1)$ processes from stationary linear trend models with structural breaks.[6] In particular, we show that when y_t and x_t in model (1) are independently generated from each other, the EG test statistic will diverge, if the variables follow linear trends with breaks. This occurs under $I(0)$ and $I(1)$ structures for y_t and x_t. One direct implication of this results is that, if divergence is towards minus infinity, the null hypothesis of no cointegration will be spuriously rejected, and this size distortion will increase with the sample size, approaching one asymptotically.

Using asymptotic arguments, section 2 shows that the EG-DF t-ratio does not possess a limiting distribution as the sample size grows. Since the normalized asymptotic distribution of the t-statistic is not pivotal, the direction of divergence can not be determined analytically. To gain insight on the behavior of the test statistic in finite samples, section 3 presents the results of simulation experiments, which show that the divergence can actually occur in either direction. Section 4 presents an empirical illustration of the results, by testing for cointegration between murders and car sales in the US, two variables which, on a priori grounds, should bear no long-run relationship. The last section concludes.

2 Structural breaks and the Engle-Granger test

The complication with the EG test, as indeed with many other tests of cointegration, is the pre-testing problem, which arises when identifying the order of integration of the variables.[7]

Given the well known difficulty in differentiating between broken trend stationary models from $I(1)$ processes, we examine the asymptotic and finite samples properties of the EG test in the presence of structural breaks for independent series. We find that when the DGP of at least one variable includes structural breaks, the EG test does not possess a limiting distribution, but diverges with probability approaching one asymptotically.

We study the asymptotic and finite sample behavior of the EG test under four different DGPs, widely used in applied work in economics. The following assumption summarizes the DGPs considered below for both the dependent and the explanatory variables in model (1).

[6] Perron (1989, 1997) has demonstrated that changes in the trend function bias unit root tests towards a non-rejection.

[7] For instance, Elliot (1995) finds overrejections of the null of no cointegration due to a root close to but less than one in the autoregressive representation of individual variables. Using simulations, Kellard (2006) also finds that the Engle-Granger test tends to find substantial spurious cointegration when assessing market efficiency.

ASSUMPTION. The DGPs for $z_t = y_t, x_t$ are as follows.

	DGP	Model
1	MS+breaks	$z_t = \mu_z + \sum_{i=1}^{N_z} \theta_{iz} DU_{izt} + u_{zt}$
2	TS+breaks	$z_t = \mu_z + \sum_{i=1}^{N_z} \theta_{iz} DU_{izt} + \beta_z t + \sum_{i=1}^{M_z} \gamma_{iz} DT_{izt} + u_{zt}$
3	I(1)	$z_t = \mu_z + \beta_z t + S_{zt}$
4	I(1)+breaks	$z_t = \mu_z + \beta_z t + \sum_{i=1}^{N_z} \gamma_{iz} DT_{izt} + S_{zt}$

where MS and TS stand for Mean Stationary and Trend Stationary, respectively, $S_{zt} = \sum_{i=1}^{t} u_{zi}$, and the innovations u_{zt} obey Assumption 1 in Phillips (1986, p. 313). $DT_{izt} = \sum_{i=1}^{t} DU_{izt}$, DU_{izt}, DT_{izt} are dummy variables allowing changes in the trend's level and slope respectively, that is, $DU_{izt} = \mathbf{1}(t > T_{b_{iz}})$ and $DT_{izt} = (t - T_{b_{iz}})\mathbf{1}(t > T_{b_{iz}})$, where $\mathbf{1}(\cdot)$ is the indicator function, and $T_{b_{iz}}$ is the unknown date of the i^{th} break in z.

The DGPs include both (nonlinear) deterministic as well as stochastic trending mechanisms, with 16 possible combinations of them among the dependent and the explanatory variables. These combinations have practical importance, given the empirical relevance of structural breaks in the time series properties of many macro variables. DGP 1 is used to model mean stationary variables, such as real exchange rates, unemployment rates, inflation rates, great ratios (i.e. output-capital ratio), and the current account. DGPs 2-4 are widely used to model growing variables, real and nominal, such as output, consumption, money, prices, etc. The main result is the following:

THEOREM. *Let y_t and x_t be independently generated according to any combination of DGPs in the Assumption (except for the case when both y_t and x_t are generated by DGP 3). If the estimated residuals from (1) are used in regression model (2), then, as the sample size $T \to \infty$,*

$$t_{\widehat{\gamma}} = O_p(T^{1/2})$$

Proof of Theorem.

We present the proof on how to obtain the order in probability of one combination of DGPs, namely, the combination 2-2, for which $z_t = \mu_z + \sum_{i=1}^{N_z} \theta_{iz} DU_{izt} + \beta_z t + \sum_{i=1}^{M_z} \gamma_{iz} DT_{izt} + u_{zt}$, for $z = y, x$. The orders in probability for the rest of cases follow the same steps. All sums run from $t = 1$ to T. The OLS estimator of γ from (2) is:

$$\widehat{\gamma} = \left(\sum \Delta \widehat{u}_t \widehat{u}_{t-1}\right) \left(\sum \widehat{u}_{t-1}^2\right)^{-1}$$

where $\sum \Delta \widehat{u}_t \widehat{u}_{t-1} = \sum \Delta y_t y_{t-1} - \widehat{\alpha} \sum \Delta y_t - \widehat{\delta} \sum \Delta y_t x_{t-1} - \widehat{\delta} \sum \Delta x_t y_{t-1} + \widehat{\alpha}\widehat{\delta} \sum \Delta x_t + \widehat{\delta}^2 \sum \Delta x_t x_{t-1}$.

From direct calculation, and using the fact that, for (1), $\widehat{\alpha} = O_p(T)$, $\widehat{\delta} = O_p(1)$, $\sum \widehat{u}_{t-1}^2 = O_p(T^3)$ (see Noriega and Ventosa-Santaulària (2006)), it is simple to show that each element of $\sum \Delta \widehat{u}_t \widehat{u}_{t-1}$ is $O_p(T^2)$.

Therefore,

$\widehat{\gamma} = \frac{O_p(T^2)}{O_p(T^3)}$,

which implies that $T\widehat{\gamma} = O_p(1)$.

Now define the residuals $\widehat{\eta}_t$ from (2) as:

$\widehat{\eta}_t = \Delta\widehat{u}_t - \widehat{\gamma}\widehat{u}_{t-1}$.

The estimated variance is:

$\widehat{\sigma}^2_\eta = T^{-1}\left[\sum(\Delta\widehat{u}_t)^2 + \widehat{\gamma}^2\sum\widehat{u}^2_{t-1} - 2\widehat{\gamma}\sum\Delta\widehat{u}_t\widehat{u}_{t-1}\right]$,

where, again, direct calculations indicate that

$\sum(\Delta\widehat{u}_t)^2 = \sum\left(\Delta y_t - \widehat{\delta}\Delta x_t\right)^2 = O_p(T)$.

Hence,

$\widehat{\sigma}^2_\eta = T^{-1}\left[O_p(T) + (T\widehat{\gamma})^2 T^{-2}O_p(T^3) - 2(T\widehat{\gamma})T^{-1}O_p(T^2)\right] = O_p(1)$.

Finally, the t-statistic $t_{\widehat{\gamma}}$ can be written as:

$T\widehat{\gamma}\left[\widehat{\sigma}^2_\eta T^3(\sum\widehat{u}^2_{t-1})^{-1}\right]^{-1/2} = T^{-1/2}t_{\widehat{\gamma}} = O_p(1)$,

which proves the Theorem for *DGP*s 2-2.

The result shows that the t-statistic diverges at rate $\sqrt{T}$, whether there are structural breaks in both variables, or just in one of them.[8] When both y_t and x_t are independently generated according to *DGP* 3 in the Assumption, it is not difficult to show that $t_{\widehat{\gamma}} = O_p(1)$, that is, the t-statistic does not diverge.

Given that the Engle-Granger DF based test for cointegration is a left tail test, the above result is not enough to establish the presence of spurious cointegration; for this the t-statistic has to diverge to minus infinity, since divergence in the opposite direction would imply nonrejection asymptotically. Divergence towards minus infinity represents a pitfall, as defined by Gonzalo and Lee (1998), since, in this case, the size of the test approaches one asymptotically (they call this a "size" pitfall).

Now, the limiting expression of this statistic depends on a number of unknown parameters in the DGP (trends, location and size of breaks, among others), which makes it difficult to establish the direction of divergence. In order to evaluate numerically the direction of divergence, several exercises were carried out for a wide range of parameter values and combinations of *DGP*s, using the asymptotic expression of the t-statistic (normalized by $T^{1/2}$), and a sample of size $T = 400,000$. Results (available upon request) show that the normalized t-statistic can assume both positive and negative values, depending on parameter values and combinations of *DGPs*.

To learn about the divergence's direction of the t-statistic in finite samples, the next section presents the results of a small Monte Carlo experiment, whose design allows a number of combinations of parameter values. Results show that, again, depending on such combination, divergence occurs in either direction.

[8] An extreme misspecification would occur if the researcher erroneously considers both dependent and explanatory variables to be I(1), when in fact they are stationary around a linear trend without breaks. In this unlikely event, it can be shown that the t-statistic will also diverge, that is $t_{\widehat{\gamma}} = O_p(T^{1/2})$.

3 Simulation results

Results from the previous section imply that the use of the EG test for cointegration leads to correct inference whenever divergence is toward infinity, since variables in the *DGP* are independent of each other. However, inference could be misleading if divergence is towards minus infinity, since this would lead the practitioner to spuriously reject the null of no cointegration. Given the difficulty in assessing analytically the direction of divergence, this section studies the small sample behavior of the test statistic under different sets of parameter values.

We simulate four combinations of the *DGP*s introduced above, and generate graphs of the EG test t-statistic, which reveal its behavior under different parameter values and sample sizes. Table 1 presents the combinations used for the simulations. For instance, combination 3-2 involves regressing a unit root process with drift against a *TS* model with a break in level and slope of trend. The values of the parameters were inspired on real data from Perron and Zhu (2005), comprising historical real per capita GDP series for industrialized economies.

Table 1.

DGPs	3 - 2	3 - 1	2 - 2	2 - 4
μ_y	0.7	0.7	0.7	0.7
μ_x	0.4	0.4	0.4	0.4
β_y	0.04	0.04	0.04	0.04
β_x	$[\mathbf{-0.01, 0.1}]$		$[\mathbf{-0.01, 0.1}]$	0.07
θ_y			0.04	0.04
θ_x	0.07	$[\mathbf{-0.1, 0.1}]$	0.07	0.07
γ_y			$[\mathbf{-0.05, 0.05}]$	0.07
γ_x	$[\mathbf{-0.05, 0.05}]$		0.02	0.02
λ_y		0.3	0.3	$[\mathbf{0, 1}]$
λ_x	0.7	$[\mathbf{0, 1}]$	0.7	$[\mathbf{0, 1}]$
ρ_y	0	0.7	0	0
ρ_x	0.7	0.7	0	0

Figure 1 shows the behavior of the t-statistic for testing the null of no cointegration for each of the four combinations of DGPs described in Table 1 and a sample of size $T = 100$. Panels (a), (b),(c), and (d) correspond to combinations 3-2, 3-1, 2-2, and 2-4, respectively. Figure 2 depicts results for $T = 500$. The graphs show that the t-statistic takes only negative values[9]. This implies that the possibility of divergence towards minus infinity cannot be ruled out. Accordingly, the possibility of spurious cointegration among independent series with breaks is prevalent in finite samples, and seems to grow with the sample size.

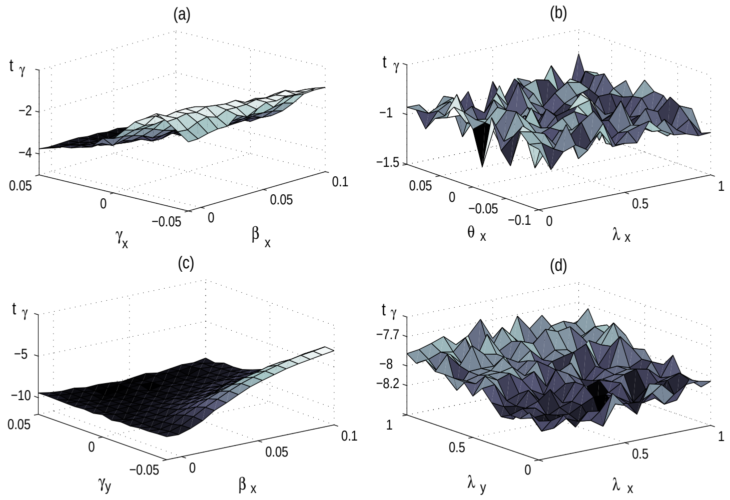


Figure 1: Graphs of $t_{\widehat{\gamma}}$. Parameter values from Table (1). T=100

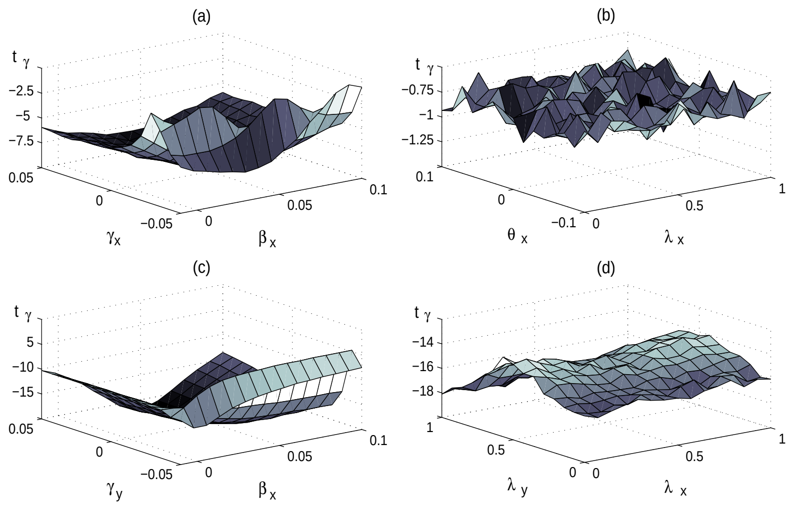


Figure 2: Graphs of $t_{\widehat{\gamma}}$. Parameter values from Table (1). T=500

From panels (d) it is interesting to note that the value of the t-statistic is uniformly below the critical value at the 1% level (-4) for any value of the location of breaks, contrary to the findings of Leybourne and Newbold (2003),

[9]Note, however, that the t-statistic is not always smaller than the critical values at, say, the 1% level, that is, -4.008 ($T = 100$) and -3.92 ($T = 500$).

who report high rejection rates for the EG test only when there is an early break in the dependent variable (i.e. $\lambda_y < 0.3$). The source of the difference is that the DGP they used is not exactly the same as the one used here (but see below).

Using parameter values from combination 2-4 in Table 1[10] we computed rejection rates based on simulated data for various sample sizes and combinations of DGPs in the Assumption. Rejection rates of the t-statistic for testing $\gamma = 0$ in (2) were computed using critical values reported in Enders (2004) at the 1% level. Results are presented in Table 2.

Table 2. Rejection Rates for $t_{\widehat{\gamma}}$

	Combinations of DGPs in the Assumption							
T	1-1	1-2	1-3	1-4	2-2	2-3	2-4	4-2
50	.99	.99	.99	.99	.99	.99	.99	.55
100	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
200	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
500	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0

The number of replications is 10,000. From Table 2, it is clear that the EG test indicates spurious cointegration in finite samples.

A second set of experiments was performed using larger values for the various parameters (see Table 3).

Table 3.

DGPs	3 - 2	3 - 1	2 - 2	2 - 4
μ_y	2.7	2.7	2.7	2.7
μ_x	0.5	0.5	0.5	0.5
β_y	0.04	0.04	0.9	0.04
β_x	$[\mathbf{-5, 5}]$		$[\mathbf{-5, 5}]$	0.9
θ_y			-1.7	-1.7
θ_x	1.5	$[\mathbf{-1.8, 1.8}]$	1.5	
γ_y			$[\mathbf{-1.5, 2}]$	0.07
γ_x	$[\mathbf{-1.5, 2}]$		1.5	1.5
λ_y		0.3	0.3	$[\mathbf{0, 1}]$
λ_x	0.7	$[\mathbf{0, 1}]$	0.7	$[\mathbf{0, 1}]$
ρ_y	0	0.7	0	0
ρ_x	0.7	0.7	0	0

Results are shown in Figures 3 and 4, corresponding to samples of size 100 and 500. As can be seen, the t-statistic takes both positive and negative values, but in this case panels (a), (c) and (d) from the figures indicate that as the sample size grows, the statistic tends to move towards positive values.

[10] With $\lambda_x = 0.3$, and $\lambda_y = 0.7$.

For this second set of experiments, our results resemble those of Leybourne and Newbold (2003), in the sense that the t-statistic tends to be more negative the closer are the breaks to the beginning of the sample, according to panel (d) in Figures 3 and 4. Although evidently limited, these two sets of experi-

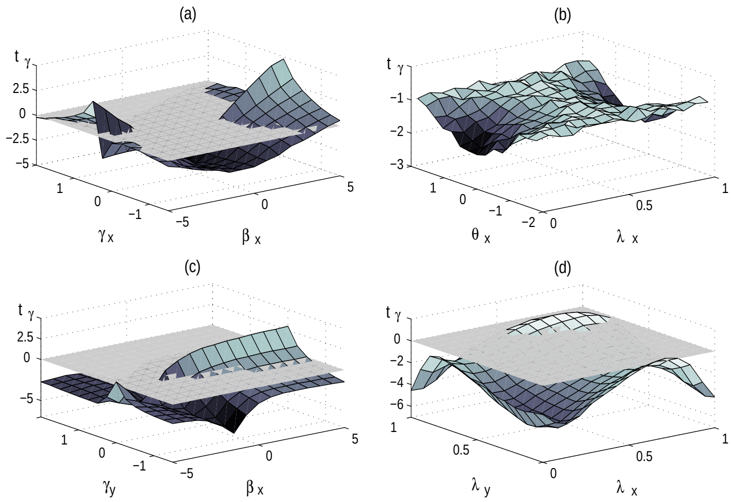


Figure 3: Graphs of $t_{\widehat{\gamma}}$. Parameter values from Table (2). T=100

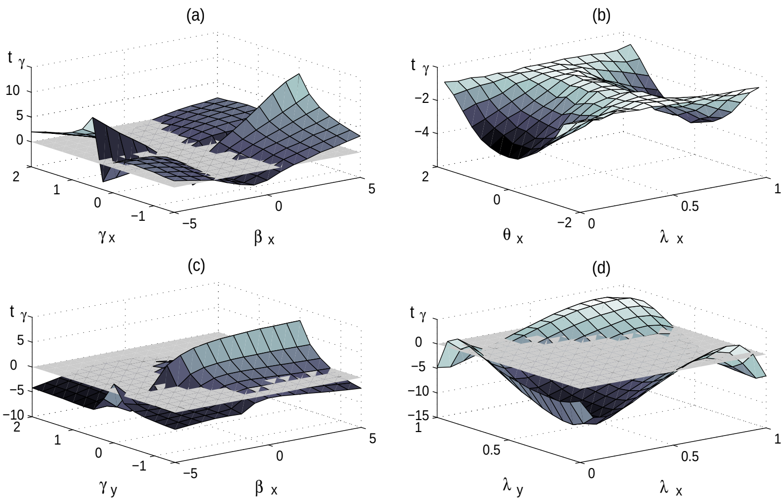


Figure 4: Graphs of $t_{\widehat{\gamma}}$. Parameter values from Table (2). T=500

ments, in combination with the asymptotic results, allow us to make our point:

the EG test can diverge in either direction, making it unreliable as a test for cointegration when there are neglected breaks in the trend function of the process generating the data. Furthermore, results from using the first (empirically relevant) set of parameter values indicate divergence towards minus infinity, implying the presence of spurious cointegration. Therefore, we recommend a careful interpretation of results from applying the EG cointegration test when there is the possibility of breaks in the trend function of the variables.

Results presented in this paper represent an extension of Gonzalo and Lee's (1998) results. We find, however, that the EG test is sensitive to misspecification of the trend behavior and can lead to spurious rejection of the null of no cointegration for independent time series with breaks.

4 Empirical Evidence

To illustrate the theoretical and simulated findings, we take monthly data on total number of vehicle sales in the US (*cars* henceforth), and number of murders in the US (*murders*), whose time series plots are shown in Figure 1[11]. Note that this section does not pretend to offer a complete time series analysis of these data. Its purpose is simply to present an illustration on the possibility of finding a cointegration relationship using real data, comprising variables which in principle have no relationship with each other.

Unit root tests on each variable indicate that it is not possible to reject a unit root[12]. Since the theoretical results presented above apply when at least one of the variables has undergone a structural break, we followed Perron (1997) and estimated a trend break in *cars*, in January 2000. Once this break is taken into account, the unit root hypothesis is rejected.[13]

An OLS regression of *cars* on *murders* yields a (spurious) regression coefficient of -0.036, implying that for each additional murder, vehicle sales decrease by 36 units (the t-statistic is significant at the 1% level).

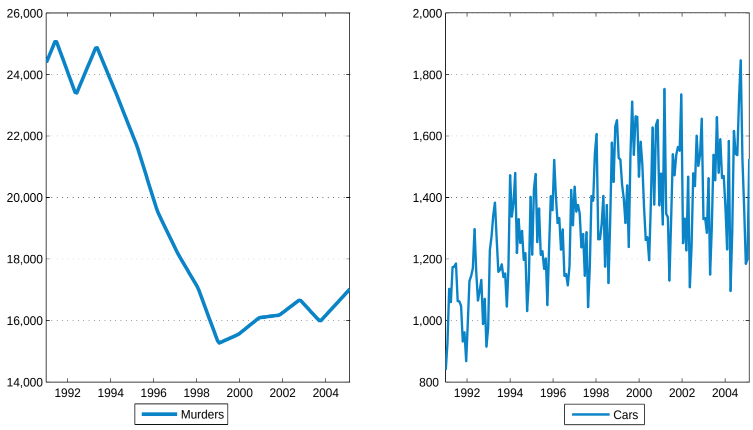
From the unit root test results discussed above, if breaks are not taken into account, both variables would appear to be I(1), and the presence of cointegration can be investigated. The EG residual-based DF $t-$test for cointegration is -8.67 (critical value at the 1% level is -4), thus allowing to reject the null of no cointegration. Therefore, there appears to be a long-run equilibrium relationship between murders and car sales in the US, according to the Engle-Granger

[11]The sources of the data are: Bureau of Economic Analysis: Auto and Truck Sales, Production, Exports and Inventories (thousands), and FBI: Crime in the United States; BOC: County City Data Book. Both series provided by www.FreeLunch.com - http://www.economy.com/freelunch. The sample period is 1991:1-2005:12, comprising 180 observations.

[12]We applied Augmented Dickey-Fuller tests following the lag length selection criterion of Perron (1997), with a maximum of 10 lags of the first differences of the dependent variable. We also applied the Ng-Perron tests using the modified Akaike information criterion, as suggested by Ng and Perron (2001). Results available upon request.

[13]For simplicity, we do not look for breaks in *murders*, which also seems to have undergone breaks in its trend function.

test. Of course, this is a spurious finding, since one does not expect to find cointegration between these two variables.



5 Conclusions

This paper has shown that the Engle-Granger test for cointegration, based on the DF t-statistic, does not posses a limiting distribution, but diverges at rate root-T. Given the dependency of the asymptotic distribution on the various parameters in the DGP, the paper analyzed the behavior of the t-statistic through Monte Carlo simulations. Results show that the divergence of the EG test statistic can occur in either direction. For a particular set of (empirically relevant) parameters, the simulation experiments indicate that the statistic tends to minus infinity, and, therefore, can misleadingly indicate cointegration among independent variables. However, we also find that a different set of parameter values indicate divergence towards infinity, which would lead to correct inference. In order to give some empirical content to our theoretical findings, the paper also showed that the application of the Engle-Granger test uncovered a spurious cointegration relationship between the number of murders and car sales in the US.

We believe the results presented are relevant, given the difficulty in distinguishing between $I(1)$ variables from stationary variables around broken trends, that is, given the low power of unit root tests against broken trend stationary alternatives. All in all, the EG test should be used with caution, since the presence of neglected breaks could produce spurious rejections of the null of no cointegration among independent time series.

Given the potential negative impact of neglected breaks on inference using the EG test, we adhere to Gonzalo and Lee's (1998) recommendation in the sense that "...pre-testing for individual unit roots is not enough. We have to be sure that the variables do not have any other trending or long-memory behavior different from that of a unit root process" (p.149).

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