

# On the robustness of cointegration tests when series are fractionally integrated\*

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*SUMMARY This paper shows that when series are fractionally integrated, but unit root tests wrongly indicate that they are  $I(1)$ , Johansen likelihood ratio (LR) tests tend to find too much spurious cointegration, while Engle-Granger test presents a more robust performance. This result holds asymptotically as well as in finite samples. The different performance of these two methods is due to the fact that they are based on different principles. Johansen procedure is based on maximizing correlations (canonical correlation) while Engle-Granger minimizes variances (in the spirit of principal components).*

## 1 Introduction

It is well established that many economic series contain dominant, smooth components, even after removal of simple deterministic trends. A stochastic process with no deterministic components is defined to be integrated of order  $d$ , denoted  $I(d)$ , if it has a stationary and invertible ARMA representation after applying the differencing operator  $(1 - B)^d$ . The components of the vector  $X_t$  are said to be cointegrated of order  $(d, b)$ , if all of components of  $X_t$  are  $I(d)$  and there exists a vector  $\alpha (\neq 0)$  such that  $\alpha' X_t$  is  $I(d - b)$ ,  $b > 0$ . Usually the case with  $d = b = 1$  is considered (for more detail see Granger 1981 and Engle and Granger 1991).

When  $d$  is not an integer, the series are said to be fractionally integrated (Granger and

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Joyeux 1980 and Hosking 1981). There is considerable evidence that the long memory properties of macroeconomic and financial time series data such as GDP, interest rate spreads, inflation rates, forward premiums, stock returns, exchange rates, and etc., can be well captured by fractional integrated processes. This paper is concerned with the robustness of cointegration tests when series are fractionally integrated, but based on unit root tests we wrongly consider them as I(1) series.

We investigate two methods to test for cointegration. One method is the one suggested by Engle and Granger (1987, EG hereafter), which looks for a linear combination of level series that minimizes the variance of the linear combination using OLS. Another method is Johansen's (1995) procedure, which maximizes the canonical correlation between the first differenced series and the level series. From the point of view of multivariate analysis, EG procedure is similar to principal components, while Johansen's method is a canonical correlations technique. The main assumption of both tests is that series are exactly I(1). When series are I( $d$ ) with  $d \neq 1$  but we wrongly consider them as I(1), this paper finds that Johansen tests tend to find spurious cointegration more often than EG test does. This result holds asymptotically as well as in finite samples.

Consider a  $(2 \times 1)$  I(1) vector  $X_t = (y_t \ x_t)'$ . The variance of an I(1) series (given some initial conditions) goes to infinity as  $t \rightarrow \infty$ , while the variance of an I(0) series is finite. Therefore if an I(1) vector  $X_t$  is cointegrated, there must exist a vector  $\alpha (\neq 0)$  such that the variance of  $\alpha'X_t$  is finite. Based on this, EG suggest to test for a unit root on the residuals  $z_t$  from the OLS cointegration regression  $y_t = \hat{a}_0 + \hat{a}_1x_t + z_t$ . The EG test is based on the augmented Dickey-Fuller (DF) statistic (see Dickey and Fuller, 1979) of order  $k$ ,  $ADF(k)$ , that is the  $t$ -value for  $\hat{\rho}$  in the OLS regression

$$\Delta z_t = \rho z_{t-1} + \rho_1 \Delta z_{t-1} + \cdots + \rho_k \Delta z_{t-k} + error. \quad (1)$$

Reduced rank regression methods, like the Johansen approach, exploit the fact that I(1) and I(0) variables are asymptotically uncorrelated and look for a vector  $\alpha$  that maximizes the correlation between  $\alpha'X_t$  and a linear combination of  $\Delta X_t$ . If that correlation is not zero,  $\alpha'X_t$  is I(0) and  $X_t$  is cointegrated. According to Granger's representation theorem (Granger, 1983), a cointegrated system admits the following vector error correction model (VECM) representation

$$\Delta X_t = \Pi X_{t-1} + \Gamma_1 \Delta X_{t-1} + \cdots + \Gamma_k \Delta X_{t-k} + \epsilon_t, \quad (2)$$

where  $\epsilon_t = (e_{1t} \ e_{2t})'$  is a vector white noise with finite variance. For simplicity we have eliminated all the deterministic components and we only consider a finite  $k$  in model (2). If  $X_t$  is cointegrated, it can be shown that the matrix  $\Pi$  can be decomposed into  $\Pi = \gamma\alpha'$ , where  $\alpha$  and  $\gamma$  are  $(2 \times 1)$  matrices. Testing for cointegration is therefore equivalent to testing the rank of  $\Pi$  (denoted as  $r$ ) equals to one, and this is exactly what Johansen method does. Formally the Johansen LR statistics for testing the null hypothesis of no cointegration  $H_0 : r = 0$  are

$$Q_1 = -T \ln(1 - \hat{\lambda}_1)(1 - \hat{\lambda}_2) \quad (3)$$

and

$$Q_2 = -T \ln(1 - \hat{\lambda}_1), \quad (4)$$

where  $(1 \geq \hat{\lambda}_1 \geq \hat{\lambda}_2 \geq 0)$  are the eigenvalues of  $\hat{M} \equiv S_{11}^{-1}S_{10}S_{00}^{-1}S_{01}$ , and  $S_{ij} = T^{-1} \sum_{t=1}^T R_{it}R'_{jt}$  ( $i, j = 0, 1$ ) are the product moment matrices of the residuals  $R_{0t}$  and  $R_{1t}$ , from the regressions of  $\Delta X_t$  and  $X_{t-1}$  on the lagged differences, respectively.  $Q_1$  tests the null hypothesis against the alternative hypothesis  $H_1 : r > 0$ , and  $Q_2$  tests  $H_0$  against  $H_1 : r = 1$ .

## 2 Fractionally Integrated Processes

Suppose  $X_t = (y_t \ x_t)'$  are generated from

$$(1 - B)^d y_t = e_{1t}, \quad (5)$$

$$(1 - B)^d x_t = e_{2t}. \quad (6)$$

The fractional difference operator  $(1 - B)^d$  defined by its Maclaurin series is

$$(1 - B)^d = \sum_{j=0}^{\infty} \frac{\Gamma(-d+j)}{\Gamma(-d)\Gamma(j+1)} B^j = \sum_{j=0}^{\infty} d_j B^j, \quad d_j = \frac{j-1-d}{j} d_{j-1}, \quad d_0 = 1, \quad (7)$$

where  $\Gamma(\cdot)$  is the gamma function. An  $I(d)$  process  $y_t$  generated from (5) has the following properties: (a)  $y_t$  is covariance stationary if  $d < 0.5$ . (b)  $y_t$  has an invertible moving average representation if  $d > -0.5$ . (c)  $y_t$  is mean-reverting when  $d < 1$ . (d) If  $d > 0$ ,  $y_t$  has long memory, the autocovariances of  $y_t$  are not absolutely summable, and the power spectrum of  $y_t$  is unbounded for frequencies approaching zero. (e)  $y_t$  has an infinite variance if  $d > 0.5$ . (f) The DF- $t$  statistic diverges to  $-\infty$  if  $d < 1$ , and diverges to  $+\infty$  if  $d > 1$  as  $T \rightarrow \infty$  (Sowell, 1990, Theorem 4). Thus if  $d > 1$ , the standard DF tests have no power asymptotically.

For simplicity, in the following proposition, we consider only the case with  $k = 0$  in the VECM to compute the LR statistics. Any finite  $k$  that is not sufficiently large enough to make the error  $\epsilon_t$  a vector white noise will lead to the same results.

**Proposition:** *Suppose  $(y_t \ x_t)'$  are  $I(d)$  processes generated from (5) – (6), and we estimate a VECM with  $k = 0$ .*

a. *If  $d \geq 1.5$ , then  $\hat{\lambda}_1$  does not converge to zero in probability as  $T \rightarrow \infty$ .*

b. *If  $1 < d < 1.5$ , then  $T^{(3-2d)}\hat{\lambda}_1 = O_p(1)$ .*

c. *If  $d = 1$ , then  $T\hat{\lambda}_1 = O_p(1)$ .*

d. *If  $0.5 < d < 1$ , then  $T^{(2d-1)}\hat{\lambda}_1 = O_p(1)$ .* □

**Proof:** a. Following Gouriéroux et al (1989), for  $d \geq 1.5$ ,  $S_{11} = O_p(T^{2d-1})$ ,  $S_{00} = O_p(T^{2d-3})$ , and  $S_{10} = O_p(T^{2d-2})$ . Therefore  $\hat{M} = O_p(1)$  and the result follows. b. For  $1 < d < 1.5$ ,  $S_{11} = O_p(T^{2d-1})$ ,  $S_{00} = O_p(1)$ , and  $S_{10} = O_p(T^{2d-2})$ . Therefore  $\hat{M} = O_p(T^{2d-3})$ . c. For  $d = 1$ ,  $S_{11} = O_p(T)$ ,  $S_{00} = O_p(1)$ , and  $S_{10} = O_p(1)$ . Therefore  $\hat{M} = O_p(T^{-1})$ . d. For  $0.5 < d < 1$ ,  $S_{11} = O_p(T^{2d-1})$ ,  $S_{00} = O_p(1)$ , and  $S_{10} = O_p(1)$ . Therefore  $\hat{M} = O_p(T^{1-2d})$  and the result follows. □

If  $d = 1$ ,  $T\hat{\lambda}_1 = O_p(1)$ . If  $d \neq 1$ ,  $T\hat{\lambda}_1 \xrightarrow{p} \infty$  as  $T \rightarrow \infty$ , and the size of the LR tests increases to one as  $T \rightarrow \infty$  because  $Q_2 \geq T\hat{\lambda}_1$  and  $Q_1 \geq T(\hat{\lambda}_1 + \hat{\lambda}_2)$ . Note that if  $1 < d < 1.5$  then  $0 < 3 - 2d < 1$ , and if  $0.5 < d < 1$  then  $0 < 2d - 1 < 1$ . Thus in these two cases,  $\hat{\lambda}_1 \xrightarrow{p} 0$  but at a slower rate than  $T$  so that  $T\hat{\lambda}_1$  diverges, and therefore the size of the LR tests goes to one asymptotically.

A sufficiently large  $k$  such that the residuals are white noise may solve the problem. But there are many situations in macroeconomics where it is not possible in practice to try a large  $k$ . As previously mentioned, our Proposition will hold not only for  $k = 0$  but also for any  $k > 0$  not sufficiently large to make the error a vector white noise.

### 3 Monte Carlo Results

We generate  $X_t = (y_t \ x_t)'$  from (5)-(6) where  $e_{1t}$  and  $e_{2t}$  are i.i.d.  $N(0, 1)$ , and  $E(\epsilon_{1i}\epsilon_{2j}) = 0$  for every  $i$  and  $j$ . In order to avoid the initial conditions ( $x_0 = 0$ ,  $y_0 = 0$ ) effect, we generate samples of sizes  $t = 1, \dots, T + q$  and discard the first  $q = 2000$  observations. We

approximated  $(1 - B)^d = \sum_{j=0}^{\infty} d_j B^j$  by assuming  $d_j = 0$  for  $j > 1000$ . It is clear that both variables are not cointegrated in any sense. In Tables 1 and 2, we report the size of the cointegration tests for various values of  $d$ .

**Table 1 about here**

**Table 2 about here**

When  $d < 1$ , the size is large for both EG and Johansen tests. These finite sample results match the asymptotic results. For EG test the asymptotic behavior is derived from Sowell (1990), where it is shown that the DF  $t$  statistic diverges to  $-\infty$  if  $d < 1$  as  $T \rightarrow \infty$ . For Johansen tests the theoretical result is in our Proposition.

When  $d > 1$ , Johansen LR tests tend to find too much spurious cointegration while the EG test does not. Again these finite sample results coincide with the asymptotic results. The performance of EG test is derived from Sowell (1990), where it is shown that if  $d > 1$ , the DF test has zero power asymptotically. The asymptotic performance of Johansen tests is derived in our Proposition.

**Table 3 about here**

Table 3 shows how difficult is to distinguish in finite samples an  $I(d, d > .5)$  variable from an  $I(1)$  using the augmented DF (ADF) test. Thus if the variables are fractionally integrated, it is likely that we proceed assuming the series are  $I(1)$ , and therefore get the incorrect conclusion that the variables are related in the long-run (i.e., cointegrated).

In order to avoid the spurious cointegration, one could think that a possible solution is to increase  $k$  with  $T$ , in a similar way Berk (1974) does for stationary and ergodic processes. We are not aware of any result in the literature on how to do this for nonstationary and non-ergodic processes. We suspect the problem must be complicated because the sum of absolute correlations for a fractional integrated process is not bounded, therefore any finite  $k$  will produce inconsistent estimates. Moreover a fractionally integrated process with  $d \geq .5$  is not ergodic. We report the results computed with  $k = 3$  and 9, but the problem remains even in the latter case. Based on our Monte Carlo experiment we have to agree with Brockwell and Davis (1991, p. 520) when they say “While a long memory process can always be approximated by an  $ARMA(p, q)$  the orders  $p$  and  $q$  required to achieve a reasonably good approximation may be so large as to make parameter estimation extremely difficult.”

How often do we have  $d > 1$  in practice? Examples of values of estimates of  $d$  reported in the literature are:  $d = 1.17$  for annual disposable income (Diebold and Rudebusch 1991),  $d = 1.29$  for quarterly real GNP (Sowell 1992a), and  $d$  is ranged from 1.04 to 1.36 for various nominal spot exchange rates (Cheung 1993). Also  $d$  is estimated about 0.6 for money growth rates (Tieslau 1991) and is ranged from 0.40 to 0.57 for inflation rates in several developed countries (Hassler and Wolters 1995), indicating money stock and price series may have  $d$  greater than one.

Another important and related question would be to see how precisely one could estimate  $d$  with the sample sizes used in applied studies. Several different approaches have been suggested for estimating  $d$ : Geweke and Porter-Hudak (1983) suggest a two step estimator from a regression of ordinates of the periodogram on a trigonometric function; Fox and Taqqu (1986) suggest an approximate ML procedure; Sowell (1992b) derives the full ML estimator, and Chung and Baillie (1993) consider the minimum conditional sum of squares estimator. Some simulation evidence on the finite sample performance of these methods has been provided by Agiakoglou, Newbold and Wohar (1992), Cheung and Diebold (1994), and Chung and Baillie (1993). They show severe biases of these estimators. In our opinion this difficulty on estimating  $d$  gives even more relevance to the results obtained in this paper.

## 4 Conclusions

In applied research once a pair of variables are considered to be  $I(1)$ , the next step is to investigate if there exists a long-run equilibrium relationship between them. Because it is very difficult to distinguish an  $I(d, d > .5)$  from an  $I(1)$ , this paper shows that asymptotically as well as in finite samples, Johansen LR tests tend to find spurious cointegration more often than EG does. Therefore a recommendation in order to detect this problem is to run both tests. If they produce different cointegration results, then proceed with a more exhaustive univariate analysis than a simple unit root test.

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TABLE 1. Size of cointegration tests ( $T = 100$ )

	$k = 0$			$k = 3$			$k = 9$		
	$EG$	$Q_1$	$Q_2$	$EG$	$Q_1$	$Q_1$	$EG$	$Q_1$	$Q_2$
$d = 0.5$	.986	1.000	.997	.361	.651	.432	.083	.233	.171
$d = 0.6$	.900	.991	.947	.223	.406	.262	.060	.180	.141
$d = 0.7$	.636	.832	.652	.146	.224	.167	.043	.152	.132
$d = 0.8$	.341	.447	.340	.094	.142	.105	.042	.129	.129
$d = 0.9$	.143	.147	.132	.065	.087	.076	.038	.132	.122
$d = 1.0$	.047	.048	.052	.048	.068	.072	.032	.133	.130
$d = 1.1$	.016	.058	.069	.037	.077	.078	.034	.153	.149
$d = 1.2$	.010	.152	.166	.028	.090	.085	.036	.163	.165
$d = 1.3$	.031	.337	.351	.021	.105	.113	.030	.171	.171
$d = 1.4$	.053	.563	.592	.024	.110	.128	.027	.188	.184
$d = 1.5$	.076	.753	.774	.019	.135	.144	.032	.221	.206
$d = 1.6$	.100	.860	.873	.016	.165	.185	.037	.236	.230
$d = 1.7$	.111	.921	.931	.012	.185	.196	.048	.274	.267
$d = 1.8$	.135	.952	.957	.016	.191	.213	.045	.312	.294
$d = 1.9$	.150	.969	.973	.029	.231	.243	.053	.357	.336
$d = 2.0$	.176	.982	.981	.039	.271	.254	.054	.400	.385

*Notes:* The frequency of rejecting the null hypothesis in 1000 replications is reported at the 5% level. The critical values for  $T = 100$  are simulated from 90000 replications using the DGP with  $d = 1$ .

TABLE 2. Size of cointegration tests ( $T = 1000$ )

	$k = 0$			$k = 3$			$k = 9$		
	$EG$	$Q_1$	$Q_2$	$EG$	$Q_1$	$Q_1$	$EG$	$Q_1$	$Q_2$
$d = 0.5$	1.000	1.000	1.000	1.000	1.000	1.000	.984	1.000	1.000
$d = 0.6$	1.000	1.000	1.000	.994	1.000	1.000	.851	.992	.936
$d = 0.7$	.998	1.000	1.000	.879	.984	.941	.572	.815	.648
$d = 0.8$	.872	.978	.946	.535	.708	.565	.269	.370	.284
$d = 0.9$	.384	.455	.376	.193	.213	.186	.134	.140	.116
$d = 1.0$	.063	.056	.056	.059	.055	.055	.059	.053	.062
$d = 1.1$	.020	.118	.124	.026	.057	.066	.037	.051	.058
$d = 1.2$	.047	.439	.464	.026	.160	.175	.023	.078	.104
$d = 1.3$	.102	.768	.805	.029	.304	.332	.023	.141	.154
$d = 1.4$	.166	.925	.925	.040	.441	.483	.021	.210	.248
$d = 1.5$	.211	.974	.977	.030	.522	.546	.018	.248	.283
$d = 1.6$	.253	.991	.990	.017	.543	.573	.014	.257	.281
$d = 1.7$	.302	.994	.995	.010	.483	.517	.008	.245	.258
$d = 1.8$	.331	.999	1.000	.004	.380	.390	.009	.216	.215
$d = 1.9$	.345	.999	.999	.007	.245	.256	.015	.196	.199
$d = 2.0$	.349	.999	.999	.029	.204	.192	.034	.208	.196

*Notes:* The frequency of rejecting the null hypothesis in 1000 replications is reported at the 5% level. The critical values for  $T = 1000$  are simulated from 90000 replications using the DGP with  $d = 1$ .

TABLE 3. Power of ADF tests for a unit root

	$T = 100$				
	ADF(0)	ADF(3)	ADF( $p_{aic}$ )	mean( $p_{aic}$ )	sd( $p_{aic}$ )
$d = 0.5$	.999	.553	.696	1.875	2.805
$d = 0.6$	.941	.355	.556	1.926	2.874
$d = 0.7$	.691	.223	.399	1.811	2.925
$d = 0.8$	.354	.129	.258	1.500	2.807
$d = 0.9$	.141	.080	.117	1.258	2.805
$d = 1.0$	.047	.055	.069	1.229	2.842
$d = 1.1$	.032	.049	.058	1.513	2.846
$d = 1.2$	.047	.038	.047	2.150	3.013
$d = 1.3$	.087	.041	.056	2.605	2.983
$d = 1.4$	.148	.047	.067	2.832	2.916
$d = 1.5$	.214	.053	.067	2.842	2.884
$d = 1.6$	.257	.056	.080	2.706	2.759
$d = 1.7$	.317	.052	.079	2.563	2.674
$d = 1.8$	.342	.049	.077	2.339	2.646
$d = 1.9$	.366	.052	.062	2.207	2.706
$d = 2.0$	.387	.050	.061	2.301	2.817
	$T = 1000$				
	ADF(0)	ADF(3)	ADF( $p_{aic}$ )	mean( $p_{aic}$ )	sd( $p_{aic}$ )
$d = 0.5$	1.000	1.000	.963	7.937	3.997
$d = 0.6$	1.000	.998	.867	7.647	3.860
$d = 0.7$	.999	.887	.674	6.602	3.606
$d = 0.8$	.825	.521	.412	4.981	3.148
$d = 0.9$	.331	.177	.187	2.959	2.705
$d = 1.0$	.055	.055	.050	1.021	2.400
$d = 1.1$	.032	.026	.030	3.368	2.993
$d = 1.2$	.104	.036	.042	5.701	3.394
$d = 1.3$	.205	.071	.050	7.322	3.598
$d = 1.4$	.285	.112	.064	8.124	3.651
$d = 1.5$	.330	.133	.068	8.452	3.688
$d = 1.6$	.368	.138	.066	8.045	3.624
$d = 1.7$	.383	.126	.069	7.081	3.372
$d = 1.8$	.388	.095	.062	5.698	3.068
$d = 1.9$	.405	.065	.052	3.813	2.688
$d = 2.0$	.398	.055	.061	2.017	2.359

Notes: 5% level. 1000 replications. ADF( $p$ ) denotes the DF tests augmented with  $p$  lagged first differences.  $p = 0, 3$ , or  $p_{aic}$ .  $p_{aic}$  is chosen using the AIC among  $p = 0, 1, \dots, 19$ . When  $p = p_{aic}$  is used, the mean and the standard deviation of  $p_{aic}$  in 1000 replications are reported.