Working Paper 97-28
Statistics and Econometrics Series 15
March 1997

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MONTE CARLO EVIDENCE ON THE POWER OF THE DURBIN-WATSON TEST AGAINST NONSENSE RELATIONSHIPS.

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Abstract

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Keywords:
Spurious relationships; nonstationary fractionally integrated processes; Durbin-Watson statistic.

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*Monte Carlo Evidence On the Power of the Durbin-Watson Test Against Nonsense Relationships**

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It is a well-known fact that, in linear regressions involving the levels of integrated processes spuriously related, the Durbin-Watson statistic converges in probability to zero. This, in turn, implies that this statistic can provide an useful testing procedure against the presence of nonsense relationships. Marmol (1997) *extends this result to the case of spurious regressions among nonstationary fractionally integrated processes. The aim of this paper is to provide a theoretical overview of these asymptotic results as well as Monte Carlo evidence on the behavior of the Durbin-Watson test in small samples.*

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J.E.L. Classification: *C*12, *C*22, *C*32.

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* The first author acknowledge grant from the *Training and Mobility of Researches Programme*. The second author thanks the DGICYT PB94-0709 for financial support.

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1. Introduction

During the last decade, the permanent nature of macroeconomic fluctuations has become an important meeting point in the debate between theoretical and applied researches since Nelson and Plosser (1982) suggested that the classical assumption that the variables in an economic system were either stationary or stationary around deterministic trends was unlikely to be satisfied either with economy-wide data or financial data. This shift from the assumption of stationarity to the explicit account of the fact that many macroeconomic time series are typically nonstationary has been radical, influencing almost every aspect of the estimation and inference, as well as the interpretation of many traditional concepts in econometrics. One illustration of the difficulties that can arise when performing regressions with nonstationary series is the problem of the so-called *spurious or nonsense regressions*, i.e., regressions in levels of nonstationary time series with statistically significant relationships in spite of the lack of possible theoretical justifications for these relationships to exist. As an illustration of this problem, Plosser and Schwert (1978) have found a statistical significant relationship between national income and sunspots while Hendry (1980) has found a strong dependence between inflation and cumulative rainfall.

In their seminal paper, Granger and Newbold (1974) have argued that, as a rule, macroeconomic data are integrated, so that in regressions involving the levels of such data, the standard significance tests, such as the t and the F tests, are usually misleading, tending to reject the null hypothesis of no relationship when, in fact, there might exist none. Likewise, they have also noted that low values of the Durbin-Watson statistic are associated with such spurious regressions. All these claims were proved in a rigorous manner by Phillips (1986) who developed an asymptotic theory for regressions between very general -in the sense of allowing for heterogeneously and weakly dependent distributed time series- $I(1)$ random processes. Since Phillips' paper, an outline to the recent contributions in this field would include Nelson (1988), Ohanian (1988, 1991), Smith (1991), Tanaka (1993), Toda and Phillips (1993), Choi (1994), Haldrup (1994), Marmol (1995, 1996) and Hassler (1996), among others.

A common feature of the literature mentioned above is the assumption about the relevant processes, becoming stationary after taking some number of integer differences. Granger and Joyeux (1980) and Hosking (1981) defined the so-called *fractionally integrated* $FI(d)$ *processes*, where now the degree of integration or memory parameter, *d*, is assumed to be a real number. These processes nest the former giving better description of nonstationary aspects, allowing for a more parsimonious models and improving long-horizon prediction intervals (e.g., Diebold and Lindner, 1996). On the other hand, they are naturally introduced when considering the aggregation of heterogeneous time series (Granger, 1980). Moreover, by allowing a rich range of spectral behaviour near the origin, they can provide better approximations to the Wold representations of many economic time series. Hence, it seems quite plausible to assume that the macroeconomic time series may achieve stationarity after applying a fractional filter (see, e.g., Baillie, 1996).

The question of spurious regressions under the fractional hypothesis is addressed by Marmol (1997). This paper studies the asymptotic distributions of the usual least squares statistics in a linear regression in the levels of nonstationary fractionally integrated processes (henceforth denoted *NFI*) spuriously related in a multivariate single-equation set-up, which allows for the existence of cointegrating relationships as well as quite general deterministic components. This paper corroborates Granger and Newbold (1974) and Phillips' (1986) findings and hence, as in the particular case where we deal with spurious regressions among integrated processes, standard least squares inference is not longer valid whereas the Durbin-Watson statistic, since it rejects with probability one the null hypothesis of correct specification, remains to be an useful misspecification test against the presence of spurious relationships.

These results are asymptotics, which means that they are exactly true only in the limit as the sample size tends to infinity. Consequently, the applied econometric work using this test must rely on asymptotic results to make small sample inference. Indeed, a test based on this statistic may have poor power properties in small samples. To the best of our knowledge, there is not experimental evidence regarding the robustness of this test to different data generating mechanisms in the fractional case.

Taking the above aspects into consideration, the purpose of this paper is to assess, via Monte Carlo simulations, the finite sample properties of the Durbin-Watson test when data generating process (hereafter denoted *DGP*) is assumed to be composed by a bivariate system of *NFI* processes with the same memory parameter, allowing for the presence of some deterministic components.

The outline of the paper is as follows. After a review of the main asymptotic results on spurious regressions with *NFI* processes in Section 2, Section 3 describes the way the Monte Carlo simulations were designed, whereas in Section 4 we report the main results obtained from these experiments. Finally, some conclusions are gathered in Section 5.

2. Theoretical Overview of Spurious Regressions with *NFI* Processes.

In this section we shall summarize the theoretical results of Marmol (1997). When a given series, y_t, becomes stationary after differentiating d times and the degree of integration or memory parameter, d, is not an integer but a real number, then the series is said to be *fractionally integrated*, denoted *FI*(d), and written as

$$\Delta^d y_t = u_t,$$

where the equilibrium error, u_t, is usually assumed to be a weak stationary and invertible process, and where the fractional difference operator Δ^d can be expressed in terms of a Maclaurin expansion as

$$\Delta^d = \sum_{k=0}^{\infty} \frac{\Gamma(k-d)B^k}{\Gamma(k+1)\Gamma(-d)} = \sum_{k=0}^{\infty} \pi_k B^k, \qquad \pi_k = \frac{k-1-d}{k}\pi_{k-1}, \qquad \pi_0 = 1, \quad (2.1)$$

with $\Gamma(\cdot)$ being the gamma function. It can be proved that a fractionally integrated process is stationary and invertible (denoted *SFI*) if $d \in (-1/2, 1/2)$ and nonstationary (denoted *NFI*) if $d \geq 1/2$. Throughout this paper we will assume that the relevant *FI* processes have memory parameters lying within the nonstationary range.

Consider now an n-dimensional time series $\{y_t, \xi_t', x_t', z_t'\}'$ generated according to

$$y_t = \gamma_y' \xi_t + y_t^0 \ , \tag{2.2}$$

$$x_t = \gamma_x' \xi_t + x_t^0, \qquad \Delta^d x_t^0 = u_{xt} , \tag{2.3}$$

$$z_t = \gamma_z' \xi_t + z_t^0, \qquad \Delta^p z_t^0 = u_{zt} , \tag{2.4}$$

and

$$y_t^0 = \beta_1' x_t^0 + \beta_2' z_t^0 + w_{yt} \ , \tag{2.5}$$

where ξ_t is an m_0-dimensional deterministic sequence of general form, x_t^0 and z_t^0 are m_1- and m_2-dimensional $(m_0 + m_1 + m_2 = m)$ *NFI* processes of order d and p, respectively, $p \geq d \geq 1/2$, the $(m_1 + m_2 + 1)$-dimensional error sequence $u_t = (u_{wt}, u_{xt}', u_{zt}')'$ is assume to be composed by zero mean stationary processes having moments of order greater than $max\{p-1/2, 2\}$ and where the one-dimensional $(m+1=n)$ time series y_t^0 is generally a *NFI* process of order p. Here, $\gamma_i, i = x, y, z$, are coefficients of the associated deterministic components as they are defined in ξ_t. Assume, without loss of generality, that the *NFI* processes y_t^0, x_t^0 and z_t^0 have initial conditions equal to zero for $t \leq 0$ and that, x_t^0 and z_t^0 are not allowed to be individually cointegrated.

Using (2.2)-(2.5), we have

$$y_t = \beta_0' \xi_t + \beta_1' x_t + \beta_2' z_t + w_{yt} , \tag{2.6}$$

with $\beta_0 = \gamma_y' - \beta_1' \gamma_x' - \beta_2' \gamma_z'$. This set-up is similar to that considered by Haldrup (1994) in the $p = 2, d = 1$ particular case, and also includes the framework of Phillips (1986) if $d = p = 1$, Marmol (1995) if $d = p = 1,2,3,...$and Marmol (1996) if $d \neq p = 1,2,3...$, $\gamma_x = \gamma_z = 0$, $\xi_t = 1$ and we do not allow for multicointegrating relationships in model (2.6).

Given this set-up, Marmol (1997) considers two possible cases of interest from the point of view of the study of the spurious regressions. The first one is the case where the equilibrium error, w_{yt}, is $NFI(p)$, i.e., if $\Delta^p w_{yt} = u_{wt}$, called the *spurious case.* On the other hand, if w_{yt} is $NFI(d)$, i.e., if $\Delta^d w_{yt} = u_{wt}$, then y_t and z_t will be fractionally cointegrated *FCI(p,p-d)* processes, i.e., such that the equilibrium error follows a *NFI* process with cointegrating vector $(1, -\beta_2)'$, and such that the process $y_t^0 - \beta_2' z_t^0$ is a

NFI(d) process that, in turn, does not fractionally cointegrate with x_t^0. This second situation is denoted as the *partially spurious case*.

Note that when $p = d$ the two cases are equivalent to the situation where the underlying series y_t^0, x_t^0 and z_t^0 are $NFI(d)$ processes spuriously related. This will be the case of interest in this paper. The case where $p > d$, which formally corresponds to the *unbalanced* model (see, e.g., Mankiw and Shapiro 1985, 1986; Banerjee et al., 1993; Marmol, 1996) is studied in Marmol and Reboredo (1997).

Consider now the analysis of the linear regression model

$$y_t = \hat{\beta}_0 \xi_t + \hat{\beta}_1 x_t + \hat{\beta}_2 z_t + \hat{w}_{yt}, \tag{2.7}$$

with $\hat{\beta}_j$, $j = \{0,1,2\}$, denoting the corresponding *OLS* estimators. In the same manner, let us denote by *DW* the usual Durbin-Watson statistic. Then, under some regularity conditions, Marmol (1997) proves the following result:

THEOREM. *Assume true the DGP* (2.2)-(2.6), *with* $p = d$, *and consider the regression model* (2.7). *Then, asymptotically,*

$$T^{2d-1} DW \equiv O_p(1),$$

if $1/2 \le d < 3/2$, *and*

$$T^2 DW \equiv O_p(1),$$

if $d \ge 3/2$.

Therefore, $DW \xrightarrow{p} 0$ for all values of $d \ge 1/2$. Hence, it seems that this statistic continues to provide a useful way of discriminating between spurious and genuine regressions in the fractional case too. However, notice that it converges to zero at the rate $O_p(T^{-2})$ if $d \ge 3/2$ and at the rate $O_p(T^{1-2d})$ if $d < 3/2$. Consequently, a test based on this statistic may have poor power properties in small samples, given that when $d < 3/2$, the rate of convergence to zero of the *DW* statistic is almost negligible, specially as d approaches $1/2$.

Moreover, it is not difficult to prove that if $\gamma_y = \gamma_x = \gamma_z = 0$ in the *DGP* (2.2)-(2.6), the *DW* statistic converges to zero at the rate $O_p(T^{-2})$ if $d \geq 3/2$ and at the rate $O_p(T^{-1})$ if $d < 3/2$ (see also Marmol, 1995). Therefore, the presence of deterministic terms in the *DGP* (2.2)-(2.6) changes the rate of convergence of the *DW* statistic for $d < 3/2$. This, in turn, implies that, as $2d - 1 < 1$ if $d < 1$, the *DW* statistic is a less powerful (resp., more powerful) test for $d < 1$ (resp., for $1 < d < 3/2$) if at least one γ_i, $i = \{x, y, z\}$ is different from zero. On the other hand, the power of the *DW* statistic is independent of the presence of deterministic terms in the *DGP* (2.2)-(2.6) for $d = 1$ and $d \geq 3/2$.

3. The Design of the Monte Carlo Experiment.

In this section we examine the performance of the *DW* statistic as a misspecification test against spurious regressions among *NFI* processes in finite samples. The parameter space we consider in this study is the following:

$$\{T = 50; 100; 200\} \times \{d = 0.5; 0.6; 0.8; 1; 1.2; 1.5; 1.8; 2\} \times \{\mu = 0; 1\} \times \{\Theta = 0; 0.4; 0.8\}.$$

Observations on the $NFI(d)$ processes were generated in the following manner: First, we simulate a stationary $\eta_t \sim SFI(\delta)$ process for $\delta \in [-1/2, 1/2)$. In this case we have that $\eta_t = \Delta^{-\delta} u_t$, where the perturbation term u_t is generated as $u_t = \varepsilon_t - \Theta\varepsilon_{t-1}$, with ε_t being generated as a sequence of identically and independently distributed $N(0,1)$ variables using the *GAUSS* matrix programming language and its pseudo random number generator mechanism for the standard normal distribution. We truncate the fractional difference operator (2.1) at lag 20,000. Then, in order to mimic the sample path of the $NFI(d)$ process y_t, for $d \in [\frac{1}{2}, 2]$, we take partial sums of η_t with initial condition $y_0 = 0$. For each sample size T in the parameter space, we generate $T + 500$ observations and the first 500 observations are discarded in order to eliminate the influence of the initial conditions. Using this procedure, we construct two independent $NFI(d)$ processes $\{y_t^0\}_{t=1}^T$ and $\{x_t^0\}_{t=1}^T$ and then the *DGP* of interest is composed in the following manner:

$$y_t = \gamma_y' \xi_t + y_t^0, \tag{3.1}$$

$$x_t = \gamma_x' \xi_t + x_t^0, \tag{3.2}$$

where we assumed that $\gamma_y = \gamma_x = (0,\mu)'$ and $\xi_t = (1,t)'$. We have also considered other possible configurations of the γ's and ξ_t terms, but the results obtained have lead us to similar conclusions and are available from the authors upon request. Finally, the estimated model along the Monte Carlo simulations is

$$y_t = \hat{\beta}_0' \xi_t + \hat{\beta}_1 x_t + res., \tag{3.3}$$

where $\beta_0 = (\alpha, 0)'$. Indeed, we only consider the case where a series y_t is regressed on one independent series because it is well-known that the power of the *DW* statistics decreases with the number of independent variables included in the regression (see, e.g., Granger and Newbold, 1986, Tables 6.4 and 6.5). Hence, by including just one regressor in the estimated model, we provide the most favourable set-up to the *DW* statistic in terms of power against spurious relationships. The results obtained from these experiments are given in Tables 1-9 according to the following possibilities:

FIGURE 1 ABOUT HERE

Hence, *Case* 1 corresponds to the situation where the two *NFI* processes have white noise innovations, *Case* 9 corresponds to the situation where the two *NFI* processes have innovations with large *MA*(1) parameters and so on. In our experiments, we choosed a *NFI* process with *MA*(1) innovations on a priori grounds because it seems that this simple specific model provides a good representation of a wide range of economic time series. See Granger and Newbold (1986), page 206, for more detailed justifications.

On the other hand, it is well-known that the true distribution of the *DW* statistic lies between that of two other statistics, d_l (the lower bound) and d_u (the upper bound), which only depend on T and the number of regressors. The null hypothesis of no autocorrelation is rejected against the alternative of positive autocorrelation if $DW < d_l^*$

(*Region* 1), against the alternative of negative autocorrelation if $DW > 4 - d_l^*$ (*Region* 5) and not rejected if $d_u^* < DW < 4 - d_u^*$ (*Region* 3), where asterisks indicate tabulated values at appropriate significance levels (e.g., Savin and White, 1977). If $d_l^* < DW < d_u^*$ (*Region* 2) or if $4 - d_u^* < DW < 4 - d_l^*$ (*Region* 4) the test is inconclusive. For each point of the parameter space, tables give percent of times for each one of these five regions containing the *DW* statistic at the 5% significance level. The results were generated by using 20,000 replications of the proposed *DGP* (3.1)-(3.3).

4. Discussion of the Results.

To begin with, note from Tables 1-9 that the power properties of the *DW* statistic against the possibility of some kind of misspecification are *homogeneous* across values of the *MA* parameter Θ_x and only change accordingly with the different values taken by the *MA* parameter Θ_y: Tables 1-3, 4-6 and 7-9 are rather similar among them. Then, it seems that the power of the *DW* test against the presence of spurious relationships is *independent* of the error structure of the independent regressor but does *depends* on the error structure of the dependent variable. Specifically, its power decreases as Θ_y becomes larger. This, in turn, it is a rather obvious conclusion of the proposed *DGP* (3.1)-(3.3), given that, under the assumed null hypothesis of no significativity $H_0 : \beta = 0$, the error term evolves in the same manner as does the proposed dependent variable y_t. Hence, in the rest of this section we will only comment the results obtained in the leading Tables 1, 4 and 7.

Looking at these tables, some results are clear and in accord with the asymptotic results presented in Section 2. With other things held constant, *power increases as T increases*. This is a reflection of the consistency of the test. In this manner, for $d \geq 1$ and $T = 200$ the *DW* statistic is significant in almost all times, independently of the value of Θ_y. However, *when* $d < 1$ *and* $\Theta_y = 0.8$ (*Case* 7) we found that the *DW* test has *serious identification problems*. For instance, when $d = 0.8$, the higher is the sample size *T*, the higher is the probability that it belongs to Region 1, but at a very slow rate. In fact, when $\mu = 1$, this increase is almost negligible for the sample sizes considered in our simulations. On the other hand, when $d < 0.8$, this statistic tends to belong to Region 5. These identification troubles would come from the following fact: Under the null hypothesis of no relationship $H_0 : \beta = 0$, the error term in the estimated model, say v_t, will evolve as the y_t *NFI*(*d*) process, i.e.,

$$\Delta^d v_t = \varepsilon_t - \Theta_y \varepsilon_{t-1}. \tag{4.1}$$

Therefore, for large values of Θ_y, (4.1) becomes unidentifiable from the following one:

$$\Delta^d v_t = \Delta \varepsilon_i, \tag{4.2}$$

or

$$\Delta^{\tilde{d}} v_t = \varepsilon_t, \tag{4.3}$$

where $\tilde{d} = d - 1$. Therefore, for $d \approx 1$, for large values of Θ_y expression (4.1) becomes unidentifiable from a white noise process $(\tilde{d} = 0)$ and hence the *DW* tends to Region 3 as *T* grows. At the same time, as $d \rightarrow 1/2$, expression (4.1) becomes unidentifiable from a *SFI* with negative memory parameter $\tilde{d}$, i.e., from what is known in the literature as an *intermediate memory process*. This process has *negative* autocorrelations (see, e.g., Baillie, 1996). Therefore, for large values of Θ_y, (4.1) becomes similar to a stationary process with negative autocorrelations and hence, the *DW* statistic will tend in probability to 4, lying in Region 5 as *T* grows.

Likewise, with other things held constant, *power is higher when d is larger*, as expected. Nowadays, it is clear from our experiments that this *power is quite uniform for* $d \geq 1$ even for moderate samples, which is not in accordance with the different rates of convergence presented in Section 2. For instance, given that the rate of convergence of the *DW* statistic is $O_p(T^{-1})$ if $d = 1$ and $O_p(T^{-2})$ if $d = 2$, one should expect that the percent of times the *DW* is significant would be greater in the $d = 2$ case, *ceteris paribus*. Yet, it appears from our Monte Carlo experiments that this intuition does not longer hold.

Finally, the presence of the deterministic term μ clearly reduces the power of the *DW* test for all values of Θ_y, even that this decreasing in the power properties of this statistic is almost negligible for $T = 200$. These results are, again, in contradiction with the asymptotic findings about the different rates of convergence of the *DW* test presented in Section 2, where we have seen that the power properties of this statistic should be independent of the presence of deterministic components for $d = 1$ and $d \geq 3/2$, whilst the inclusion of deterministic terms should imply an increasing (decreasing) in the power of the *DW* test with respect to the nondeterministic case for $1 < d < 3/2$ $(d < 1)$. None of these claims show up from our experiments.

5. Conclusions.

Marmol (1997) shows that, in the presence of spurious regressions among *NFI(d)* processes, possibly including deterministic terms, the *DW* statistic converges in probability to zero for all values of *d*. This property, in turn, implies that this statistic can be an useful tool in detecting the presence of these nonsense relationships. Nowadays, this result is exactly true only in the limit as the sample size tends to infinity and can be different in finite samples.

This paper has investigated the sampling properties of this testing procedure through simulation exercises. Since the *DGP* employed in this study is relatively simple, it would be unwise to make strong general claims from this simulation study on the performance of the *DW* statistic as a misspecification test against the presence of nonsense relationships. Indeed, it appears that the *DW* statistic has good power properties for the major part of the points of the parameter space of our simulations. Specifically, for $T = 200$ and $d \geq 1$, the *DW* test is particularly recommendable.

In moderate samples, however, when $d < 1$, the optimism of the above message depends crucially on the error structure of the true model and rather large samples are needed in this case in order to avoid the identification problems induced by the presence of large $MA(1)$ coefficients in the innovation terms.

Figure 1: Values of the *MA*(1) parameters of the innovation processes

	Θ_x	0	0.4	0.8
Θ_y				
0		*CASE* 1	*CASE* 2	*CASE* 3
0.4		*CASE* 4	*CASE* 5	*CASE* 6
0.8		*CASE* 7	*CASE* 8	*CASE* 9

TABLE 1

Power of the *DW* statistic against spurious regressions. CASE 1: $\Theta_y = \Theta_x = 0$

			Value of d							
T	μ	*Region*	0.5	0.6	0.8	1	1.2	1.5	1.8	2
50	0	1	0.9090	0.9810	0.9990	1.0000	1.0000	1.0000	1.0000	1.0000
50	0	2	0.0310	0.0100	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
50	0	3	0.0600	0.0090	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000
50	0	4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
50	0	5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
50	1	1	0.8130	0.9400	0.9930	0.9980	1.0000	1.0000	1.0000	1.0000
50	1	2	0.0620	0.0220	0.0050	0.0010	0.0000	0.0000	0.0000	0.0000
50	1	3	0.1250	0.0380	0.0020	0.0010	0.0000	0.0000	0.0000	0.0000
50	1	4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
50	1	5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	0	1	0.9990	0.9990	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
100	0	2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	0	3	0.0010	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	0	4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	0	5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	1	1	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
100	1	2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	1	3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	1	4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	1	5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	0	1	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
200	0	2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	0	3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	0	4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	0	5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	1	1	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
200	1	2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	1	3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	1	4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	1	5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

True DGP: $\begin{pmatrix} y_t \\ x_t \end{pmatrix} = \mu t + \begin{pmatrix} y_t^0 \\ x_t^0 \end{pmatrix}, \quad \Delta^d \begin{pmatrix} y_t^0 \\ x_t^0 \end{pmatrix} = \begin{pmatrix} u_{yt} \\ u_{xt} \end{pmatrix},$

$$u_{it} = \varepsilon_{it} - \Theta_i \varepsilon_{i,t-1}, \quad \varepsilon_{it} \sim NIID(0,1), \quad i = \{y, x\}.$$

Estimated model: $y_t = \hat{\alpha} + \hat{\beta} x_t + res., \ t = 1, \ldots, T$.

Regions 1 and 5: regions of rejection of the null hypothesis of correct specification. *Region* 3: region of no rejection of the null hypothesis of correct specification. *Regions* 2 and 4: inconclusive regions. 5% significance level.

TABLE 2

Power of the *DW* statistic against spurious regressions. CASE 2: $\Theta_y = 0, \Theta_x = 0.4$

			Value of d							
T	μ	*Region*	0.5	0.6	0.8	1	1.2	1.5	1.8	2
50	0	1	0.9300	0.9750	1.0000	1.0000	0.9990	0.9990	0.9990	1.0000
50	0	2	0.0260	0.0070	0.0000	0.0000	0.0000	0.0010	0.0000	0.0000
50	0	3	0.0440	0.0180	0.0000	0.0000	0.0010	0.0000	0.0010	0.0000
50	0	4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
50	0	5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
50	1	1	0.8590	0.9420	0.9950	0.9990	1.0000	0.9990	1.0000	0.9980
50	1	2	0.0370	0.0250	0.0010	0.0010	0.0000	0.0010	0.0000	0.0010
50	1	3	0.1040	0.0330	0.0040	0.0000	0.0000	0.0000	0.0000	0.0010
50	1	4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
50	1	5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	0	1	0.9980	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
100	0	2	0.0020	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	0	3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	0	4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	0	5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	1	1	0.9940	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
100	1	2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	1	3	0.0060	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	1	4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	1	5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	0	1	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
200	0	2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	0	3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	0	4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	0	5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	1	1	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
200	1	2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	1	3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	1	4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	1	5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

True DGP: $\begin{pmatrix} y_t \\ x_t \end{pmatrix} = \mu t + \begin{pmatrix} y_t^0 \\ x_t^0 \end{pmatrix}, \quad \Delta^d \begin{pmatrix} y_t^0 \\ x_t^0 \end{pmatrix} = \begin{pmatrix} u_{yt} \\ u_{xt} \end{pmatrix},$

$u_{it} = \varepsilon_{it} - \Theta_i \varepsilon_{i,t-1}, \quad \varepsilon_{it} \sim NIID(0,1), \quad i = \{y, x\}.$

Estimated model: $y_t = \hat{\alpha} + \hat{\beta} x_t + res., \; t = 1, \ldots, T.$

Regions 1 and 5: regions of rejection of the null hypothesis of correct specification. *Region* 3: region of no rejection of the null hypothesis of correct specification. *Regions* 2 and 4: inconclusive regions. 5% significance level.

TABLE 3

Power of the *DW* statistic against spurious regressions. CASE 3: $\Theta_y = 0, \Theta_x = 0.8$

			Value of d							
T	μ	*Region*	0.5	0.6	0.8	1	1.2	1.5	1.8	2
50	0	1	0.9370	0.9840	0.9980	1.0000	1.0000	1.0000	1.0000	1.0000
50	0	2	0.0290	0.0110	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000
50	0	3	0.0340	0.0050	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000
50	0	4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
50	0	5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
50	1	1	0.8790	0.9570	0.9990	1.0000	1.0000	1.0000	1.0000	0.9990
50	1	2	0.0410	0.0170	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000
50	1	3	0.0800	0.0260	0.0000	0.0000	0.0000	0.0000	0.0000	0.0010
50	1	4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
50	1	5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	0	1	0.9980	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
100	0	2	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	0	3	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	0	4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	0	5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	1	1	0.9970	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
100	1	2	0.0020	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	1	3	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	1	4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	1	5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	0	1	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
200	0	2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	0	3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	0	4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	0	5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	1	1	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
200	1	2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	1	3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	1	4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	1	5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

True DGP: $\begin{pmatrix} y_t \\ x_t \end{pmatrix} = \mu t + \begin{pmatrix} y_t^0 \\ x_t^0 \end{pmatrix}, \quad \Delta^d \begin{pmatrix} y_t^0 \\ x_t^0 \end{pmatrix} = \begin{pmatrix} u_{yt} \\ u_{xt} \end{pmatrix},$

$u_{it} = \varepsilon_{it} - \Theta_i \varepsilon_{i,t-1}, \quad \varepsilon_{it} \sim NIID(0,1), \quad i = \{y, x\}.$

Estimated model: $y_t = \hat{\alpha} + \hat{\beta} x_t + res., \; t = 1, \ldots, T.$

Regions 1 and 5: regions of rejection of the null hypothesis of correct specification. *Region* 3: region of no rejection of the null hypothesis of correct specification. *Regions* 2 and 4: inconclusive regions. 5% significance level.

TABLE 4

Power of the *DW* statistic against spurious regressions. CASE 4: $\Theta_y = 0.4, \Theta_x = 0$

			Value of d							
T	μ	*Region*	0.5	0.6	0.8	1	1.2	1.5	1.8	2
50	0	1	0.1670	0.3810	0.8220	0.9850	0.9780	0.9740	0.9820	0.9760
50	0	2	0.0620	0.0840	0.0330	0.0070	0.0080	0.0100	0.0090	0.0050
50	0	3	0.7400	0.5220	0.1450	0.0080	0.0140	0.0160	0.0090	0.0190
50	0	4	0.0150	0.0070	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
50	0	5	0.0160	0.0060	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
50	1	1	0.0720	0.2020	0.6600	0.9100	0.9110	0.9220	0.9220	0.9250
50	1	2	0.0460	0.0750	0.0740	0.0350	0.0310	0.0250	0.0210	0.0210
50	1	3	0.7950	0.6990	0.2620	0.0550	0.0580	0.0530	0.0570	0.0530
50	1	4	0.0330	0.0160	0.0030	0.0000	0.0000	0.0000	0.0000	0.0000
50	1	5	0.0540	0.0080	0.0010	0.0000	0.0000	0.0000	0.0000	0.0010
100	0	1	0.3980	0.7690	0.9940	1.0000	1.0000	1.0000	1.0000	1.0000
100	0	2	0.0530	0.0350	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000
100	0	3	0.5300	0.1950	0.0050	0.0000	0.0000	0.0000	0.0000	0.0000
100	0	4	0.0040	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	0	5	0.0150	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	1	1	0.2360	0.5740	0.9800	1.0000	0.9990	1.0000	1.0000	0.9990
100	1	2	0.0500	0.0640	0.0030	0.0000	0.0000	0.0000	0.0000	0.0010
100	1	3	0.6910	0.3550	0.0170	0.0000	0.0010	0.0000	0.0000	0.0000
100	1	4	0.0120	0.0030	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	1	5	0.0110	0.0040	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	0	1	0.7160	0.9760	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
200	0	2	0.0290	0.0030	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	0	3	0.2530	0.0210	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	0	4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	0	5	0.0020	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	1	1	0.5910	0.9290	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
200	1	2	0.0440	0.0130	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	1	3	0.3620	0.0580	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	1	4	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	1	5	0.0020	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

True DGP: $\begin{pmatrix} y_t \\ x_t \end{pmatrix} = \mu t + \begin{pmatrix} y_t^0 \\ x_t^0 \end{pmatrix}, \quad \Delta^d \begin{pmatrix} y_t^0 \\ x_t^0 \end{pmatrix} = \begin{pmatrix} u_{yt} \\ u_{xt} \end{pmatrix},$

$u_{it} = \varepsilon_{it} - \Theta_i \varepsilon_{i,t-1}, \quad \varepsilon_{it} \sim NIID(0,1), \quad i = \{y, x\}.$

Estimated model: $y_t = \hat{\alpha} + \hat{\beta} x_t + res.,\ t = 1, \ldots, T.$

Regions 1 and 5: regions of rejection of the null hypothesis of correct specification. *Region* 3: region of no rejection of the null hypothesis of correct specification. *Regions* 2 and 4: inconclusive regions. 5% significance level.

TABLE 5

Power of the *DW* statistic against spurious regressions. CASE 5: $\Theta_y = 0.4, \Theta_x = 0.4$

			Value of d							
T	μ	*Region*	0.5	0.6	0.8	1	1.2	1.5	1.8	2
50	0	1	0.1910	0.4300	0.8640	0.9750	0.9750	0.9730	0.9770	0.9640
50	0	2	0.0580	0.0830	0.0340	0.0060	0.0050	0.0100	0.0090	0.0080
50	0	3	0.7160	0.4830	0.1000	0.0190	0.0200	0.0170	0.0140	0.0280
50	0	4	0.0100	0.0010	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000
50	0	5	0.0250	0.0030	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000
50	1	1	0.0870	0.2200	0.6830	0.9140	0.9350	0.9240	0.9320	0.9280
50	1	2	0.0420	0.0840	0.0730	0.0250	0.0230	0.0260	0.0220	0.0270
50	1	3	0.7950	0.6670	0.2420	0.0610	0.0410	0.0500	0.0460	0.0440
50	1	4	0.0300	0.0170	0.0010	0.0000	0.0010	0.0000	0.0000	0.0010
50	1	5	0.0460	0.0120	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000
100	0	1	0.4280	0.7940	0.9940	1.0000	1.0000	1.0000	1.0000	1.0000
100	0	2	0.0620	0.0400	0.0030	0.0000	0.0000	0.0000	0.0000	0.0000
100	0	3	0.4980	0.1660	0.0030	0.0000	0.0000	0.0000	0.0000	0.0000
100	0	4	0.0070	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	0	5	0.0050	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	1	1	0.2270	0.6060	0.9840	1.0000	1.0000	0.9990	1.0000	1.0000
100	1	2	0.0600	0.0670	0.0020	0.0000	0.0000	0.0000	0.0000	0.0000
100	1	3	0.6910	0.3230	0.0140	0.0000	0.0000	0.0010	0.0000	0.0000
100	1	4	0.0100	0.0020	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	1	5	0.0120	0.0020	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	0	1	0.7510	0.9840	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
200	0	2	0.0250	0.0020	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	0	3	0.2230	0.0130	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	0	4	0.0010	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	0	5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	1	1	0.6060	0.9360	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
200	1	2	0.0290	0.0090	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	1	3	0.3580	0.0550	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	1	4	0.0040	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	1	5	0.0030	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

True DGP: $\begin{pmatrix} y_t \\ x_t \end{pmatrix} = \mu t + \begin{pmatrix} y_t^0 \\ x_t^0 \end{pmatrix}, \quad \Delta^d \begin{pmatrix} y_t^0 \\ x_t^0 \end{pmatrix} = \begin{pmatrix} u_{yt} \\ u_{xt} \end{pmatrix},$

$u_{it} = \varepsilon_{it} - \Theta_i \varepsilon_{i,t-1}, \quad \varepsilon_{it} \sim NIID(0,1), \quad i = \{y, x\}.$

Estimated model: $y_t = \hat{\alpha} + \hat{\beta} x_t + res., \; t = 1, \ldots, T.$

Regions 1 and 5: regions of rejection of the null hypothesis of correct specification. *Region* 3: region of no rejection of the null hypothesis of correct specification. *Regions* 2 and 4: inconclusive regions. 5% significance level.

TABLE 6

Power of the *DW* statistic against spurious regressions. CASE 6: $\Theta_y = 0.4, \Theta_x = 0.8$

			Value of d							
T	μ	Region	0.5	0.6	0.8	1	1.2	1.5	1.8	2
50	0	1	0.2040	0.5020	0.8990	0.9860	0.9890	0.9870	0.9930	0.9820
50	0	2	0.0810	0.0860	0.0280	0.0070	0.0080	0.0060	0.0050	0.0110
50	0	3	0.6780	0.4020	0.0730	0.0070	0.0030	0.0070	0.0020	0.0070
50	0	4	0.0140	0.0050	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
50	0	5	0.0230	0.0050	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
50	1	1	0.1100	0.2540	0.7460	0.9380	0.9570	0.9310	0.9520	0.9520
50	1	2	0.0560	0.0780	0.0640	0.0210	0.0170	0.0170	0.0110	0.0220
50	1	3	0.7610	0.6460	0.1880	0.0410	0.0260	0.0510	0.0370	0.0260
50	1	4	0.0290	0.0120	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
50	1	5	0.0440	0.0100	0.0020	0.0000	0.0000	0.0010	0.0000	0.0000
100	0	1	0.4640	0.8250	0.9990	1.0000	1.0000	1.0000	1.0000	1.0000
100	0	2	0.0450	0.0250	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	0	3	0.4810	0.1500	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000
100	0	4	0.0030	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	0	5	0.0070	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	1	1	0.3020	0.6530	0.9870	1.0000	1.0000	0.9990	1.0000	1.0000
100	1	2	0.0520	0.0500	0.0060	0.0000	0.0000	0.0000	0.0000	0.0000
100	1	3	0.6300	0.2940	0.0070	0.0000	0.0000	0.0010	0.0000	0.0000
100	1	4	0.0090	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
100	1	5	0.0070	0.0020	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	0	1	0.7710	0.9870	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
200	0	2	0.0420	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	0	3	0.1860	0.0120	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	0	4	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	0	5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	1	1	0.6190	0.9610	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
200	1	2	0.0320	0.0060	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	1	3	0.3430	0.0330	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	1	4	0.0020	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
200	1	5	0.0040	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

True DGP: $\begin{pmatrix} y_t \\ x_t \end{pmatrix} = \mu t + \begin{pmatrix} y_t^0 \\ x_t^0 \end{pmatrix}, \quad \Delta^d \begin{pmatrix} y_t^0 \\ x_t^0 \end{pmatrix} = \begin{pmatrix} u_{yt} \\ u_{xt} \end{pmatrix},$

$u_{it} = \varepsilon_{it} - \Theta_i \varepsilon_{i,t-1}, \quad \varepsilon_{it} \sim NIID(0,1), \quad i = \{y, x\}.$

Estimated model: $y_t = \hat{\alpha} + \hat{\beta} x_t + res., \ t = 1, \ldots, T.$

Regions 1 and 5: regions of rejection of the null hypothesis of correct specification. *Region* 3: region of no rejection of the null hypothesis of correct specification. *Regions* 2 and 4: inconclusive regions. 5% significance level.

TABLE 7

Power of the *DW* statistic against spurious regressions. CASE 7: $\Theta_y = 0.8, \Theta_x = 0$

			Value of d							
T	μ	*Region*	0.5	0.6	0.8	1	1.2	1.5	1.8	2
50	0	1	0.0000	0.0010	0.0310	0.3250	0.3330	0.3190	0.3280	0.2950
50	0	2	0.0000	0.0000	0.0180	0.0700	0.0870	0.0720	0.0690	0.0760
50	0	3	0.3340	0.5130	0.8190	0.5900	0.5700	0.5870	0.5830	0.6120
50	0	4	0.1130	0.1170	0.0490	0.0070	0.0020	0.0090	0.0070	0.0080
50	0	5	0.5530	0.3690	0.0830	0.0080	0.0080	0.0130	0.0130	0.0090
50	1	1	0.0000	0.0010	0.0060	0.1210	0.1510	0.1340	0.1230	0.1090
50	1	2	0.0000	0.0000	0.0080	0.0570	0.0480	0.0640	0.0560	0.0540
50	1	3	0.2910	0.4570	0.8020	0.7900	0.7660	0.7690	0.7900	0.7870
50	1	4	0.1390	0.1270	0.0770	0.0190	0.0150	0.0160	0.0130	0.0240
50	1	5	0.5700	0.4150	0.1070	0.0130	0.0200	0.0170	0.0180	0.0260
100	0	1	0.0000	0.0000	0.1240	0.7370	0.7720	0.7740	0.7370	0.7370
100	0	2	0.0000	0.0000	0.0300	0.0380	0.0330	0.0370	0.0420	0.0380
100	0	3	0.1090	0.3210	0.7700	0.2230	0.1940	0.1860	0.2210	0.2230
100	0	4	0.0400	0.0820	0.0220	0.0000	0.0000	0.0010	0.0000	0.0010
100	0	5	0.8510	0.5970	0.0540	0.0020	0.0010	0.0020	0.0000	0.0010
100	1	1	0.0000	0.0000	0.0280	0.4920	0.5520	0.4820	0.4710	0.4820
100	1	2	0.0000	0.0000	0.0150	0.0630	0.0520	0.0520	0.0660	0.0450
100	1	3	0.0810	0.2520	0.8020	0.4410	0.3910	0.4620	0.4610	0.4680
100	1	4	0.0410	0.0790	0.0530	0.0000	0.0020	0.0020	0.0010	0.0030
100	1	5	0.8780	0.6690	0.1020	0.0040	0.0030	0.0020	0.0010	0.0020
200	0	1	0.0000	0.0000	0.3980	0.9830	0.9850	0.9860	0.9850	0.9800
200	0	2	0.0000	0.0000	0.0360	0.0060	0.0030	0.0040	0.0000	0.0020
200	0	3	0.0150	0.2050	0.5280	0.0110	0.0120	0.0100	0.0150	0.0180
200	0	4	0.0110	0.0290	0.0140	0.0000	0.0000	0.0000	0.0000	0.0000
200	0	5	0.9740	0.7660	0.0240	0.0000	0.0000	0.0000	0.0000	0.0000
200	1	1	0.0000	0.0000	0.1540	0.9410	0.9600	0.9280	0.9160	0.9360
200	1	2	0.0000	0.0000	0.0220	0.0080	0.0070	0.0180	0.0090	0.0120
200	1	3	0.0050	0.0830	0.7410	0.0510	0.0330	0.0540	0.0750	0.0520
200	1	4	0.0020	0.0370	0.0210	0.0000	0.0000	0.0000	0.0000	0.0000
200	1	5	0.9930	0.8800	0.0620	0.0000	0.0000	0.0000	0.0000	0.0000

True DGP: $\begin{pmatrix} y_t \\ x_t \end{pmatrix} = \mu t + \begin{pmatrix} y_t^0 \\ x_t^0 \end{pmatrix}, \quad \Delta^d \begin{pmatrix} y_t^0 \\ x_t^0 \end{pmatrix} = \begin{pmatrix} u_{yt} \\ u_{xt} \end{pmatrix},$

$u_{it} = \varepsilon_{it} - \Theta_i \varepsilon_{i,t-1}, \quad \varepsilon_{it} \sim NIID(0,1), \quad i = \{y,x\}.$

Estimated model: $y_t = \hat{\alpha} + \hat{\beta} x_t + res., \; t = 1,\ldots,T.$

Regions 1 and 5: regions of rejection of the null hypothesis of correct specification. *Region* 3: region of no rejection of the null hypothesis of correct specification. *Regions* 2 and 4: inconclusive regions. 5% significance level.

TABLE 8

Power of the *DW* statistic against spurious regressions. CASE 8: $\Theta_y = 0.8, \Theta_x = 0.4$

			Value of d							
T	μ	*Region*	0.5	0.6	0.8	1	1.2	1.5	1.8	2
50	0	1	0.0000	0.0010	0.0480	0.3100	0.3600	0.3240	0.3010	0.3210
50	0	2	0.0000	0.0000	0.0280	0.0780	0.0880	0.0800	0.0880	0.0820
50	0	3	0.3460	0.5210	0.8020	0.5920	0.5390	0.5820	0.6030	0.5850
50	0	4	0.1370	0.1160	0.0470	0.0110	0.0070	0.0090	0.0020	0.0030
50	0	5	0.5170	0.3630	0.0750	0.0090	0.0060	0.0050	0.0060	0.0090
50	1	1	0.0000	0.0000	0.0130	0.1190	0.1390	0.1230	0.1300	0.1270
50	1	2	0.0010	0.0010	0.0090	0.0440	0.0560	0.0600	0.0590	0.0690
50	1	3	0.3210	0.4850	0.7790	0.7990	0.7560	0.7760	0.7730	0.7610
50	1	4	0.1250	0.1240	0.0660	0.0180	0.0210	0.0170	0.0200	0.0140
50	1	5	0.5530	0.3900	0.1330	0.0200	0.0280	0.0200	0.0180	0.0290
100	0	1	0.0000	0.0000	0.1260	0.7240	0.7790	0.7360	0.7410	0.7270
100	0	2	0.0000	0.0000	0.0210	0.0430	0.0280	0.0450	0.0330	0.0300
100	0	3	0.1170	0.3390	0.7680	0.2320	0.1930	0.2190	0.2250	0.2400
100	0	4	0.0490	0.0820	0.0240	0.0001	0.0000	0.0010	0.0010	0.0010
100	0	5	0.8340	0.5790	0.0610	0.0000	0.0000	0.0020	0.0000	0.0020
100	1	1	0.0000	0.0000	0.0280	0.4870	0.5120	0.4990	0.4860	0.4670
100	1	2	0.0000	0.0000	0.0090	0.0500	0.0470	0.0500	0.0700	0.0540
100	1	3	0.0860	0.2430	0.8280	0.4570	0.4380	0.4480	0.4420	0.4740
100	1	4	0.0370	0.0760	0.0320	0.0030	0.0020	0.0010	0.0010	0.0020
100	1	5	0.8770	0.6810	0.1030	0.0030	0.0010	0.0020	0.0010	0.0030
200	0	1	0.0000	0.0010	0.3950	0.9810	0.9810	0.9800	0.9750	0.9770
200	0	2	0.0000	0.0000	0.0240	0.0040	0.0040	0.0030	0.0060	0.0070
200	0	3	0.0140	0.1750	0.5560	0.0150	0.0150	0.0170	0.0190	0.0160
200	0	4	0.0010	0.0440	0.0050	0.0000	0.0000	0.0000	0.0000	0.0000
200	0	5	0.9760	0.7800	0.0200	0.0000	0.0000	0.0000	0.0000	0.0000
200	1	1	0.0000	0.0000	0.1430	0.9230	0.9350	0.9200	0.9150	0.9280
200	1	2	0.0000	0.0000	0.0230	0.0140	0.0080	0.0090	0.0150	0.0130
200	1	3	0.0040	0.1000	0.7500	0.0630	0.0570	0.0710	0.0700	0.0590
200	1	4	0.0010	0.0240	0.0200	0.0000	0.0020	0.0000	0.0000	0.0000
200	1	5	0.9950	0.8760	0.0640	0.0000	0.0000	0.0000	0.0000	0.0000

True DGP: $\begin{pmatrix} y_t \\ x_t \end{pmatrix} = \mu t + \begin{pmatrix} y_t^0 \\ x_t^0 \end{pmatrix}, \quad \Delta^d \begin{pmatrix} y_t^0 \\ x_t^0 \end{pmatrix} = \begin{pmatrix} u_{yt} \\ u_{xt} \end{pmatrix},$

$u_{it} = \varepsilon_{it} - \Theta_i \varepsilon_{i,t-1}, \quad \varepsilon_{it} \sim NIID(0,1), \quad i = \{y, x\}.$

Estimated model: $y_t = \hat{\alpha} + \hat{\beta} x_t + res., \ t = 1, \dots, T.$

Regions 1 and 5: regions of rejection of the null hypothesis of correct specification. *Region* 3: region of no rejection of the null hypothesis of correct specification. *Regions* 2 and 4: inconclusive regions. 5% significance level.

TABLE 9

Power of the *DW* statistic against spurious regressions. CASE 9: $\Theta_y = 0.8, \Theta_x = 0.8$

			Value of d							
T	μ	*Region*	0.5	0.6	0.8	1	1.2	1.5	1.8	2
50	0	1	0.0000	0.0010	0.0580	0.3950	0.4400	0.4010	0.3800	0.3850
50	0	2	0.0000	0.0000	0.0310	0.0780	0.0740	0.1050	0.0810	0.0810
50	0	3	0.3770	0.5890	0.7220	0.5180	0.4800	0.4820	0.5310	0.5260
50	0	4	0.1300	0.1130	0.0130	0.0030	0.0050	0.0050	0.0030	0.0020
50	0	5	0.4930	0.2980	0.0380	0.0060	0.0010	0.0070	0.0050	0.0060
50	1	1	0.0000	0.0000	0.0120	0.1530	0.1900	0.1650	0.1610	0.1600
50	1	2	0.0010	0.0010	0.0160	0.0630	0.0680	0.0610	0.0770	0.0780
50	1	3	0.3300	0.4940	0.7900	0.7550	0.7190	0.7440	0.7350	0.7300
50	1	4	0.1390	0.1450	0.0580	0.0160	0.0110	0.0180	0.0170	0.0190
50	1	5	0.5310	0.3600	0.1240	0.0130	0.0120	0.0120	0.0100	0.0130
100	0	1	0.0000	0.0000	0.1960	0.7740	0.8070	0.7690	0.7920	0.7780
100	0	2	0.0000	0.0010	0.0310	0.0290	0.0310	0.0450	0.0260	0.0350
100	0	3	0.1170	0.3840	0.7220	0.1960	0.1620	0.1850	0.1810	0.1850
100	0	4	0.0450	0.0730	0.0130	0.0010	0.0000	0.0010	0.0000	0.0020
100	0	5	0.8380	0.5420	0.0380	0.0000	0.0000	0.0000	0.0010	0.0000
100	1	1	0.0000	0.0000	0.0410	0.5660	0.5810	0.5360	0.5550	0.5560
100	1	2	0.0000	0.0000	0.0190	0.0470	0.0710	0.0690	0.0460	0.0440
100	1	3	0.1060	0.2970	0.8150	0.3840	0.3450	0.3920	0.3980	0.3950
100	1	4	0.0460	0.0640	0.0310	0.0010	0.0020	0.0000	0.0010	0.0020
100	1	5	0.8480	0.6390	0.0940	0.0020	0.0010	0.0030	0.0000	0.0030
200	0	1	0.0000	0.0010	0.4840	0.9800	0.9880	0.9840	0.9910	0.9840
200	0	2	0.0000	0.0010	0.0350	0.0060	0.0020	0.0000	0.0030	0.0050
200	0	3	0.0160	0.2040	0.4580	0.0140	0.0100	0.0160	0.0060	0.0110
200	0	4	0.0030	0.0360	0.0060	0.0000	0.0000	0.0000	0.0000	0.0000
200	0	5	0.9810	0.7580	0.0170	0.0000	0.0000	0.0000	0.0000	0.0000
200	1	1	0.0000	0.0000	0.2110	0.9310	0.9700	0.9430	0.9480	0.9370
200	1	2	0.0000	0.0000	0.0170	0.0140	0.0040	0.0100	0.0100	0.0070
200	1	3	0.0070	0.1200	0.7150	0.0550	0.0260	0.0470	0.0420	0.0560
200	1	4	0.0070	0.0200	0.0120	0.0000	0.0020	0.0000	0.0000	0.0000
200	1	5	0.9860	0.8600	0.0450	0.0000	0.0000	0.0000	0.0000	0.0000

True DGP: $\begin{pmatrix} y_t \\ x_t \end{pmatrix} = \mu t + \begin{pmatrix} y_t^0 \\ x_t^0 \end{pmatrix}, \quad \Delta^d \begin{pmatrix} y_t^0 \\ x_t^0 \end{pmatrix} = \begin{pmatrix} u_{yt} \\ u_{xt} \end{pmatrix},$

$u_{it} = \varepsilon_{it} - \Theta_i \varepsilon_{i,t-1}, \quad \varepsilon_{it} \sim NIID(0,1), \quad i = \{y, x\}.$

Estimated model: $y_t = \hat{\alpha} + \hat{\beta} x_t + res., \; t = 1, \ldots, T.$

Regions 1 and 5: regions of rejection of the null hypothesis of correct specification. *Region* 3: region of no rejection of the null hypothesis of correct specification. *Regions* 2 and 4: inconclusive regions. 5% significance level.

6. References.

Baillie, R., 1996. Long Memory Processes and Fractional Integration in Econometrics. *Journal of Econometrics*, 73, pp. 5-59.

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

Choi, I., 1994. Spurious Regressions and Residual-Based Tests for Cointegration when Regressors are Cointegrated. *Journal of Econometrics*, 60, pp. 313-320.

Diebold, F.X. and P. Lindner, 1996. Fractional Integration and Interval Prediction. *Economics Letters*, 50, pp. 305-313.

Durlauf, S.N. and P.C.B. Phillips, 1988. Trends versus Random Walks in Time Series Analysis. *Econometrica*, 56, pp. 1333-1354.

Granger, C.W.J., 1980. Long Memory Relationships and the Aggregation of Dynamic Models. *Journal of Econometrics*, 14, pp. 227-238.

Granger, C.W.J. and R. Joyeux, 1980. An Introduction to Long-Memory Time Series Models and Fractional Differencing. *Journal of Time Series Analysis*, 1, pp. 15-39.

Granger, C.W.J. and P. Newbold, 1974. Spurious Regressions in Econometrics. *Journal of Econometrics*, 2, pp. 111-120.

Granger, C.W.J. and P. Newbold, 1986. *Forecasting Economic Time Series*. New York, Academic Press.

Haldrup, N., 1994. The Asymptotics of Single-Equation Cointegration Regressions with $I(1)$ and $I(2)$ Variables. *Journal of Econometrics*, 63, pp. 153-181.

Hassler, U., 1996. Spurious Regressions when Stationary Regressors are Included. *Economics Letters*, 50, pp. 25-31.

Hendry, D., 1980. Econometrics -Alchemy or Science?. *Economica*, 47, pp. 387-406.

Hosking, J., 1981. Fractional Differencing, *Biometrika*, 68, pp. 165-176.

Mankiw, N.G. and M.D. Shapiro, 1985. Trends, Random Walks and Tests of the Permanent Income Hypothesis. *Journal of Monetary Economics*, 16, pp. 165-174.

Mankiw, N.G. and M.D. Shapiro, 1986. Do We Reject Too Often? Small Sample Properties of Tests of Rational Expectations Models. *Economics Letters*, 20, pp. 139-145.

Marmol, F., 1995. Spurious Regressions between $I(d)$ Processes. *Journal of Time Series Analysis*, 16, pp. 313-321.

Marmol, F., 1996. Nonsense Regressions between Integrated Processes of Different Orders. *Oxford Bulletin of Economics and Statistics*, 58, pp. 525-536.

Marmol, F., 1997. "Spurious Regression Theory with Nonstationary Fractionally Integrated Processes. Forthcoming in *Journal of Econometrics*.

Marmol, F. and J.C. Reboredo, 1997. A Theoretical Overview and a Simulation Study on the Power of the Durbin-Watson Tests Against Unbalanced Relationships. *Preprint*, Universidad Carlos III de Madrid.

Nelson, C.R., 1988. Spurious Trend and Cycle in the State Space Decomposition of a Time Series with a Unit Root. *Journal of Economic Dynamics and Control*, 12, pp. 475-488.

Nelson, C.R. and C.I. PLOSSER, 1982. Trends and Random Walks in Macroeconomic Time Series: Some Evidence and Implications. *Journal of Monetary Economics*, 10, pp. 139-162.

Ohanian, L.E., 1988. The Spurious Effects of Unit Roots on Vector Autoregressions. *Journal of Econometrics*, 39, pp. 251-266.

Ohanian, L.E., 1991. A Note on Spurious Inference in a Linearly Detrended Vector Autoregression. *Review of Economics and Statistics*, 73, pp. 568-571.

Plosser, C.I. and G.W. Schwert, 1978. Money, Income and Sunspots: Measuring Economic Relationships and the Effects of Differencing. *Journal of Monetary Economics*, 4, pp. 637-660.

Phillips, P.C.B., 1986. Understanding Spurious Regressions in Econometrics. *Journal of Econometrics*, 33, pp. 311-340.

Savin, N.E. and K.J. White, 1977. The Durbin-Watson Test for Serial Correlation with Extreme Sample Sizes or Many Regressors. *Econometrica*, 45, pp. 1989-1996.

Smith, R.P., 1991. Spurious Structural Stability. *The Manchester School*, 59, pp. 419-423.

Tanaka, K., 1993. An Alternative Approach to the Asymptotic Theory of Spurious Regression, Cointegration, and Near Cointegration. *Econometric Theory*, 9, pp. 36-61.

Toda, H. and P.C.B. Phillips, 1993. The Spurious Effect of Unit Roots on Vector Autoregressions. *Journal of Econometrics*, 59, pp. 229-255.