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SPURIOUS REGRESSIONS BETWEEN STATIONARY SERIES: SOME FURTHER INVESTIGATIONS

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SPURIOUS REGRESSIONS BETWEEN STATIONARY SERIES: SOME FURTHER INVESTIGATIONS

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ABSTRACT

This paper examines whether the convergent t-test of Kiefer and Vogelsang (2002) and Sun (2004) is able to solve spurious regressions with stationary series. In brief, we find that the convergent t-test provides a better control over size compared to the usual t-test and its Newey-West modification. Also, implementing the convergent t-test with a pre-whiting procedure produces further control over size but with a few exceptions. However, there are occasions that the likelihood of bias rejection is still much too high when the convergent t-test is applied.

Keywords: spurious regression, heteroskedasticity-autocorrelation robust test, pre-whitening

JEL Classification: C22

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1. INTRODUCTION

It is a well-known fact that the use of nonstationary data can lead to spurious regressions. Granger and Newbold (1974) first found via Monte Carlo simulations that, given two independent random walks, it is likely that a regression of one on the other will produce a "significant" slope coefficient according to the usual t-test. Since the two walks are actually unrelated the statistical significance is spurious and misleading. Later, Phillips (1986) developed an asymptotic theory for regression between two unrelated I(1) processes, showing that the usual t-statistic does not have a limiting distribution but diverges as the sample size goes to infinity. Similar divergent behaviour of the usual t-statistic can also be found in a regression between two nonstationary fractionally-integrated (I(d)) processes. See Marmol (1998) for details.

Spurious regression may also occur in stationary environments as well. Tsay and Chung (2000) found that the usual t-statistic diverges in a regression between two stationary I(d) processes, as long as their fractional parameters sum up to a value greater than 0.5. Granger, Hyung and Jeon (2001; hereafter, GHJ) found that a spurious regression can even occur in an occasion that the usual t-statistic is actually convergent. Using extensive finite-sample simulations, GHJ gave evidence that the null hypothesis of zero-slope in a regression with two independent stationary autoregressive series or medium-to-long moving averages is severely (spuriously) over-rejected. Moreover, Ferson, Sarkissian and Simin (2003; hereafter, FSS) showed that stock return predictability found in the literature might be spurious. Consider a predictive model that regresses a stock return on persistent lagged regressors. Since stock returns are typically not very persistent, there is no doubt that the usual t-statistic is convergent and spurious regression problems seem unlikely. However, as argued by FSS, a stock return may be considered as the sum of an unobservable expected return plus unpredictable noise. If the underlying expected return is persistent (not necessarily nonstationary), there is a risk of spurious regression.

The use of the standard t-statistic might be the blame for the spurious results since the test is valid only in a regression with serially-uncorrelated errors; yet the errors in a spurious regression are of course autocorrelated. Both GHJ (2000) and FSS (2003) found that over-rejections remain even if a heteroskedasticity-autocorrelation (HAC) robust t-statistic of Newey-West (1987) is considered. See also Phillips (1998) for an analytical explanation of why the Newey-West type test does not provide a rescue for the spurious regression. Recently, Sun (2004) documented that the seemingly inevitable divergent behaviour of the usual t-test (and its Newey-West modification) is due to the use of a standard error that underestimates the true variation of the slope estimator. He showed that once an appropriate standard error estimate, such as the one suggested in Kiefer and Vogelsang (2002; hereafter, KV), is used, the resulting t-statistic no longer diverges in a regression between two independent I(d) processes for any $d \geq 0$.

The finding of Sun (2004) is undoubtedly a breakthrough in attacking the spurious regression problem. Yet, there are still a couple of issues unresolved. First, as shown in Sun (2004), the asymptotic distribution of the suggested robust test (the KV test) actually depends on d, the memory parameter. In other words, unless d is known in priori (or is correctly estimated), the KV test can still induce bias results. Second, the finding of Sun (2004) can't be applied to issues raised by GHJ (2000) and FSS (2003) because a divergent t-statistic is not a concern in these two works. Instead, GHJ (2000) and FSS (2003) provided finite-sample evidence that spurious regression can occur in situations when the convergence of usual t-statistic is ensured by the asymptotic theory.

In this paper, we are interested in the performance of the convergent t-statistic of KV (2002) and Sun (2004) in regressions with stationary but highly persistent processes. Specifically, we address two questions. [1] How well does the convergent t-test put those spurious results found in GHJ (2001) and FSS (2003) into control? [2] How severe a bias rejection might be in a regression between two independent stationary I(d) series if an incorrect parameter is assumed (so incorrect critical values are used)? To answer them, intensive Monte-Carlo experiments are conducted. We find that the convergent t-test provides much better control over size than the usual t-test and its Newey-West modification. In most cases, although the convergent t-test does not produce correct size, the situation is not too bad (particularly when the sample size is large). However, there are occasions that the likelihood of over-rejection is still high when the test is used. We also find that implementing an AR(1) pre-whitening procedure may produce further control over size, but with a few exceptions.

The paper is organised as follows. Section 2 provides a short review regarding HAC robust tests and spurious regressions. Section 3 reports and discusses our simulation results. Finally, Section 4 concludes.

2. HAC ROBUST TESTS AND SPURIOUS REGRESSIONS

Consider the regression

$$Y_t = \alpha + \beta X_t + u_t \,, \quad t=1, 2, \ldots, T. \tag{1}$$

The OLS estimate of β is given by

$$\hat{\beta} = \frac{\sum_{t=1}^{T}(X_t - \bar{X})(Y_t - \bar{Y})}{\sum_{t=1}^{T}(X_t - \bar{X})^2} \,,$$

where $\bar{X} = T^{-1}\sum_{t=1}^{T} X_t$ and $\bar{Y} = T^{-1}\sum_{t=1}^{T} Y_t$. The usual t-ratio is defined as

$$t = \frac{\hat{\beta}}{\hat{s}_{\hat{\beta}}} = \frac{\hat{\beta}}{\left(\hat{\sigma}_u^2 / \sum_{t=1}^{T}\left(X_t - \bar{X}\right)^2\right)^{1/2}} \,, \tag{2}$$

where $\hat{s}_{\hat{\beta}}^2 = \hat{\sigma}_u^2 / \sum_{t=1}^{T}\left(X_t - \bar{X}\right)^2$, $\hat{\sigma}_u^2 = T^{-1}\sum_{t=1}^{T}\hat{u}_t^2$, and $\hat{u}_t = (Y_t - \bar{Y}) - \hat{\beta}(X_t - \bar{X})$. It is well known that when the error term in (1) is heteroskedastic or autocorrelated $\hat{s}_{\hat{\beta}}^2$ is not consistent for estimating the variance of $\hat{\beta}$ and consequently t is asymptotically invalid. Alternatively, a kernel-based HAC robust t-statistic can be defined as follows:

$$t^* = \frac{\hat{\beta}}{\hat{\sigma}_{\hat{\beta}}} = \frac{\hat{\beta}}{\left[T\hat{\Omega}_M \Big/ \left(\sum_{t=1}^{T}\left(X_t - \bar{X}\right)^2\right)^2\right]^{1/2}} \,, \tag{3}$$

where

$$\hat{\sigma}_{\hat{\beta}}^2 = \frac{T\hat{\Omega}_M}{\left(\sum_{t=1}^{T}\left(X_t - \bar{X}\right)^2\right)^2} \,,$$

$$\hat{\Omega}_M = \frac{1}{T}\sum_{j=-(T-1)}^{T-1}\kappa(j/M)\,\hat{\Gamma}(j) \,,$$

$$\hat{\Gamma}(j) = \sum_{t=j+1}^{T}\left(X_t - \bar{X}\right)^2 \hat{u}_t \hat{u}_{t-j} \quad for \;\; j \geq 0, \;\; \hat{\Gamma}(j) = \hat{\Gamma}(-j) \;\; for \;\; j < 0 \,.$$

Here, M is the bandwidth parameter and $\kappa(x)$ is a kernel function. Following Newey and West (1987), we consider the Bartlett kernel, $\kappa(x) = \left(1 - |x|\right)^{-1}$ if $|x| < 1$ and 0 otherwise, throughout paper.

To ensure that $\hat{\sigma}_{\hat{\beta}}^2$ is a consistent estimate for the variance of $\hat{\beta}$, the conventional approach requires that "$M, T \to \infty$ and $M = o(T)$." See Newey and West (1987) for an early development and den Haan and Levin (1997) for a recent review. Alternatively, Kiefer and Vogelsang (2002) suggest using $M = T$ (the full bandwidth) in the calculation of $\hat{\Omega}_M$ (denoted by $\hat{\Omega}_{M=T}$)[1]. This rate for M clearly violates the $M = o(T)$ rule and $\hat{\Omega}_{M=T}$ is not consistent. However, as shown in Kiefer and Vogelsang (2002), the test statistic using $\hat{\Omega}_{M=T}$ is asymptotically pivotal and exhibits a better finite-sample size control than the conventional approach. In this paper, we will refer the HAC robust t-test assuming "$M, T \to \infty$ and $M = o(T)$" as t_{NW}^* and the test using "$M = T$" as t_{KV}^*.

Consider the following assumption that X_t and Y_t are both I(0) (short memory) and independent to each other.

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[1] Recently, Kiefer and Vogelsang (2005) suggest using M=bT, where b$\in$(0,1] is a fixed number. An obvious trade-off is found: a small bandwidth (small b) leads to tests with higher power but greater size distortions and a large bandwidth (large b) leads to tests with lower power but less size distortions. Since controlling for size distortions is our main concern, we stick to the choice of "M=T" (i.e. b=1).

Assumption 1 (i) $T^{-1}\sum_{t=1}^{T} X_t^2 \to_p \sigma_x^2$ and $T^{-1}\sum_{t=1}^{T} Y_t^2 \to_p \sigma_y^2$ with $0 < \sigma_x^2, \sigma_y^2 < \infty$. (ii) $T^{-1/2}\sum_{t=1}^{[rT]} X_t Y_t \Rightarrow \lambda W(r)$ where λ is the long-run variance of "$X_t Y_t$" and $W(r)$ is a standard Wiener process. Denote [rT] as the integer part of rT, "$\to_p$" as convergence in probability and "$\Rightarrow$" as convergence in distribution.

Under Assumption 1, it can be shown that

$$t \Rightarrow N(0, \lambda^2/(\sigma_x^2 \sigma_y^2)),$$

$$t_{NW}^* \Rightarrow N(0,1),$$

$$t_{KV}^* \Rightarrow W(1)/[2\int_0^1 (W(r) - rW(1))^2 dr]^{1/2}.$$

See Newey and West (1987) and KV (2002) for details. Obviously, the usual t-statistic does not converge to the standard normal distribution unless $\lambda = \sigma_x \sigma_y$. Therefore, the usual t-test is asymptotically pivotal only when both X_t and Y_t are not serially-correlated. On the other hand, the NW test and the KV test are both asymptotically pivotal: the NW test converges to the standard normal distribution but the limiting distribution of the KV test is non-standard.[2]

It is well-known that the use of nonstationary data can lead to spurious regressions. A leading example is a regression with two independent I(1) (unit-root) series. In such a case, the usual t-test diverges at the rate $T^{1/2}$ (Phillips (1986)) and the Newey-West test diverges at the rate $(T/M)^{1/2}$, which is slower than the usual t-statistic by a factor of $M^{1/2}$ (Phillips (1998)). In contrast, Sun (2004) showed that the KV test converges, but to a distribution that is different to the one when I(0) is assumed.[3]

The finding of Sun (2004) is indeed a breakthrough in the literature regarding spurious regressions. However, this finding does not directly apply to issues raised in GHJ (2000) and FSS (2003) since the main concern in them is about the finite-sample over-rejection in situations when the convergence of usual t-statistic and its Newey-West modification is ensured by the asymptotic theory. Therefore, it is of importance to assess whether the KV test provides correct size in such occasions. Also, as shown in Sun (2004), the asymptotic distribution of the KV test actually depends on d, the memory parameter. In other words, unless d is known in priori (or is correctly estimated), the suggested test can still induce bias rejections. It is well known that testing I(0) against I(d) with $d \in (0,1/2)$ can result in low power. In particular, it is very difficult to classify a series as a stationary AR process or an I(d) process – see, for example, Lee and Schmidt (1996). This motivates us to study how likely an over-rejection might be when the KV test is applied to a regression between two independent stationary long-memory processes (i.e. I(d) with $d \in (0,1/2)$) by using critical values from "I(0)".

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[2] Critical values of the KV test are tabulated in KV (2002, Table 1) via simulations.

[3] In fact, as shown in Sun (2004), the KV test is convergent in a regression between two independent I(d) series for any $d \geq 0$.

3. MONTE CARLO SIMULATIONS

In this section we report the results of Monte Carlo experiments designed to investigate finite-sample size of the three previously discussed tests – namely, t, t^*_{NW} and t^*_{KV}. The bandwidth parameter (M) in t^*_{NW} is set equal to the integer part of $4\left(T/100\right)^{1/4}$, as in GHJ (2001). Also, an AR(1) pre-whitening procedure of Andrew and Monahan (1992) is implemented for t^*_{NW} and t^*_{KV} – denoted by $t^*_{NW,PW}$ $t^*_{NW,PW}$ respectively. All simulations are preformed in GAUSS and the results (the rejection rates) are calculated by comparing critical values at 5% (that is, 1.96 for the usual t-test and the NW test and 3.764 for the KV test) via 5,000 iterations. In the following, simulation results of several Monte Carlo experiments relating to the works of GHJ (2001), FSS (2003), and Tsay and Chung (2000) are reported and discussed.

<u>CASE I</u>: Spurious regression between AR processes

The first experiment is done by considering Y_t and X_t in (1) defined by independent AR(1) processes:

$$Y_t = \phi_y Y_{t-1} + \varepsilon_{y,t} \text{ and } X_t = \phi_x X_{t-1} + \varepsilon_{x,t},$$

where $\varepsilon_{y,t}, \varepsilon_{x,t}$ are each i.i.d. $N(0,1)$, independent to one another. Simulations results at sample size T=100, 250, 500, 1000, and 2000 are reported in Tables 1 for $\phi_x = \phi_y = \phi$ and Table 2 for $\phi_x \neq \phi_y$. These results correspond to those reported in Tables 1 and 2 of GHJ (2001).

The results in Table 1 can be summarized as follows. Spurious rejections appear frequently if the usual t-test is used and the test is evidently divergent as T increases for $\phi = 0.99$ or larger. The Newey-West method is helpful; but its advantage is less impressive if ϕ is close to 1.0 and T is large. Also, its divergent behaviour becomes apparent for $\phi = 1.0$ but at a slower rate, as predicted in Phillips (1998). These results are generally in agreement with those found in GHJ (2001). Performance of the KV test is quite impressive compared to the other two tests – the size is accurate for $\phi = 0.90$ or less and still under control even for $\phi = 0.99$ if the sample size is large. Moreover, the test is convergent for random walks ($\phi = 1.0$), which is in accordance to the asymptotic theory of Sun (2004). However, the frequency of rejection is still much higher than the nominal size when $\phi > 0.95$. In the random walk case, the size of the KV test is about 0.33 regardless the sample size.

Implementing a pre-whiting procedure does help for the NW test in taming size distortion. Taking $\phi = 0.9$ and T=500 for example, the rejection rate is reduced dramatically from 0.224 to 0.091. Even so, the procedure fails to make the NW test convergent when ϕ is larger than 0.99. When the KV test is considered, a pre-whiting procedure can successfully reduce size distortion, provided that the autoregression parameter ϕ is no larger than 0.95.

Taking $\phi = 0.95$ and T=500 for example, the rejection rate is reduced from 0.098 to 0.076, which is close to the nominal size. However, for $\phi = 0.99$ or larger, the procedure actually inflates the rejection rate and makes the test divergent when T is large. For example, at T=2000, the rejection rate increases from 0.151 to 0.285 and from 0.326 to 0.667 for ϕ equals 0.995 and 1.0, respectively. Therefore, a warning should be addressed in implementing a pre-whitening procedure.

Table 2 generally agrees with Table 1. The KV test is obviously the best. Performing a pre-whiting procedure is a plus in all cases. Also, as shown in GHJ (2001), rejection rates are similar for ($\phi_x = a$, $\phi_y = b$) and ($\phi_x = b$, $\phi_y = a$) if $a \neq b$ according to the usual t-test and the NW test. Such a symmetry does not appear for the KV test: rejection rates for ($\phi_x = a$, $\phi_y = b$) tend to be larger than those for ($\phi_x = a$, $\phi_y = b$) if $a > b$.

<u>CASE II</u>: Spurious regression between MA processes

The second experiment assumes that Y_t and X_t are generated by two independent MA(K) processes:

$$Y_t = \sum_{j=0}^{K} \varepsilon_{y,t-j} \text{ and } X_t = \sum_{j=0}^{K} \varepsilon_{x,t-j} ,$$

where ε_{xt} , ε_{yt} are each i.i.d. $N(0,1)$. Table 3 reports the simulation results for K taking the values 5, 10, 20, 50, or 75 and sample size varying from 100 to 2000. The results correspond to those reported in Tables 4 of GHJ (2001).

The results are generally consistent with those of the previous case. The usual t-test over-rejects frequently, almost one-half for K=10; the rejection frequency increases steadily with K, but is relatively stable over T. Frequency of over-rejection is greatly reduced using the NW test, and is reduced further when the KV test is used. Taking T=250 and K=10 for example, rejection rates of the usual t-test, the NW test and the KV test are 0.491, 0.200 and 0.082, respectively. For both HAC robust tests, rejection frequency increases steadily with K when T is fixed but decreases with T when K is fixed. Also, in all cases studied, size distortion is reduced further if a pre-whitening procedure is performed. Consider the KV test with pre-whitening, the rejection rate of K=75 is around 0.1 at T=500 and less than 0.1 at T>500. The pre-whitened NW test seems to be very conservative when K is small and T is large – the null hypothesis tends to be under-rejected.

<u>CASE III</u>: Spurious Predictability

Equation (1) can be seen as a predictive model if Y_t is a series of asset returns and X_t is a lagged variable of, say, interest rates, payout-to-price ratios or yield spreads. Following FSS (2003), consider that Y_t is generated by

$$Y_t = X^*_{t-1} + \eta_t , \tag{4}$$

where X^*_{t-1} is a lagged latent variable that follows an AR(1) process: $X^*_t = \phi^* X^*_t + \varepsilon^*_t$ and η_t is a white-noise perturbed term. If the latent variable were observable then the returns would be predictable and according to FSS (2003) the predictability can be captured by the "true" R^2:

$$R^2 = \frac{\mathrm{var}(X^*)}{\mathrm{var}(X^*) + \mathrm{var}(\eta)}.$$

However, since X^*_{t-1} is not observable in reality, a proxy (lagged) variable X_t (or, more precisely, X_{t-1}) is used in a regression model like equation (1). Spurious regression may arise if indeed X_t and X^*_t are independent to each other (so X_t should exhibit no predictive power for Y_t) but the null hypothesis: $\beta = 0$ in equation (1) is rejected much too often.[4]

The third experiment is set in accordance to FSS (2003) as follows. First, Y_t is generated according to (4) and, similar to X^*_t, X_t is generated by an AR(1) process: $X_t = \phi X_{t-1} + \varepsilon_t$. Without lost of generality, both ε_t and ε^*_t are assumed to be iid N(0,1) and independent to each other (so X_t and X^*_t are independent to each other). Also, η_t is an iid $N(0, \mathrm{var}(\eta))$ with $\mathrm{var}(\eta) = ((1-R^2)/R^2)\,\mathrm{var}(X^*)$ and $\mathrm{var}(X^*) = 1/(1-\phi^2)$. For simplicity, only $\phi^* = \phi$ is considered. Table 4 reports the simulation results for different combinations of ϕ (ϕ =0.9, 0.95 and 0.99) and R^2 (R^2 =0.01, 0.05, 0.10 and 0.15) at T=100, 500 and 1000.

Table 4 shows that for all tests rejection rate increases when ϕ is larger and when R^2 is larger. Comparing tests, once again, the KV test is the best. For example, for R^2=0.1, ϕ =0.95, T=500, compare size of 0.082 for the KV test to 0.222 for the usual t-test and 0.181 for the NW test. Also, the usual t-test and the NW test are clearly divergent when ϕ =0.99 but things become less clear when ϕ =0.95 or less. As expected, the KV test is always convergent as expected. Its rejection rate seems to be fairly close to the nominal size except for the cases that $\phi = 0.99$ and $R^2 \geq 0.10$. Even in the worst scenario, the likelihood of over-rejection is not very high, the rejection rate of the KV test never goes beyond 0.15. Finally, an AR(1) pre-whiting procedure provides moderate help for the KV test, but it is not much helpful for the NW test.

<u>CASE IV</u>: Spurious regression between stationary I(d) processes

The final experiment considers that Y_t and X_t are two independent fractionally-integrated (I(d)) processes, generated by

$$Y_t = (1-L)^{-d_y}\, \varepsilon_{y,t} \text{ and } X_t = (1-L)^{-d_x}\, \varepsilon_{x,t},$$

[4] In FSS (2003), the interaction of two problems, spurious regression bias and naïve data mining, is demonstrated in producing spurious stock return predictability. In this paper, spurious regression bias is our focus.

where ε_{xt} and ε_{yt} are each i.i.d. $N(0,1)$, independent of one another. For simplicity, we assume that $d_x = d_y = d$. Table 5 reports our simulation results for d=0.1, 0.2, 0.3, 0.4, 0.45 and 0.49 at T=100, 250, 500, 1000 and 2000.

Table 5 shows that the divergent behaviour of the usual t-test becomes apparent when d is larger than 0.3. This is generally in line with the theoretical finding of Tsay and Chung (2000). Similarly, the NW test (with or without pre-whitening) appears to be divergent when d is larger than 0.3 but at a slower rate. The NW test outperforms the usual t-test in all but one case (d=0.2, T=100). The KV test is again the best and is convergent for all d's, as predicted in Sun (2004). Also, our simulation result shows that, for the KV test, even if an incorrect critical value is used (i.e. when d=0.3 or larger) size distortion is only moderate – in particular, when T is large. For both the NW test and the KV test, an implementation of a pre-whitening procedure does provide better control over size. Taking d=0.45 and T=500 for example, rejection rate is 0.468 for the usual t-test, 0.285 for the NW test without pre-whitening and 0.256 with pre-whitening, and for the KV test 0.102 and 0.100 without and with pre-whitening respectively.

4. CONCLUSION

This paper assesses whether the convergent t-test of KV (2002) and Sun (2004) is able to solve spurious regressions found in GHJ (2001) and FSS (2003). To do so, intensive Monte-Carlo experiments have been conducted. In brief, it has been found that the convergent t-test delivers much better control over size comparing to the usual t-statistic and its Newey-West modification. Also, for most cases studied, implementing the convergent t-test with an AR(1) pre-whiting procedure produced further control over size. Even so, in many occasions, the rate of bias rejection is still much higher than the nominal size when the convergent test is used.

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Table 1: Spurious regression between AR processes (ϕ_x=ϕ_y=ϕ)

ϕ	T	t	t^*_{NW}	$t^*_{NW,PW}$	t^*_{KV}	$t^*_{KV,PW}$
0.50	100	.138	.110	.096	.069	.063
	250	.135	.079	.068	.051	.047
	500	.135	.073	.056	.051	.050
	1000	.126	.065	.055	.050	.049
	2000	.131	.059	.052	.050	.048
0.75	100	.292	.174	.125	.096	.077
	250	.289	.123	.079	.064	.057
	500	.308	.114	.073	.061	.058
	1000	.300	.086	.054	.058	.056
	2000	.300	.083	.053	.052	.050
0.9	100	.522	.312	.178	.140	.106
	250	.523	.243	.115	.094	.077
	500	.525	.224	.091	.073	.063
	1000	.525	.168	.072	.060	.056
	2000	.524	.151	.058	.058	.056
0.95	100	.616	.412	.230	.199	.149
	250	.653	.381	.162	.136	.103
	500	.659	.362	.118	.098	.076
	1000	.662	.305	.091	.077	.067
	2000	.663	.267	.073	.066	.059
0.99	100	.739	.557	.334	.299	.207
	250	.804	.612	.288	.252	.170
	500	.822	.625	.236	.197	.145
	1000	.832	.597	.188	.138	.114
	2000	.839	.578	.174	.116	.121
0.995	100	.741	.573	.343	.308	.213
	250	.827	.648	.325	.295	.200
	500	.856	.697	.301	.250	.181
	1000	.879	.695	.336	.205	.200
	2000	.880	.687	.407	.151	.285
1.0	100	.769	.613	.372	.339	.231
	250	.856	.699	.382	.327	.222
	500	.887	.772	.439	.328	.253
	1000	.923	.810	.624	.334	.435
	2000	.942	.849	.793	.326	.667

Table 2: Spurious regression between two AR processes ($\phi_x \neq \phi_y$)

(ϕ_y, ϕ_x)	T	t	t^*_{NW}	$t^*_{NW,PW}$	t^*_{KV}	$t^*_{KV,PW}$
(0.75, 0.90)	100	.387	.217	.132	.107	.088
	500	.382	.137	.069	.065	.059
	1000	.399	.112	.060	.057	.052
(0.90, 0.75)	100	.379	.218	.140	.102	.083
	500	.391	.149	.075	.063	.057
	1000	.387	.111	.061	.055	.051
(0.75, 0.95)	100	.401	.219	.141	.120	.091
	500	.427	.159	.073	.077	.069
	1000	.417	.127	.067	.069	.064
(0.95, 0.75)	100	.406	.230	.147	.100	.078
	500	.423	.153	.070	.064	.056
	1000	.418	.121	.058	.053	.048
(0.75, 1.0)	100	.443	.237	.142	.133	.092
	500	.448	.174	.075	.099	.081
	1000	.464	.140	.064	.089	.080
(1.0, 0.75)	100	.444	.243	.156	.100	.076
	500	.452	.167	.077	.053	.040
	1000	.467	.139	.066	.066	.060
(0.90, 0.95)	100	.553	.337	.194	.171	.122
	500	.576	.263	.090	.084	.069
	1000	.576	.226	.074	.066	.060
(0.95, 0.90)	100	.558	.344	.192	.165	.118
	500	.585	.276	.094	.081	.066
	1000	.591	.223	.080	.063	.057
(0.9, 1.0)	100	.611	.394	.206	.189	.128
	500	.648	.346	.107	.122	.089
	1000	.651	.278	.080	.098	.079
(1.0, 0.9)	100	.608	.406	.245	.178	.134
	500	.647	.348	.117	.082	.063
	1000	.649	.280	.086	.060	.048
(0.95, 1.0)	100	.687	.495	.266	.243	.157
	500	.731	.469	.144	.146	.099
	1000	.747	.424	.099	.113	.084
(1.0, 0.95)	100	.670	.484	.295	.241	.172
	500	.735	.481	.172	.120	.089
	1000	.747	.418	.121	.085	.063

Table 3: Spurious Regression between MA(k) processes

K	T	t	t^*_{NW}	$t^*_{NW,PW}$	t^*_{KV}	$t^*_{KV,PW}$
2	100	.176	.103	.073	.062	.051
	250	.178	.081	.056	.058	.051
	500	.179	.072	.048	.054	.048
	1000	.178	.066	.048	.051	.050
	2000	.179	.063	.045	.050	.049
5	100	.339	.165	.087	.084	.060
	250	.330	.118	.046	.063	.050
	500	.338	.113	.037	.059	.051
	1000	.325	.085	.034	.052	.047
	2000	.333	.083	.035	.052	.051
10	100	.490	.269	.129	.122	.083
	250	.491	.200	.070	.082	.062
	500	.478	.166	.037	.060	.048
	1000	.462	.132	.029	.060	.053
	2000	.470	.104	.022	.048	.045
15	100	.579	.359	.172	.156	.104
	250	.569	.267	.081	.094	.066
	500	.561	.227	.046	.069	.054
	1000	.559	.174	.036	.060	.052
	2000	.557	.150	.028	.060	.053
20	100	.637	.420	.217	.193	.126
	250	.620	.325	.107	.108	.074
	500	.607	.285	.061	.083	.061
	1000	.604	.226	.041	.064	.049
	2000	.604	.181	.023	.054	.049
50	100	.752	.585	.352	.327	.232
	250	.743	.533	.206	.191	.128
	500	.747	.483	.126	.121	.080
	1000	.747	.412	.070	.087	.060
	2000	.735	.348	.037	.061	.049
75	100	.771	.622	.367	.337	.237
	250	.792	.610	.272	.250	.173
	500	.791	.571	.164	.153	.101
	1000	.784	.490	.096	.096	.070
	2000	.779	.456	.060	.072	.060

Table 4: Spurious Predictability

R^2	ϕ	T	t	t^*_{NW}	$t^*_{NW,PW}$	t^*_{KV}	$t^*_{KV,PW}$
.01	.90	100	.062	.094	.098	.077	.076
		500	.061	.065	.066	.059	.058
		1000	.062	.062	.062	.053	.053
	.95	100	.066	.100	.105	.083	.077
		500	.069	.072	.072	.065	.064
		1000	.072	.072	.072	.067	.066
	.99	100	.067	.102	.108	.095	.089
		500	.106	.116	.118	.101	.099
		1000	.134	.135	.135	.101	.101
.05	.90	100	.099	.131	.133	.092	.090
		500	.096	.090	.090	.070	.068
		1000	.096	.076	.075	.056	.055
	.95	100	.105	.133	.136	.108	.104
		500	.142	.123	.123	.079	.078
		1000	.150	.118	.116	.062	.062
	.99	100	.098	.125	.132	.114	.105
		500	.279	.260	.269	.150	.147
		1000	.344	.305	.304	.129	.128
.10	.90	100	.128	.139	.141	.097	.093
		500	.142	.108	.106	.070	.068
		1000	.148	.098	.094	.056	.057
	.95	100	.163	.179	.180	.127	.121
		500	.222	.181	.177	.082	.081
		1000	.229	.159	.156	.066	.065
	.99	100	.131	.165	.171	.130	.121
		500	.398	.362	.361	.165	.163
		1000	.475	.403	.399	.140	.139
.15	.90	100	.167	.164	.162	.103	.098
		500	.191	.129	.122	.067	.066
		1000	.191	.115	.112	.058	.056
	.95	100	.205	.216	.215	.144	.139
		500	.286	.215	.208	.088	.086
		1000	.307	.188	.184	.070	.070
	.99	100	.173	.205	.208	.147	.140
		500	.467	.415	.410	.171	.169
		1000	.557	.461	.458	.151	.151

Table 5: Spurious regression between I(d) processes

d	T	t	t^*_{NW}	$t^*_{NW,PW}$	t^*_{KV}	$t^*_{KV,PW}$
0.1	100	.060	.082	.083	.057	.055
	250	.060	.065	.065	.051	.050
	500	.055	.058	.057	.051	.049
	1000	.059	.059	.058	.053	.052
	2000	.057	.055	.053	.049	.045
0.2	100	.078	.087	.084	.059	.057
	250	.086	.078	.075	.055	.054
	500	.093	.078	.076	.058	.055
	1000	.094	.073	.072	.053	.053
	2000	.086	.065	.063	.052	.052
0.3	100	.131	.115	.111	.068	.061
	250	.153	.112	.105	.064	.061
	500	.189	.125	.117	.066	.063
	1000	.208	.125	.119	.060	.059
	2000	.245	.147	.143	.057	.057
0.4	100	.212	.170	.155	.095	.087
	250	.298	.187	.168	.090	.086
	500	.372	.227	.202	.083	.081
	1000	.433	.254	.240	.080	.079
	2000	.508	.310	.294	.078	.078
0.45	100	.276	.205	.185	.110	.101
	250	.369	.233	.209	.099	.095
	500	.468	.285	.256	.102	.100
	1000	.538	.320	.299	.098	.097
	2000	.624	.404	.385	.097	.098
0.49	100	.314	.224	.197	.115	.105
	250	.438	.279	.251	.109	.104
	500	.529	.344	.318	.114	.113
	1000	.616	.394	.368	.101	.100
	2000	.701	.462	.443	.107	.106

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