Effects of simultaneity on testing Granger-causality – a cautionary note about statistical problems and economic misinterpretations

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Effects of simultaneity on testing Granger-causality – a cautionary note about statistical problems and economic misinterpretations[1]

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Abstract

Interpreting Granger causality as economic causality implies that the underlying VAR model is a structural economic model. However, this is wrong if simultaneity occurs. Magnitude and stability of possible errors are analysed in a simulation study. It is shown that economic misinterpretations of tests of Granger causality can occur with probability one for realistic parameter values. Furthermore, the power of the test can be rather low even with a sample size of T=50.

Keywords: Granger causality, test, simultaneity, instantaneous causality

JEL classification: C32

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1. Introduction

After the seminal paper of Granger (1969) testing Granger causality has become a workhorse in applied econometrics. By using a two-dimensional VAR model it is tested whether lagged values of y_2 improve the forecast of y_1. Although it is well known that a VAR model is only a reduced form if instantaneous causality exists, its parameters are sometimes interpreted as structural economic coefficients. Consider e.g. Hartwig (2010). He analysed whether health stimulates economic growth based on five year averages of annual data. Depending on the estimation method he found either none or a negative effect of lagged health on economic growth and interpreted this structurally. However, economic growth might be a function of health in the same five year period. Thus, a simultaneous equation model with instantaneous causality might be the correct specification, and the results for the lagged coefficients might be misleading. Further examples in the recent literature are amongst others Braunerhjelm et.al. (2010, economic growth and entrepreneurship, annual data), Casu and Girardone (2009, competition and efficiency in banking sectors, annual data), Fiordelisi et.al. (2011, capital ratio, risk and cost efficiency of banks, annual data), Handa and Khan (2008, financial development and economic growth, annual data) and Mah (2010, foreign direct investment and economic growth, annual data).

Interpreting VAR coefficients structurally in the presence of instantaneous causality clearly contradicts even to the seminal paper of Granger. He named a VAR-model as (simple) causal model only if instantaneous causality can be excluded theoretically (p. 427). However, if instantaneous causality occurs, tests of Granger causality may run into a dilemma. On the one hand, the tests may decide statistically correct about significance and sign of lagged values in the reduced form. On the other hand, a conclusion on economic causality might be misleading because instantaneous causality might change the results or might be not detected.

Nevertheless, it is not obvious, whether this matters in empirical practice. Therefore, this paper presents a simulation study that analyses the magnitude and the stability of possible errors. It distinguishes between statistical problems (like size distortions or a low power) and errors in the economic interpretation of Granger causality tests (e.g. a wrong conclusion of no causality). It can be seen that – given the usual stochastic assumptions – most problems are such of an economic misinterpretation.

Section 2 describes simulation design and results for a static simultaneous model, whereas in section 3 a dynamic model is considered. Section 4 concludes.

2. A static simultaneous equation model

The first part of the simulation is a static simultaneous equation model (model A):

$$\begin{aligned} y_{1t} &= \gamma_1 y_{2t} + u_{1t} \\ y_{2t} &= \gamma_2 y_{1t} + u_{2t} \end{aligned}, \quad u_t = \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix} \text{ iid } N(0,\Sigma). \tag{1}$$

It is well known that the system (1) is not identified (cf. e.g. Greene 2008, ch. 13.3, for a detailed depiction of identification issues). Either γ_1 and γ_2 or Σ have to be restricted to ensure identification. Since the gammas are the parameters of interest, Σ is restricted to a diagonal matrix, i.e. the correlation between u_{1t} and u_{2t} is restricted to zero.

The reduced form of (1) is

$$\begin{aligned} y_{1t} &= \frac{u_{1t} + \gamma_1 u_{2t}}{1-\gamma_1\gamma_2} =: v_{1t} \\ y_{2t} &= \frac{\gamma_2 u_{1t} + u_{2t}}{1-\gamma_1\gamma_2} =: v_{2t} \end{aligned}, \quad v_t = \begin{pmatrix} v_{1t} \\ v_{2t} \end{pmatrix} \text{ iid } N(0,\Sigma_v). \tag{2}$$

Although Σ is restricted to a diagonal matrix, Σ_v is not, i.e. v_{1t} and v_{2t} are usually correlated. (2) is the data generating process that is used to simulate the data. The sample size is chosen as T=50 (small sample) and T=500 (large sample). Thus, it can be seen whether asymptotic characteristics help to reduce the problems.

For the purpose of simplicity, Granger causality of y_2 for y_1 is tested by using an AR(1) structure:

$$\begin{aligned} y_{1t} &= \phi_{11} y_{1,t-1} + \phi_{12} y_{2,t-1} + \varepsilon_{1t} \\ y_{2t} &= \phi_{21} y_{1,t-1} + \phi_{22} y_{2,t-1} + \varepsilon_{2t} \end{aligned} \tag{3}$$

Thus, the usual F-test reduces to a t-test of

$$H_0: \phi_{12} = 0 \quad \text{vs.} \quad H_1: \phi_{12} \neq 0. \tag{4}$$

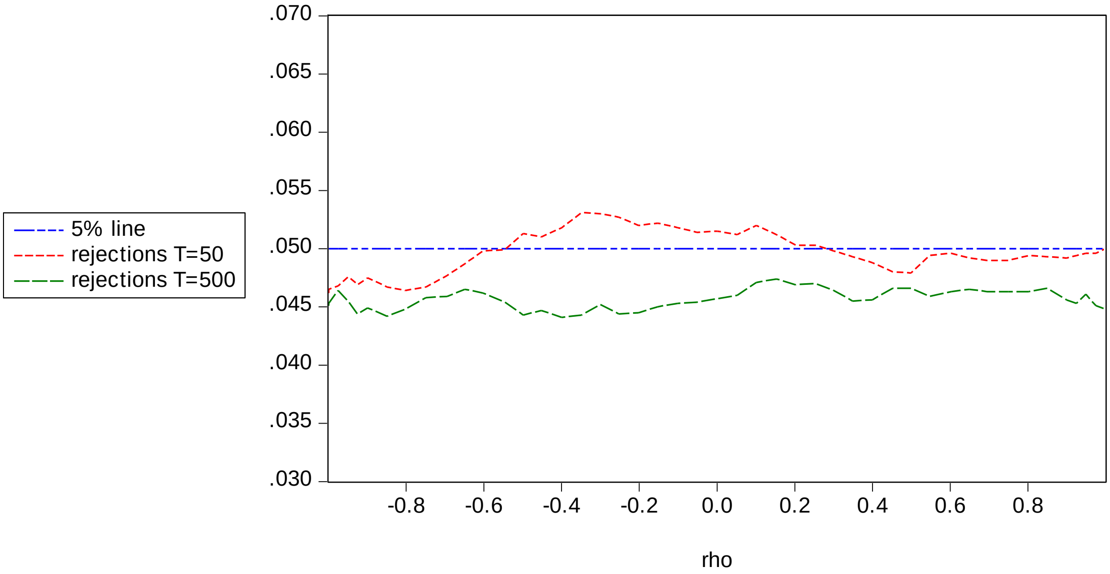
Comparing (2) and (3) points out the dilemma. The parameter ϕ_{12} is equal to zero in the data generating process. Thus, in a statistical sense the hypothesis (4) should not be rejected. Wrong rejections should only occur at the given level of significance. If H_0 is rejected too often, size distortion occurs. If it is rejected too scarcely, the power of the test might be rather low. However, in an economic sense, acceptance of H_0 is "bad" because the causality of y_2 for y_1 is not detected.

The unknown parameters of the data generating process (2) are γ_1, γ_2, $\sigma_{u1}^2 = \text{Var}(u_{1t})$, and $\sigma_{u2}^2 = \text{Var}(u_{2t})$. A broad range of these parameters and the usual levels of significance (1, 5, 10%) were taken into account.[2] However, the results were always similar. Figure 1 pictures the

[2] All simulations were done with R. The R codes of both models are attached in Appendix 1. The codes involve random number generation of u_t, transformation of u_t into v_t, calculation of y_{1t} and y_{2t} according to (2) (model A) or (6) (model B), OLS estimation of the first equation of (3) or (6), and calculation of the t-statistic and its p-values of ϕ_{12} or π_{12}. For both models 10000 replications were done, and the shares of rejections were calculated.

results at the 5% level according to a broad variation of the correlation between $y_{1,t-1}$ and $y_{2,t-1}$ (rho):[3]

Figure 1: Share of rejections of H_0 (5% level)



Model A with $\gamma_1 = -0.5$, $\gamma_2 = 0.5$, $\sigma_{u1} \in [0.01, 4]$, $\sigma_{u2} \in [0.01, 4]$, 10000 replications

If the sample size is large, no size distortions are observed. And even if the sample size is low, only small size distortions occur.[4] Thus, in a statistical sense, the test of Granger causality behaves well. However, in an economic sense, the decision would be wrong. It would be decided that there is no causality although a relevant instantaneous causality exists.

3. A dynamic simultaneous equations model

The simulation design of the second part is dynamic (model B):

$$\begin{aligned} y_{1t} &= \gamma_1 y_{2t} + \beta_1 y_{1,t-1} + u_{1t} \\ y_{2t} &= \gamma_2 y_{1t} + \beta_2 y_{2,t-1} + u_{2t} \end{aligned}, \quad u_t \text{ iid } N\left(0, \begin{pmatrix} \sigma_{u1}^2 & 0 \\ 0 & \sigma_{u2}^2 \end{pmatrix}\right). \tag{5}$$

In (5) no identification problem occurs because any linear combination of the two equations differs from the original equations. Nevertheless, Σ is again chosen as diagonal matrix to keep it as simple as possible.

[3] This correlation can influence the estimation results in (3). Because of (2) and correlation stationarity the correlation between $y_{1,t-1}$ and $y_{2,t-1}$ is equal to the correlation between v_{1t} and v_{2t}. This correlation can be varied either by variation of γ_1 and γ_2 or by variation of σ_{u1} and σ_{u2}. The data of figure 1 were calculated with the latter variation.

[4] A detailed table of the results can be found in Appendix 2a). Only for the 1% level, also in large samples the share of rejections is occasionally larger than the nominal size.

The reduced form of (5) is:

$$y_{1t} = \underbrace{\frac{\beta_1}{1-\gamma_1\gamma_2}}_{\pi_{11}} y_{1,t-1} + \underbrace{\frac{\gamma_1\beta_2}{1-\gamma_1\gamma_2}}_{\pi_{12}} y_{2,t-1} + v_{1t}$$
$$y_{2t} = \underbrace{\frac{\gamma_2\beta_1}{1-\gamma_1\gamma_2}}_{\pi_{21}} y_{1,t-1} + \underbrace{\frac{\beta_2}{1-\gamma_1\gamma_2}}_{\pi_{22}} y_{2,t-1} + v_{2t} \quad , \qquad (6)$$

where definitions and stochastic assumptions of v_{1t} and v_{2t} are the same as in (2). The initial values are chosen as $y_{11} = y_{21} = 0$.

Since (6) is a dynamic system, the time series y_{1t} and y_{2t} can be non-stationary. Therefore, the eigenvalues of $\Pi = \begin{pmatrix} \pi_{11} & \pi_{12} \\ \pi_{21} & \pi_{22} \end{pmatrix}$ are checked. The parameters in (5) are chosen such that all eigenvalues of Π are absolutely smaller than 0.9. Thus, non-stationarity *and* "near" non-stationarity are avoided.

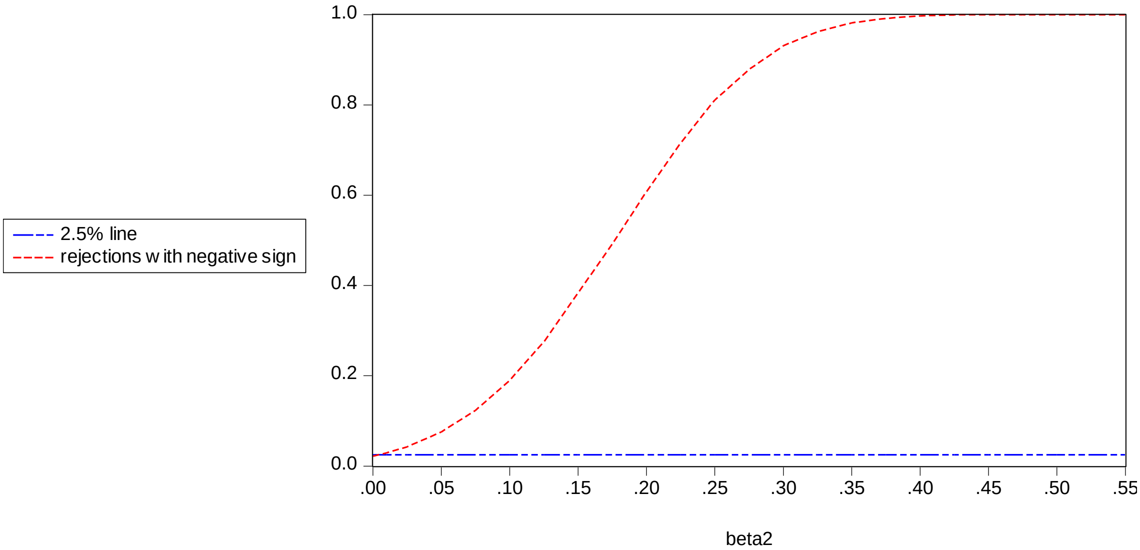
a) Wrong sign

In (6) π_{12} is always unequal to zero if the system is simultaneous (i.e. $\gamma_1 \neq 0$) and dynamic (i.e. $\beta_2 \neq 0$). Thus, rejecting H_0: $\pi_{12} = 0$ is statistically correct and leads to the "correct" economic decision that y_2 is causal for y_1 (only the lag is still wrong because y_2 is instantaneous causal). However, the sign of π_{12} might be different from that of γ_1. Let all parameters of (5) be positive. Furthermore, choose $\gamma_1\gamma_2 > 1$. This implies a negative value of π_{12} although the structural effect of y_2 on y_1 is positive. Therefore, rejecting H_0 and concluding a significant negative value of π_{12} is statistically correct. However, the conclusion of a negative causal effect of y_2 on y_1 would be wrong. That could explain for instance the counterintuitive result of Hartwig (2010).[5]

The magnitude of this problem may depend on the value of β_2. The higher β_2 is the larger the problem might be because the test becomes more powerful. H_0 is rejected with a higher probability. Therefore, it may also be concluded more often that increasing y_2 reduces y_1 although the opposite is true. Figure 2 pictures a result at the 5% level given fixed values of all other parameters.

[5] Another explanation could be the measurement of health. This is for instance done by expenditures for health. If the health system is inefficient, higher expenditures for health may reduce economic growth.

Figure 2: Share of rejections of H_0 concluding a negative effect of y_2 on y_1 (5% level)



Model B with $\gamma_1 = 2$, $\gamma_2 = 1$, $\beta_1 = 0.2$, $\sigma_{u1} = 2$, $\sigma_{u2} = 1$, T=500, 10000 replications

The probability of a wrong decision converges to one. Thus, a negative effect of y_2 on y_1 is concluded with probability one although in the true model (5) $y_{2,t-1}$ itself does not influence y_{1t} structurally and the instantaneous effect of y_2 on y_1 is positive. Therefore, all policy conclusions based on the Granger causality test would be completely wrong with probability one – given that ß$_2$ is enough different from zero. Changing the simulation design sometimes led to less extreme results. However, the tendency was always the same.

b) Low power in small samples

So far no statistical problems have been reported. However, kinds of byproducts of the simulation study have been power comparisons between small and large samples. An example is presented in figure 3. In contrast to the analysis above, the gamma parameters are chosen such that the sign of π_{12} is equal to the sign of γ_1 for any positive β_2. Therefore, concluding a positive or negative structural effect of y_2 on y_1 is right if the sign of $\hat{\pi}_{12}$ is equal to the sign of π_{12}. Only the time is still wrong because lagged instead of instantaneous causality is concluded. The right branch of figure 3 pictures the rejections with correct sign.[6] The left branch is just for the purpose of comparison. Here, the sign of π_{12} differs from the sign of γ_1 so that the economic conclusion would be wrong again.

Thus, the power of the test is rather low for T=50, i.e. for a sample size that is large for annual data and might be large even for quarterly data. Much more distance from zero is needed to get a high probability of rejection. Although the power still rises with β_2, it remains considerably below one for those values of β_2 that guarantee stationarity. In contrast to this the power for T=500 converges rapidly to one.

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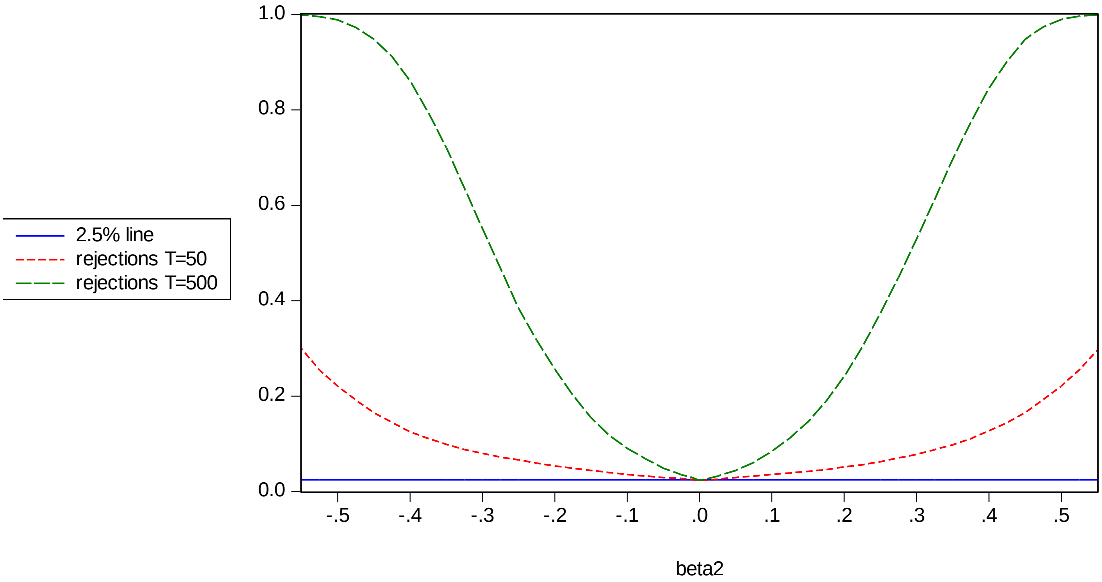
[6] The whole results can be found in Appendix 2b).

Figure 3: Share of rejections where the sign of $\hat{\pi}_{12}$ is equal to the sign of π_{12} (5% level)



Model B with $\gamma_1 = 0.6$, $\gamma_2 = 0.4$, $\beta_1 = 0.1$, $\sigma_{u1} = 2$, $\sigma_{u2} = 1$, 10000 replications

4. Conclusion

Using tests of Granger causality in case of simultaneity is not only problematic in an ivory tower. It is also empirically relevant. In a static simultaneous model without lagged dependent variables, the Granger test detects causality of y_2 for y_1 only with probability alpha, i.e. the level of significance, for a broad range of parameters. In a dynamic simultaneous model with an AR(1) structure, the detected sign of causality can be wrong with probability one. Thus, the issue of simultaneity should be treated more carefully in applied econometrics. If simultaneity cannot be excluded theoretically testing the correlation of the error terms of the test equations might be useful (cf. Lütkepohl 2005, p. 47).

Appendix 1: R codes for the simulation

a) R code for model A

```
# Load MASS (write.matrix requires MASS)
grkau<-function(replikat,gamma2){
n=50
n10=10*n
gamma1=-0.5
k=1   # k = order of AR process
i=1   # i = replicationindex
kq_erg=matrix(nrow=replikat,ncol=8)

set.seed(310465)
repeat{
      u1=rnorm(n10,mean=0,sd=4) # 4 is an example
      u2=rnorm(n10,mean=0,sd=0.01) # 0.01 is an example
      v1=(u1+gamma1*u2)/(1-gamma1*gamma2)
      v2=(gamma2*u1+u2)/(1-gamma1*gamma2)
      y1=v1
      y2=v2

reg=lm(y1[(k+1):n10]~y1[k:(n10-1)] + y2[k:(n10-1)] -1)
      ergebnis=summary(reg)
      kq_erg[i,1]=ergebnis$coefficients[1,1] # estimate of phi11
      kq_erg[i,3]=ergebnis$coefficients[2,1] # estimate of phi12
      kq_erg[i,5]=ergebnis$coefficients[1,4] # p-value of t-test phi11

      kq_erg[i,7]=ergebnis$coefficients[2,4] # p-value of t-test phi12

reg=lm(y1[(k+1):n]~y1[k:(n-1)] + y2[k:(n-1)]-1)
      ergebnis_n=summary(reg)
      kq_erg[i,2]=ergebnis_n$coefficients[1,1]
      kq_erg[i,4]=ergebnis_n$coefficients[2,1]
      kq_erg[i,6]=ergebnis_n$coefficients[1,4]
      kq_erg[i,8]=ergebnis_n$coefficients[2,4]

i=i+1
if(i==replikat+1){break}}

granger_out=matrix(nrow=replikat+1,ncol=8)
granger_out[1,]=c("phi11","phi11_n","phi12","phi12_n","pvalue_phi11","
pvalue_phi11_n","pvalue_phi12","pvalue_phi12_n")
granger_out[2:(replikat+1),]=kq_erg
write.matrix(granger_out,sep="\t",file="C:\\name.r")
}
#_____________________________________________
grkau(10000,0.5)
```

b) R code for model B

```
# Load MASS
grkau<-function(replikat,gamma2){
n=50
n10=10*n
gamma1=0.6
beta1=0.1
beta2=-0.5 # -0.5 is an example
k=1
i=1
kq_erg=matrix(nrow=replikat,ncol=8)
y1=vector(mode="numeric",length=n10)
      y1[1]=0
y2=vector(mode="numeric",length=n10)
      y2[1]=0

set.seed(310465)
repeat{
      u1=rnorm(n10,mean=0,sd=2)
      u2=rnorm(n10,mean=0,sd=1)
      v1=(u1+gamma1*u2)/(1-gamma1*gamma2)
      v2=(gamma2*u1+u2)/(1-gamma1*gamma2)
for(j in 2:n10) {
      y1[j]=(beta1/(1-gamma1*gamma2))*y1[j-1]+(gamma1*beta2/(1-
      gamma1*gamma2))*y2[j-1]+v1[j]
      y2[j]=(gamma2*beta1/(1-gamma1*gamma2))*y1[j-1]+(beta2/(1-
      gamma1*gamma2))*y2[j-1]+v2[j]
      }

reg=lm(y1[(k+1):n10]~y1[k:(n10-1)] + y2[k:(n10-1)] -1)
      ergebnis=summary(reg)
      kq_erg[i,1]=ergebnis$coefficients[1,1]
      kq_erg[i,3]=ergebnis$coefficients[2,1]
      kq_erg[i,5]=ergebnis$coefficients[1,4]
      kq_erg[i,7]=ergebnis$coefficients[2,4]

reg=lm(y1[(k+1):n]~y1[k:(n-1)] + y2[k:(n-1)]-1)
      ergebnis_n=summary(reg)
      kq_erg[i,2]=ergebnis_n$coefficients[1,1]
      kq_erg[i,4]=ergebnis_n$coefficients[2,1]
      kq_erg[i,6]=ergebnis_n$coefficients[1,4]
      kq_erg[i,8]=ergebnis_n$coefficients[2,4]

i=i+1
if(i==replikat+1){break}}

granger_out=matrix(nrow=replikat+1,ncol=8)
granger_out[1,]=c("phi11","phi11_n","phi12","phi12_n","pvalue_phi11","
pvalue_phi11_n","pvalue_phi12","pvalue_phi12_n")
granger_out[2:(replikat+1),]=kq_erg
write.matrix(granger_out,sep="\t",file="C:\\name.r")
}
#_____________________________________________
grkau(10000,0.4)
```

Appendix 2: Simulation results

a) Share of rejections for model A (γ_1 = -0.5, γ_2 = 0.5)

sigma u1/ sigma u2	rho	T=500, 10% level	T=500, 5% level	T=500, 1% level	T=50, 10% level	T=50, 5% level	T=50, 1% level
3.75/ 4	-0.0516	0.098	0.0454	0.0084	0.1017	0.0514	0.0095
3.525/ 4	-0.1009	0.0985	0.0453	0.0082	0.102	0.0518	0.0097
3.3/ 4	-0.1530	0.1004	0.045	0.0082	0.1019	0.0522	0.0095
3.1/ 4	-0.2019	0.0994	0.0445	0.0086	0.1021	0.052	0.0089
2.9/ 4	-0.2532	0.0988	0.0444	0.0084	0.1012	0.0527	0.0091
2.725/ 4	-0.3001	0.098	0.0452	0.0086	0.1001	0.053	0.0087
2.55/ 4	-0.3490	0.098	0.0443	0.0084	0.1005	0.0531	0.0088
2.375/ 4	-0.3998	0.0977	0.0441	0.0078	0.1012	0.0518	0.0088
2.2/ 4	-0.4524	0.0971	0.0447	0.0075	0.1017	0.051	0.0081
2.05/ 4	-0.4988	0.0961	0.0443	0.0074	0.1005	0.0513	0.008
1.9/ 4	-0.5462	0.0963	0.0454	0.0072	0.0998	0.0499	0.0087
1.725/ 4	-0.6026	0.0954	0.0462	0.0071	0.0968	0.0498	0.009
1.58/ 4	-0.6497	0.0949	0.0465	0.0067	0.0973	0.0487	0.0088
1.44/ 4	-0.6952	0.0924	0.0459	0.007	0.0974	0.0477	0.009
1.27/ 4	-0.7497	0.0948	0.0458	0.0072	0.097	0.0467	0.0092
1.1/ 4	-0.8024	0.0926	0.0448	0.0075	0.0967	0.0464	0.009
0.94/ 4	-0.8492	0.0942	0.0442	0.0082	0.0957	0.0467	0.0088
0.75/ 4	-0.8995	0.0959	0.0449	0.0075	0.0963	0.0475	0.0081
0.64/ 4	-0.9251	0.0947	0.0444	0.0073	0.0962	0.0469	0.008
0.52/ 4	-0.9495	0.0952	0.0455	0.008	0.0959	0.0476	0.0079
0.36/ 4	-0.9752	0.0944	0.0464	0.0079	0.0944	0.0468	0.0072
0.05/ 4	-0.9995	0.096	0.0453	0.0076	0.0943	0.0465	0.008
0.01/ 4	-0.99998	0.0971	0.0451	0.0084	0.0941	0.0462	0.0083
4/ 3.75	0.0516	0.098	0.046	0.0091	0.1012	0.0512	0.0088
4/ 3.525	0.1009	0.0972	0.0471	0.0092	0.1015	0.052	0.0091
4/ 3.3	0.1530	0.097	0.0474	0.0092	0.1021	0.0512	0.0093
4/ 3.1	0.2019	0.0976	0.0469	0.0094	0.1026	0.0503	0.0098
4/ 2.9	0.2532	0.0951	0.047	0.0093	0.1022	0.0503	0.0099
4/ 2.725	0.3001	0.0952	0.0464	0.0095	0.1027	0.0498	0.0099
4/ 2.55	0.3490	0.0953	0.0455	0.0095	0.1033	0.0493	0.0103
4/ 2.375	0.3998	0.0949	0.0456	0.0092	0.1027	0.0488	0.0107
4/ 2.2	0.4524	0.0952	0.0466	0.0091	0.1029	0.048	0.0106
4/ 2.05	0.4988	0.0953	0.0466	0.0093	0.1014	0.0479	0.0106
4/ 1.9	0.5462	0.0953	0.0459	0.0095	0.1012	0.0494	0.0105
4/ 1.725	0.6026	0.0954	0.0463	0.0101	0.1013	0.0496	0.0104
4/ 1.58	0.6497	0.0947	0.0465	0.0103	0.1004	0.0492	0.0104
4/ 1.44	0.6952	0.0943	0.0463	0.0106	0.0996	0.049	0.0105
4/ 1.27	0.7497	0.0928	0.0463	0.0106	0.0994	0.049	0.0105
4/ 1.1	0.8024	0.0929	0.0463	0.0107	0.0993	0.0494	0.0108
4/ 0.94	0.8492	0.0926	0.0466	0.0107	0.0992	0.0493	0.0107
4/ 0.75	0.8995	0.0927	0.0456	0.0111	0.0978	0.0492	0.0106
4/ 0.64	0.9251	0.0931	0.0453	0.0109	0.0978	0.0494	0.0103
4/ 0.52	0.9495	0.094	0.0461	0.0112	0.0973	0.0496	0.0101
4/ 0.36	0.9752	0.0954	0.0451	0.0109	0.0989	0.0496	0.0099
4/ 0.05	0.9995	0.0955	0.0448	0.0108	0.0985	0.05	0.0097
4/ 0.01	0.99998	0.0954	0.045	0.0107	0.0981	0.0497	0.0097

Further results are available on request.

b) Share of rejections for model B (γ_1 = 0.6, γ_2 = 0.4, β_1 = 0.1, σ_{u1} = 2, σ_{u2} = 1)

beta2	T=500 10% level	T=500, 5% level	thereof negative sign	T=500, 1% level	T=50, 10% level	T=50, 5% level	thereof negative sign	T=50, 1% level
0.6	1	1	0	0.9998	0.5428	0.4132	0.0002	0.1959
0.575	1	0.9999	0	0.9988	0.4795	0.3481	0.0003	0.1549
0.55	0.9997	0.9993	0	0.9931	0.4189	0.2973	0.0006	0.1216
0.525	0.9987	0.9961	0	0.9813	0.3738	0.2558	0.0006	0.0959
0.5	0.9951	0.9892	0	0.9553	0.3308	0.2215	0.0006	0.0783
0.475	0.9879	0.9735	0	0.908	0.295	0.1934	0.0013	0.0634
0.45	0.9724	0.9473	0	0.8403	0.266	0.1668	0.0016	0.0529
0.425	0.9468	0.9015	0	0.7547	0.2389	0.1468	0.0024	0.043
0.4	0.9076	0.8452	0	0.6568	0.2141	0.1296	0.0028	0.0363
0.375	0.8584	0.7737	0	0.5588	0.1949	0.1146	0.0037	0.0311
0.35	0.7939	0.6965	0	0.4608	0.1785	0.102	0.0043	0.0275
0.325	0.7234	0.6113	0	0.3746	0.1659	0.0926	0.0052	0.0238
0.3	0.6496	0.5298	0	0.2909	0.1524	0.0836	0.0058	0.0218
0.275	0.5729	0.4487	0.0001	0.2182	0.141	0.0772	0.007	0.0195
0.25	0.5002	0.3739	0.0002	0.1663	0.1327	0.0704	0.0079	0.0178
0.225	0.4265	0.3031	0.0003	0.122	0.126	0.0653	0.0092	0.0164
0.2	0.3536	0.2416	0.0008	0.0886	0.1181	0.0625	0.011	0.015
0.175	0.2931	0.191	0.0012	0.0632	0.1135	0.0583	0.0126	0.0129
0.15	0.2426	0.1482	0.0019	0.0464	0.1102	0.0559	0.0139	0.0117
0.125	0.1932	0.1149	0.0027	0.0328	0.1059	0.0545	0.0156	0.0107
0.1	0.1572	0.089	0.0048	0.024	0.1011	0.053	0.0171	0.0103
0.075	0.131	0.0681	0.0074	0.0177	0.0979	0.052	0.0196	0.0094
0.05	0.1121	0.0551	0.0111	0.0135	0.0967	0.0502	0.0207	0.009
0.025	0.0992	0.0494	0.0171	0.0103	0.0977	0.0487	0.0227	0.0091
0.01	0.0956	0.0482	0.0218	0.0097	0.0984	0.0477	0.0237	0.0087
0	0.0959	0.0487	0.0254	0.0094	0.0974	0.0472	0.0243	0.009
-0.01	0.0972	0.049	0.0295	0.01	0.0973	0.0474	0.0254	0.0092
-0.025	0.1031	0.0519	0.0353	0.0103	0.0967	0.0487	0.0276	0.0091
-0.05	0.1173	0.0603	0.0491	0.0138	0.096	0.0484	0.0293	0.0094
-0.075	0.1354	0.0763	0.0687	0.0186	0.0984	0.0487	0.0322	0.0109
-0.1	0.1655	0.0951	0.0903	0.0268	0.1005	0.0512	0.036	0.0113
-0.125	0.204	0.1215	0.1183	0.0362	0.1027	0.0541	0.0398	0.0122
-0.15	0.2507	0.157	0.1552	0.0519	0.1059	0.0566	0.0441	0.0127
-0.175	0.3051	0.2033	0.2025	0.0725	0.1095	0.0592	0.0488	0.0139
-0.2	0.3654	0.2567	0.2563	0.099	0.1157	0.0626	0.0534	0.0139
-0.225	0.4303	0.3168	0.3168	0.1341	0.1201	0.0678	0.0595	0.0155
-0.25	0.515	0.3843	0.3843	0.1817	0.127	0.0741	0.0663	0.0177
-0.275	0.5937	0.4677	0.4677	0.2409	0.137	0.0786	0.0719	0.0201
-0.3	0.67	0.5518	0.5518	0.3104	0.1468	0.0862	0.0802	0.0233
-0.325	0.7464	0.6362	0.6362	0.3894	0.1587	0.0929	0.088	0.0261
-0.35	0.8153	0.7208	0.7208	0.4852	0.1742	0.1031	0.0991	0.0303
-0.375	0.8718	0.7952	0.7952	0.583	0.1932	0.1141	0.111	0.0351
-0.4	0.9166	0.8609	0.8609	0.6828	0.2136	0.1278	0.1251	0.0402
-0.425	0.9496	0.9121	0.9121	0.775	0.2353	0.147	0.1447	0.0477
-0.45	0.9722	0.948	0.948	0.8512	0.2609	0.1668	0.1651	0.0567
-0.475	0.9872	0.9724	0.9724	0.9125	0.2929	0.1928	0.1916	0.0679
-0.5	0.9949	0.9885	0.9885	0.9528	0.3324	0.2218	0.2209	0.0821
-0.525	0.9986	0.9952	0.9952	0.9779	0.37	0.2552	0.2545	0.0983
-0.55	0.9997	0.9989	0.9989	0.9926	0.4174	0.3006	0.2999	0.1216
-0.575	0.9999	0.9998	0.9998	0.9978	0.465	0.3493	0.3487	0.1561
-0.6	1	1	1	0.9997	0.5207	0.4024	0.4019	0.1955

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