Dahlberg, Matz; Johansson, Eva; Tovmo, Per

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Power properties of the Sargan test in the presence of measurement errors in dynamic panels‡

Matz Dahlberg#, Eva Johansson♣ and Per Tovmo*

Abstract

This paper investigates the power properties of the Sargan test in the presence of measurement errors in dynamic panel data models. The general conclusion from the Monte Carlo simulations is that the Sargan test, in many cases, leads the econometrician to accept misspecified models with sometimes severely biased parameter estimates as a result. This is especially true when the number of cross-sectional units is small and when there are measurement errors in the dependent variable. To investigate if the simulation results have any bearing in real applications, we used the data in Arellano and Bond (1991) and re-estimated their employment equations with the difference that we deliberately imposed additive and multiplicative measurement errors in the employment and wage variables. It turned out that the Sargan test always accepted the misspecified models while we at the same time ended up with biased parameter estimates. The conclusion from this paper is that in the very likely case of measurement errors in either the dependent or any of the independent variables, we will, if we rely on the Sargan test, quite likely accept a misspecified model and end up with biased results.

Keywords: Sargan test, Measurement errors, Dynamic panels

JEL Classification: C12, C15, C23

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Department of Economics, Uppsala University, P.O. Box 513, SE-751 20 Uppsala, Sweden.

♣ Institute for Labour Market Policy Evaluation, and Department of Economics, Uppsala University, P.O. Box 513, SE-751 20 Uppsala, Sweden.

* Department of Economics, Norwegian University of Science and Technology, N-7491, Trondheim, Norway.

1. Introduction

In empirical work, some specification test to test the initial model is desirable. In GMM estimations of dynamic panel data models, the Sargan test for over-identifying restrictions has become the standard one to use. This performs a joint test of the model specification and the validity of the instruments (i.e. it tests if the moments are fulfilled). However, very little is known about the test's power.[1] Can we feel comfortable with our model specification if the Sargan test does not reject, or might there still be some misspecification leading to serious misinterpretations of the empirical results?

The purpose of this paper is to investigate the power properties of the Sargan test in dynamic panels, when the moments are not fulfilled. Questions that we will try to answer are the following: Will the Sargan test reject the false null that the moments are fulfilled? If it doesn't, will the estimated coefficients be biased? In order to answer these questions we will perform Monte Carlo simulations where we impose measurement errors in the data, either in the dependent variable or in an independent variable. We will also deliberately impose measurement errors in real data and investigate the consequences for the specification tests and for the estimated coefficients (using the Arellano and Bond (1991) data).

We find that it is quite possible to get a model where the Sargan test has very bad power properties (i.e., we accept a misspecified model too often) while, at the same time, the estimates of all coefficients are severely biased. The problem is especially pronounced for small sample sizes and for measurement errors in the dependent variable (and hence in the

lagged dependent variable). The results from the empirical application are in line with the Monte Carlo findings: when imposing measurement errors, the estimated coefficients change, but the Sargan test does not detect the misspecification.

2. Measurement errors in *x*

2.1 Experimental Design

We start by investigating a case with measurement errors in the independent variable x. Our intention is to study the performance of the Sargan test both when x is treated as exogenous and when it is treated as endogenous.

We use the following data generating process (DGP):

$$y_{it} = a_t + by_{it-1} + dx_{it} + f_i + e_{it} \tag{1}$$

$$y_{i0} = \frac{f_i}{(1-b)} + u_i \tag{2}$$

where cross-sections are denoted by $i = 1,\ldots,N$ and time periods by $t = 1,\ldots,T$. a_t are time dummies and f_i are individual specific effects.

We let x follow an AR(1)-process:

$$x_{it} = gx_{it-1} + u_{it} \tag{3}$$

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[1] An exception to this is Bowsher (2000), where the power properties of the Sargan test is explored when the error term follows an AR(1) process.

In the simulations, we will use sample sizes of $N = (100,...,1000)$ and $T = 7$, and let data be generated by $b = 0.5$, $d = 1$, $g = (0.5, 0.8)$, $x_{i0} \sim NID(0,1)$, $e_{it} \sim NID(0,1)$, $u_i \sim NID(0,1/(1-b_1^2))$, $u_{it} \sim NID(0,1)$, $f_i \sim NID(0,1)$, and $a_t \sim NID(0,1)$.

To investigate how the Sargan test works when we have problems with measurement errors, we consider three different types of errors. The first one is an additive error, where the observed x (denoted $\hat{x}$) is generated as

$$\hat{x}_{it} = x_{it} + h_{it} \tag{4}$$

with the measurement error generated as $h_{it} \sim NID(0,1)$ (yielding rather severe measurement errors: the standard deviation of the errors is the same as the standard deviation of x) or as $h_{it} \sim NID(0,0.1)$ (yielding less severe errors: the standard deviation of the measurement errors is 10 times smaller than the standard deviation of x).[2] The second measurement error is a multiplicative one, where the observed x ($\hat{x}$) is generated as

$$\hat{x}_{it} = x_{it} * h_{it} \tag{5}$$

with h generated as $h_{it} \sim NID(1,0.5)$ and $h_{it} \sim NID(1,0.1)$ respectively. Finally, we consider an exponential measurement error given by

$$\hat{x}_{it} = x_{it} * e^{h_{it}} \tag{6}$$

[2] In the Appendix we show that the moments are not fulfilled when there is measurement errors in x or y.

where $h_{it} \sim NID(0,0.1)$.

We estimate equation (1) in first-differenced form, using the GMM-estimator described in Holtz-Eakin, Newey and Rosen (1988) and Arellano and Bond (1991).[3] All Monte Carlo experiments are carried out in GAUSS, using the program's pseudo-random number generator. In each experiment we carry out 1000 Monte Carlo replications.

2.2 Results

The results from the simulations with measurement errors in *x* are presented in tables 1 and 2. The presented results are for $g = 0.8$[4]. Regarding choice of instruments, we consider two different cases. In the first case, we treat *x* as exogenous and hence use contemporaneous *x* as an instrument (in first-differenced form) as well as lags of *y* dated two periods back and more. These results are presented in Table 1. In the second case, we treat *x* as endogenous and use lags of *x* as instruments (dated one period back and more) instead of contemporaneous values of *x*.[5] These results are presented in Table 2.

In the base case, where *x* is measured without errors and contemporaneous *x* is treated as an exogenous regressor, we note from the first panel in Table 1 that the Sargan test has good size properties and that there is virtually no bias in d. For small sample sizes, there is however a bias in the coefficient for the lagged dependent variable.

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[3] The weighting matrix we use is the one proposed by Holtz-Eakin, Newey and Rosen.

[4] For $g = 0.5$ and measurement errors in *x*, the Sargan test get worse power properties compared to the $g = 0.8$ case (no matter if *x* is treated as exogenous or endogenous). The results for $g = 0.5$ are available upon request.

When we impose an additive and severe measurement error in x, it turns out that the Sargan test has low power at small sample sizes when contemporaneous x is treated as an exogenous instrument (see the second panel of Table 1). To get a rejection rate over 80 percent when testing at the five percent level, we need a sample of more than 600 cross-sections (see Figure 1). In applications we would hence far too often accept the false null of a well-specified model when we have a small number of cross-sectional units. This wouldn't be so problematic if the estimates were unbiased, but here we have a rather severe bias in both b and d.

In the third panel we investigate the performance when the additive measurement error is less severe. We find that the Sargan test has very low power, but the bias in b and d is rather low, even though there might be a problem for small sample sizes: for $N = 100$, the bias is approximately 27 percent for b and 5 percent for d. These results are very similar to the cases of multiplicative and exponential measurement errors with a small variation in the errors (c.f. the fourth and last panels of Table 1). However, also for multiplicative measurement errors, the results are sensitive to how severe the errors are. When the standard deviation of the measurement errors is half that of x, we see from the fifth panel that the Sargan test has bad power when N is low and that we have a severe bias in both b and d. From Figure 2 we see that we need a sample of at least 900 cross-sectional units to get a rejection rate over 80 percent (when testing at the five percent level).

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[5] It can be noted that we always use lags of y as instruments (dated two periods back and more).

The results when x is treated as endogenous are presented in Table 2. We find a similar pattern as the one found when x was treated as exogenous. There are some differences however; the bias in b is less serious when x is treated as endogenous (c.f. the second panels in the two tables) and the power increases faster when the sample sizes grow.

3. Measurement errors in *y*

3.1 Experimental Design

Let us now consider measurement errors in the dependent variable y. Since we estimate a dynamic model, this will induce measurement errors in one of the regressors as well (namely the lagged dependent variable). We will consider three types of measurement errors: one additive ($\hat{y}_{it} = y_{it} + h_{it}$), one multiplicative ($\hat{y}_{it} = y_{it} * h_{it}$), and one exponential ($\hat{y}_{it} = y_{it} * e^{h_{it}}$), where h is generated as in Section 2. There is no measurement error in x and the rest of the DGP is as above. As instruments we use lags of y dated two periods back or more together with contemporaneous x in first differences.

3.2 Results

The Monte Carlo results from the case with measurement errors in y are given in Table 3. When the error is additive and severe (the second panel) the estimates of b are severely biased (60 percent when $N = 1000$) and so are the ones of d, however to a smaller extent (approximately 8 percent). The power increases as the sample size grows, but is still relatively low: for example, when $N = 500$ the Sargan test rejects the false null in only 40 % of the Monte Carlo simulations (testing at the ten percent significance level). The worst case is when the measurement error is exponential (see the last panel). The bias is substantial in

both of the estimated coefficients and the power is extremely low; when testing at the ten percent significance level, the Sargan test rejects in only 17 percent of the times even for large N. When the error is multiplicative, the size of the error matters for the results. When imposing a small error (see the fourth panel), there is virtually no bias in d, whereas b is biased, even though the bias diminishes when the sample size grows. When we increase the standard deviation in the error (the fifth panel), the bias in b increases dramatically even for large N (for $N = 1000$, the bias is as large as 80 percent). The power of the Sargan test is however low; when testing at the five-percent level, the Sargan test rejects in only 38 percent of the cases for a sample size as large as 1000.[6]

The general conclusion from the simulations is hence that it is quite possible to get a model where the Sargan test has very bad power properties (i.e., we accept a misspecified model too often) while at the same time the estimates of both b and d are severely biased. This is especially true for small sample sizes and for measurement errors in the dependent variable.[7] [8]

4. Application: The Arellano and Bond (1991) data

[6] The power properties are unaffected of the size of g when there are measurement errors in y. However, the lower the autoregressive process in x is, the lower is the bias in b.

[7] Can the power of the Sargan test be improved by relying on bootstrap critical values using the GMM bootstrap estimator proposed by Hall and Horowitz (1996)? The answer is no. It turns out that in the experiments conducted, the bootstrapped Sargan test almost never rejects a false null.

[8] It has been suggested, see for example Bowsher (2000), that the power of the Sargan test can be improved by using fewer moment conditions. Doing this does not solve the problem in our case. Some simulation results showing this are available upon request.

As we have seen from the simulations, the Sargan test for overidentifying restrictions often leads us to accept models where the moments are not fulfilled with sometimes severely biased parameter estimates as a result. This is especially true when the number of cross-sectional units is small. But of course, the models in the Monte Carlo experiments are very stylized and parsimonious. Do the results have any bearing in real applications? To investigate this, we will use the data in Arellano and Bond (1991) and re-estimate their employment equations with the difference that we have deliberately imposed measurement errors in the employment and wage variables. In their application, they have 140 cross-sectional units (quoted U.K. companies) for the period 1979-1984.

We estimate the following equation

$$n_{it} = a_1 n_{it-1} + a_2 n_{it-2} + b_1 w_{it} + b_2 w_{it-1} + g k_{it} + d_1 ys_{it} + d_2 ys_{it-1} + l_t + h_i + u_{it} \qquad (9)$$

where n_{it} denotes the logarithm of U.K. employment in company i at the end of year t, w_{it} is the log of the real wage, k_{it} is the log of gross capital, ys_{it} is the log of industry output, l_t is a time effect that is common to all companies, h_i is a fixed but unobservable firm-specific effect, and u_{it} is the error term.[9] Replicating the earlier study, the estimation of equation (9) yields the results in column b in Table 4 in Arellano and Bond (1991). Our re-estimations are presented in tables 4 and 5. The first two columns in each of these tables restate the results in Arellano and Bond.

[9] For exact definitions of the variables, see Arellano and Bond (1991).

In Table 4, we impose measurement errors in the dependent variable, i.e. the employment variable. In the middle columns we have imposed additive measurement errors, while we in the final columns have imposed multiplicative measurement errors. In both cases the errors are distributed NID(5,1). A standard deviation of one corresponds to approximately 6.5 percent of the standard deviation in the employment variable.[10] As can be seen from the bottom rows in the table, the Sargan test does not give us any reason to believe that the moments are not fulfilled. Neither does the m_2 statistic, which tests for lack of second-order serial correlation in the first-differenced residuals. As a matter of fact, both the Sargan and the m_2 statistics are very similar to the ones obtained when no measurement errors are imposed in the data. What is affected, though, is the parameter estimates. For example, we seem to end up with less dynamics when there are additive errors: the second lag of both employment and wages is insignificant. The coefficients estimates in the Arellano and Bond estimations suggest a short-run wage elasticity of –0.51 while the corresponding figure with additive errors is –0.21 and with multiplicative errors –0.39.[11]

In Table 5, we impose measurement errors in one of the independent variables, namely the wage variable. In the middle columns we have imposed additive measurement errors, while we in the final columns have imposed multiplicative measurement errors. In the additive case, the errors are distributed $NID(0,1)$. In the multiplicative case, the errors are distributed $NID(3,1)$. A standard deviation of one corresponds to approximately 18 percent of the

[10] The standard deviation of the employment variable is 15.9 (unlogged values). The measurement errors are imposed before the variables are logged. The reason for having a mean of five in the errors is to ensure that the resulting employment variable is positive.

standard deviation in the wage variable.[12] Neither the Sargan statistic nor the m_2 statistic gives us any reason to believe that something is wrong. As for the results in Table 4, both the Sargan and the m_2 statistics are very similar to the ones obtained when no measurement errors are imposed in the data. However, turning to the parameter estimates, we see that they are indeed affected by the imposed measurement errors. Taking the case of additive errors as an example, we see that the short-run wage elasticity decreases from –0.51 to –0.19 and there seems to be less dynamics when measurement errors are imposed.

5. Conclusions

In this paper we have investigated the power properties of the Sargan test in the presence of measurement errors either in the dependent variable or in an independent variable (other than the lagged dependent variable) in dynamic panels.

The general conclusion from the Monte Carlo simulations is that the Sargan test for overidentifying restrictions often leads us to accept models where the moments are not fulfilled with sometimes severely biased parameter estimates as a result. The problem is most pronounced when the number of cross-sectional units is small and when there are measurement errors in the dependent variable.

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[11] The long-run wage elasticity is –0.5 in the Arellano and Bond estimations, –0.33 with additive errors, and –0.63 with multiplicative errors.

[12] The standard deviation of the wage variable is 5.6 (unlogged values). We have also estimated with less variation in the measurement errors (we have used distributions of the errors that corresponds to five and ten percent of the distribution in the wage variable). This did, however, not change the results substantially.

Do our simulation results have any bearing in real applications? To investigate this, we used the data in Arellano and Bond (1991) and re-estimated their employment equations with the difference that we deliberately imposed additive and multiplicative measurement errors in the employment and wage variables. It turned out that the specification tests (Sargan and the test for second-order serial correlation in the first-differenced variables) always accepted the misspecified models while we at the same time ended up with biased parameter estimates (we would, for example, reach the wrong conclusions of less dynamics in the model and considerably lower wage elasticities).

Arellano and Bond conclude after their empirical application: "The GMM estimator offers significant efficiency gains compared to simpler IV alternatives, and produces estimates that are well-determined in dynamic panel data models. … The robust m_2 statistics perform satisfactorily as do the two-step Sargan …" (p. 293). From the results in this study, we do however think that this statement must be qualified. The Sargan statistic performs satisfactorily and the GMM estimator will produces estimates that are well-determined in dynamic panel data models given that the models are correctly specified. In the very likely case of measurement errors in either the dependent or any of the independent variables, we will with a rather high probability accept a misspecified model and end up with biased results.

References

Arellano, M. and S. Bond (1991), "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations", *Review of Economic Studies* 58, 277-297.

Bowsher, C. (2000), "On Testing Overidentifying Restrictions in Dynamic Panel Data Models", Working paper 2000-W28, Nuffield College, University of Oxford.

Hall, P. and J. L. Horowitz (1996), "Bootstrap Critical Values for Tests Based on Generalized-Method-of-Moments Estimators", *Econometrica* 64, 891-916.

Holtz-Eakin, D., W. Newey, and H. S. Rosen (1988), "Estimating Vector Autoregressions with Panel Data", *Econometrica* 56, 1371-1395.

Table 1. Measurement errors in x. x treated as exogenous.

	Sargan rejection rates (%)			Bias (%)	
N	10	5	1	b	d
		No measurement errors			
100	11.5	5.5	0.3	-28.0	-3.8
500	13.5	7.0	1.8	-4.7	-0.7
1000	10.1	5.2	1.3	-2.0	-0.3
		$\hat{x} = x + h\ ,\ h \sim NID(0,1)$			
100	28.8	13.7	4.0	-8.1	-64.9
500	80.1	70.8	47.9	43.4	-62.3
1000	97.8	96.3	89.1	50.8	-61.8
		$\hat{x} = x + h\ ,\ h \sim NID(0,0.1)$			
100	12.0	5.3	0.4	-27.2	-5.5
500	13.7	6.2	1.8	-3.2	-2.3
1000	10.9	5.0	1.3	-0.5	-1.8
		$\hat{x} = x * h\ ,\ h \sim NID(1,0.1)$			
100	13.0	5.7	0.5	-26.4	-7.4
500	14.4	7.0	1.8	-1.5	-4.2
1000	11.3	5.9	1.6	1.3	-3.8
		$\hat{x} = x * h\ ,\ h \sim NID(1,0.5)$			
100	21.7	12.7	2.5	-12.7	-50.5
500	63.7	51.5	28.0	31.6	-47.8
1000	91.2	85.1	63.6	37.6	-47.3
		$\hat{x} = x * e^{h}\ ,\ h \sim NID(0,0.1)$			
100	13.0	5.6	0.5	-26.4	-7.9
500	14.7	7.0	1.7	-1.5	-4.7
1000	11.3	6.0	1.6	1.3	-4.3

Note: As instruments we use lags of y dated two periods back and more and x in first-differenced form. b is the coefficient for the lagged dependent variable y and d is the coefficient for x.

Table 2. Measurement errors in x. x treated as endogenous.

	Sargan rejection rates (%)			Bias (%)	
N	10	5	1	b	d
			No measurement errors		
100	6.6	2	0.1	-8.9	-7.4
500	9.6	4.4	1	-1.5	-1.5
1000	10.2	5.6	0.8	-0.8	-0.8
			$\hat{x} = x + h\ ,\ h \sim NID(0,1)$		
100	16.4	6.6	0.7	-12.1	-74.2
500	97.0	94.4	80.3	13.0	-61.6
1000	100	100	100	17.5	-58.8
			$\hat{x} = x + h\ ,\ h \sim NID(0,0.1)$		
100	6.4	2.5	0.1	-8.4	-8.7
500	8.7	4.1	0.5	-0.6	-1.9
1000	9.6	4.8	1	0.2	-1.2
			$\hat{x} = x * h\ ,\ h \sim NID(1,0.1)$		
100	6.3	2.2	0.2	-8.1	-10.3
500	9.3	4.1	0.5	0.4	-2.5
1000	12.4	5.7	1.4	1.3	-1.7
			$\hat{x} = x * h\ ,\ h \sim NID(1,0.5)$		
100	12.3	4	0.2	-12.1	-60.1
500	94.8	91	68.4	8.0	-45.1
1000	100	100	99.6	11.5	-42.1
			$\hat{x} = x * e^{h}\ ,\ h \sim NID(0,0.1)$		
100	6.6	2.2	0.2	-8.1	-10.8
500	10.1	4.7	1.2	0.4	-3.1
1000	11.1	5.3	0.9	1.2	-2.2

Note: As instruments we use lags of y dated two periods back and more and lags of x dated one period back and more. b is the coefficient for the lagged dependent variable y and d is the coefficient for x.

Table 3. Measurement errors in *y*.

	Sargan rejection rates (%)			Bias (%)	
N	10	5	1	b	d
		No measurement errors			
100	11.5	5.5	0.3	-28.0	-3.8
500	13.5	7.0	1.8	-4.7	-0.7
1000	10.1	5.2	1.3	-2.0	-0.3
		$\hat{y} = y + h$, $h \sim NID(0,1)$			
100	15.3	6.7	1.4	-74.8	-9.3
500	40.4	27.5	10.6	-62.2	-7.6
1000	69.3	58.5	33.6	-60.8	-7.7
		$\hat{y} = y + h$, $h \sim NID(0,0.1)$			
100	11.6	15.7	0.3	-28.8	-3.9
500	12.3	7.1	1.6	-5.3	-0.8
1000	10.1	4.2	1.5	-2.8	-0.4
		$\hat{y} = y * h$, $h \sim NID(1,0.1)$			
100	15.0	7.1	1.0	-37.0	-5.6
500	17.1	9.4	2.8	-12.2	-1.8
1000	18.8	9.5	3.1	-9.9	-1.6
		$\hat{y} = y * h$, $h \sim NID(1,0.5)$			
100	16.8	6.9	0.8	-92.6	-13.4
500	32.1	20.6	7.5	-80.0	-9.8
1000	51.4	38.2	18.6	-79.0	-9.7
		$\hat{y} = y * e^{h}$, $h \sim NID(0,0.1)$			
100	9.5	4.5	0.5	-106.0	26.6
500	17.4	8.0	1.1	-96.4	41.0
1000	17.1	9.4	2.8	-95.2	42.5

Note: As instruments we use lags of *y* dated two periods back and more and *x* in first-differenced form. b is the coefficient for the lagged dependent variable *y* and d is the coefficient for *x*.

Table 4. Measurement error in employment (the dependent variable)

	Arellano and Bond[a]		Additive error[b]		Multiplicative error[c]	
Variable	**Coeff**	**T-ratio**	**Coeff**	**T-ratio**	**Coeff**	**T-ratio**
n(-1)	0.47	5.56	0.29	3.28	-0.13	-1.14
n(-2)	-0.05	-1.94	0.10	1.56	-0.10	-1.87
w	-0.51	-10.40	-0.21	-2.20	-0.39	-2.19
w(-1)	0.22	2.81	0.01	0.06	-0.22	-1.36
k	0.29	7.42	0.09	1.56	0.42	5.36
ys	0.61	5.62	0.34	1.42	0.66	2.09
ys(-1)	-0.45	-3.58	-0.21	-0.89	-0.24	-0.62
	Statistic	P-value	Statistic	P-value	Statistic	P-value
Sargan	30.11	(0.220)	32.18	(0.153)	28.66	(0.278)
m_2	-0.33	(0.739)	0.51	(0.611)	-0.48	(0.633)

Notes: a) Column b in Table 4 in Arellano and Bond (1991)
b) The measurement error is generated as NID(5,1)
c) The measurement error is generated as NID(5,1)
Time dummies are included in all equations.

Table 5. Measurement error in wages

	Arellano and Bond[a]		Additive error[b]		Multiplicative error[c]	
Variable	**Coeff**	**T-ratio**	**Coeff**	**T-ratio**	**Coeff**	**T-ratio**
n(-1)	0.47	5.56	0.29	4.76	0.29	5.36
n(-2)	-0.05	-1.94	-0.02	-1.15	-0.04	-1.9
w	-0.51	-10.4	-0.19	-3.97	0.002	0.361
w(-1)	0.22	2.81	-0.004	-0.08	-0.01	-1.77
k	0.29	7.42	0.32	7.65	0.32	7.47
ys	0.61	5.62	0.39	3.39	0.31	2.82
ys(-1)	-0.45	-3.58	-0.04	-0.43	0.04	0.487
	Statistic	P-value	Statistic	P-value	Statistic	P-value
Sargan	30.11	(0.220)	31.35	(0.178)	27.17	(0.347)
m_2	-0.33	(0.739)	-0.00	(0.998)	0.18	(0.858)

Notes: a) Column b in Table 4 in Arellano and Bond (1991)
b) The measurement error is generated as NID(0,1)
c) The measurement error is generated as NID(3,1)
Time dummies are included in all equations.

Figure 1. Power function when additive and severe measurement error in x (and x treated as exogenous). Testing at the 5% significance level.

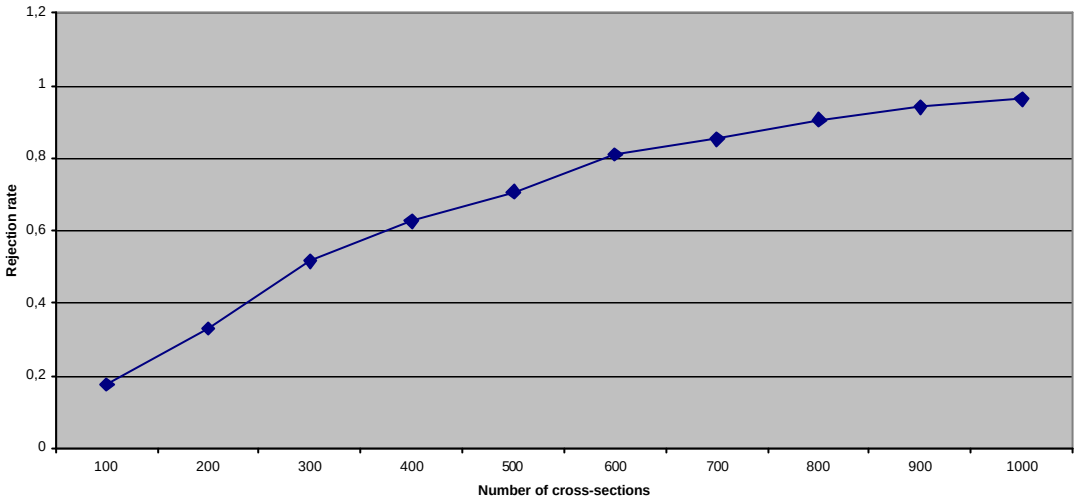
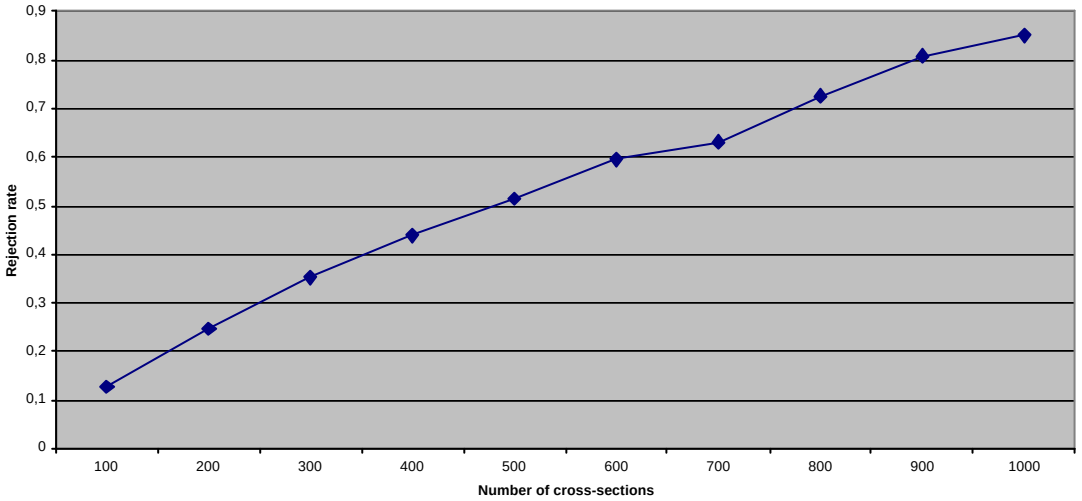


Figure 2. Power function when multiplicative error in x (and x treated as exogenous). Testing at the 5% significance level.



Appendix

In this appendix we will show that the identifying assumptions behind the GMM estimator are not fulfilled in the experiments we conduct, implying that the models are misspecified and hence that the null hypothesis the Sargan test is testing is false. We show it for additive measurement errors. For simplicity, we assume that $T = 3$ and that there are no time dummies.

Measurement error in *x*

$$y_{i3} = by_{i2} + dx_{i3} + f_i + e_{i3} \tag{A.1}$$

$$\hat{x}_{it} = x_{it} + h_{it} \tag{A.2}$$

(A.2) into (A.1) yields:

$$y_{i3} = by_{i2} + d\left(\hat{x}_{i3} - h_{i3}\right) + f_i + e_{i3} \tag{A.3}$$

First-differencing (A.3) yields:

$$y_{i3} - y_{i2} = b\left(y_{i2} - y_{i1}\right) + d\left(\hat{x}_{i3} - \hat{x}_{i2}\right) - \underbrace{d\left(h_{i3} + h_{i2}\right) + \left(e_{i3} - e_{i2}\right)}_{\Delta u_{i3}} \tag{A.4}$$

If *x* is treated as exogenous, the identifying assumptions behind the GMM estimator are:

$$E\left[y_{i1}\Delta u_{i3}\right] = E\left[y_{i1}\left(e_{i3} - e_{i2} - d\left(h_{i3} + h_{i2}\right)\right)\right] = 0 \tag{A.5}$$

$$E\left[\Delta\hat{x}_{i3}\Delta u_{i3}\right] = E\left[\left(x_{i3} + h_{i3} - x_{i2} - h_{i2}\right)\left(e_{i3} - e_{i2} - d\left(h_{i3} + h_{i2}\right)\right)\right] = 0 \tag{A.6}$$

However, (A.6) is not fulfilled since $E\left(h_{i2}h_{i2}\right) \neq 0$ and $E\left(h_{i3}h_{i3}\right) \neq 0$.

If we instead treat *x* as endogenous, the identifying assumptions are (A.5) and

$$E[\hat{x}_{i2}\Delta u_{i3}] = E[(x_{i2} + h_{i2})(e_{i3} - e_{i2} - d(h_{i3} + h_{i2}))] = 0 \quad \text{(A.7)}$$

which is not fulfilled since $E(h_{i2}h_{i2}) \neq 0$.

Measurement error in *y*

$$\hat{y}_{it} = y_{it} + h_{it} \quad \text{(A.8)}$$

(A.8) into (A.1) yields:

$$\hat{y}_{i3} - h_{i3} = b(\hat{y}_{i2} - h_{i2}) + dx_{i3} + f_i + e_{i3} \quad \text{(A.9)}$$

First-differencing (A.9) yields:

$$\hat{y}_{i3} - \hat{y}_{i2} = b(\hat{y}_{i2} - \hat{y}_{i1}) + d(x_{i3} - x_{i2}) + \underbrace{(e_{i3} - e_{i2}) + (h_{i3} - h_{i2}) - b(h_{i2} - h_{i1})}_{\Delta u_{i3}} \quad \text{(A.10)}$$

The identifying assumptions are:

$$E[\hat{y}_{i1}\Delta u_{i3}] = E[(y_{i1} + h_{i1})((e_{i3} - e_{i2}) + (h_{i3} - h_{i2}) - b(h_{i2} - h_{i1}))] = 0 \quad \text{(A.11)}$$

$$E[\Delta x_{i3}\Delta u_{i3}] = E[(x_{i3} - x_{i2})((e_{i3} - e_{i2}) + (h_{i3} - h_{i2}) - b(h_{i2} - h_{i1}))] = 0 \quad \text{(A.12)}$$

(A.11) is not fulfilled since $E(h_{i1}h_{i1}) \neq 0$.