Small Sample Performance of Instrumental Variables Probit Estimators: A Monte Carlo Investigation

Lee C. Adkins

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Motivation

Estimators

- LIML
- Newey
- Small Sample Performance?

Design

- Goals
- Equations
- Regressors and Errors
- Parameters

Results

Example

- Reduced Form
- Some Things Change
- Others Don't
- Download Complete Paper

Motivation

- Does managerial compensation affect the decision to hedge using foreign exchange derivatives?

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- Stata offers 2 choices.

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- Approximate significance tests of parameters are statistically valid and, if the MLE can be computed, the tests are easy to compute

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- Asymptotically normally distributed
- Asymptotically efficient is some cases
- Approximate significance tests of parameters are statistically valid and easy to compute
- Much easier to compute the estimators, making it possible to bootstrap or jackknife

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The basic design was first used by Rivers and Vuong. They vary degree of correlation between probit and the reduced form to study the bias and mse of several estimators.
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- Minimize the scaling problem
- Focus on significance test rather than bias

Probit and Reduced Form

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- (Probit) The underlying regression equation:

$$y_{1i}^{*} = \gamma y_{2i} + \beta_1 + \beta_2 x_{2i} + u_i \tag{1}$$

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- and the over-identified case,

$$y_{2i} = \pi_1 + \pi_2 x_{2i} + \pi_3 x_{3i} + \pi_4 x_{4i} + \nu_i \tag{3}$$

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- The exogenous variables (x_{2i}, x_{3i}, x_{4i}) are drawn from multivariate normal distribution with zero means, variances equal 1 and covariances of .5.

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- ν_i and η_i standard normals
- λ is varied on the interval $[-2, 2]$ to generate correlation between the endogenous explanatory variable and the regression's error.

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- Sample sizes: 200 and 1000

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- When there is no endogeneity, ols and probit work well (as expected).
- It is clear that OLS and Probit should be avoided when you have an endogenous regressor.
- Linear instrumental variables can be used for significance testing, though their performance is not as good as AGLS. The Linear IV estimator performs better when the model is just identified.

Weak Instruments and Size

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- Size of IVP is acceptable. Puzzling and deserves more study.
- The size of the significance tests based on the AGLS estimator is reasonable, but the standard errors are too small–a situation that gets worse as severity of the endogeneity problem increases. When instruments are very weak, the actual test size can be double the nominal.

Sample Size, Pretesting, MLE

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- Pretesting for endogeneity doesn't help. When Instruments are extremely weak it is outperformed by the other estimators considered, except when the no endogeneity hypothesis is true (and probit should be used).
- ML tests are better if the sample is large (1000) or instruments strong. In small samples with weak instruments, AGLS is better for significance testing (size).

Summary Results from Reduced-form Equations

Instruments	Reduced Form Equation		
	Leverage	Options	Bonus
	Coefficient P-values		
Number of Employees	0.182	0.000	0.000
Number of Subsidiaries	0.000	0.164	0.008
Number of Offices	0.248	0.000	0.000
CEO Age	0.026	0.764	0.572
12 Month Maturity Mismatch	0.353	0.280	0.575
CFA	0.000	0.826	0.368
R-Square	0.296	0.698	0.606

Parameters that change significance

	AGLS	ML
Leverage	21.775	12.490
	(0.104)	(0.021)
Total Assets	0.365	0.190
	(0.032)	(0.183)
Return on Equity	-0.034	-0.020
	(0.230)	(0.083)
Market-to-Book ratio	-0.002	-0.001
	(0.132)	(0.098)
Dividends Paid	-8.43E-07	-4.84E-07
	(0.134)	(0.044)

Parameters that are significant in both

- Option Awards
- Bonuses
- Insider Ownership
- Institutional Ownership

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Table 1a Bias of each estimator based on samples of size 200. Monte Carlo used 1000 samples.
The model is just identified. The approximate proportion of 1's in each sample is .5.

Design		Estimator						
θ	λ	ols	probit	IV probit	Linear IV	agls	tscml	pretest
0.05	2	0.818	2.103	-6.807	-1.533	-1.858	-1.858	0.699
0.05	1	0.575	1.034	2.934	1.005	1.572	1.572	1.082
0.05	0.5	0.326	0.510	-6.885	-3.057	-3.717	-3.717	-0.600
0.05	0	0.004	0.006	-12.681	-7.284	-8.732	-8.732	0.105
0.05	-0.5	-0.330	-0.515	-5.085	-2.915	-4.721	-4.721	-0.210
0.05	-1	-0.573	-1.028	-0.853	-0.834	-0.302	-0.302	-0.700
0.05	-2	-0.817	-2.078	-1.478	-0.972	-2.429	-2.429	-1.980
0.1	2	0.813	2.043	22.393	6.184	7.702	7.702	8.046
0.1	1	0.572	1.023	3.000	0.041	-0.423	-0.423	0.446
0.1	0.5	0.324	0.509	1.580	0.473	0.960	0.960	0.628
0.1	0	-0.001	-0.001	12.316	6.766	8.767	8.767	0.007
0.1	-0.5	-0.328	-0.510	-0.196	-0.182	-0.405	-0.405	-0.324
0.1	-1	-0.570	-1.020	0.251	0.095	0.221	0.221	-0.217
0.1	-2	-0.813	-2.037	-0.069	-0.052	-0.285	-0.285	-1.023
0.25	2	0.785	1.848	-0.625	-0.188	-0.508	-0.508	-0.482
0.25	1	0.547	0.966	-0.286	-0.137	-0.199	-0.199	-0.010
0.25	0.5	0.312	0.488	-0.127	-0.104	-0.075	-0.075	0.189
0.25	0	-0.005	-0.004	0.027	-0.057	0.018	0.018	-0.016
0.25	-0.5	-0.317	-0.487	0.150	0.040	0.143	0.143	-0.111
0.25	-1	-0.550	-0.965	0.183	0.111	0.273	0.273	0.049
0.25	-2	-0.782	-1.840	0.288	0.175	0.456	0.456	0.400
0.5	2	0.694	1.390	-0.086	-0.030	-0.053	-0.053	-0.053
0.5	1	0.485	0.809	-0.065	-0.039	-0.040	-0.040	-0.031
0.5	0.5	0.274	0.425	-0.045	-0.041	-0.029	-0.029	0.055
0.5	0	-0.005	-0.002	-0.005	-0.031	-0.004	-0.004	-0.006
0.5	-0.5	-0.283	-0.427	0.014	-0.014	0.013	0.013	-0.070
0.5	-1	-0.487	-0.807	0.036	0.015	0.049	0.049	0.040
0.5	-2	-0.696	-1.385	0.030	0.013	0.056	0.056	0.056
1	2	0.478	0.738	0.005	-0.001	0.004	0.004	0.004
1	1	0.335	0.505	-0.003	-0.008	-0.002	-0.002	-0.002
1	0.5	0.186	0.280	0.001	-0.011	0.001	0.001	0.010
1	0	-0.004	0.002	0.009	-0.010	0.006	0.006	0.004
1	-0.5	-0.198	-0.285	0.007	-0.006	0.007	0.007	-0.001
1	-1	-0.338	-0.498	0.011	0.001	0.016	0.016	0.016
1	-2	-0.480	-0.730	0.014	0.006	0.028	0.028	0.028

Table 1b Bias of each estimator based on samples of size 1000. Monte Carlo used 1000 samples.
The model is just identified. The approximate proportion of 1's in each sample is .5.

Design		Estimator						
θ	λ	ols	probit	IV probit	Linear IV	agls	tscml	pretest
0.05	2	0.811	2.008	1.397	0.382	0.551	0.551	0.551
0.05	1	0.572	1.008	0.474	0.089	0.212	0.212	0.212
0.05	0.5	0.327	0.501	-0.158	-0.056	-0.310	-0.310	-0.310
0.05	0	0.000	0.000	1.266	0.204	0.895	0.895	0.895
0.05	-0.5	-0.328	-0.501	-1.216	-0.770	-1.386	-1.386	-1.386
0.05	-1	-0.569	-1.001	-10.904	-7.669	-14.615	-14.615	-14.615
0.05	-2	-0.811	-2.011	-1.135	-0.761	-1.850	-1.850	-1.850
0.1	2	0.808	1.982	-0.229	-0.087	-0.196	-0.196	-0.196
0.1	1	0.568	0.997	-3.672	-1.381	-1.869	-1.869	-1.869
0.1	0.5	0.326	0.499	-0.923	-0.448	-0.549	-0.549	-0.549
0.1	0	-0.002	-0.002	-0.092	-0.112	-0.065	-0.065	-0.065
0.1	-0.5	-0.328	-0.501	-0.072	-0.075	-0.095	-0.095	-0.095
0.1	-1	-0.567	-0.993	0.136	0.072	0.184	0.184	0.184
0.1	-2	-0.809	-1.981	-0.208	-0.137	-0.227	-0.227	-0.227
0.25	2	0.778	1.782	-0.040	-0.017	-0.029	-0.029	-0.029
0.25	1	0.547	0.946	-0.023	-0.022	-0.017	-0.017	-0.017
0.25	0.5	0.314	0.481	-0.026	-0.030	-0.016	-0.016	-0.016
0.25	0	-0.002	-0.001	0.001	-0.021	0.001	0.001	0.001
0.25	-0.5	-0.316	-0.481	0.023	-0.004	0.023	0.023	0.023
0.25	-1	-0.547	-0.944	0.015	-0.001	0.021	0.021	0.021
0.25	-2	-0.779	-1.779	0.039	0.019	0.058	0.058	0.058
0.5	2	0.690	1.352	0.003	-0.002	0.002	0.002	0.002
0.5	1	0.484	0.795	-0.002	-0.007	0.000	0.000	0.000
0.5	0.5	0.278	0.418	-0.001	-0.010	-0.001	-0.001	-0.001
0.5	0	-0.002	0.000	-0.003	-0.012	-0.002	-0.002	-0.002
0.5	-0.5	-0.279	-0.417	0.005	-0.005	0.005	0.005	0.005
0.5	-1	-0.486	-0.796	-0.003	-0.009	-0.003	-0.003	-0.003
0.5	-2	-0.689	-1.344	0.010	0.004	0.014	0.014	0.014
1	2	0.474	0.719	-0.002	-0.002	-0.004	-0.004	-0.004
1	1	0.331	0.491	-0.002	-0.004	0.000	0.000	0.000
1	0.5	0.190	0.279	-0.002	-0.005	-0.001	-0.001	-0.001
1	0	-0.001	0.002	0.004	-0.004	0.003	0.003	0.003
1	-0.5	-0.193	-0.277	0.000	-0.005	0.000	0.000	0.000
1	-1	-0.334	-0.492	0.002	-0.002	0.003	0.003	0.003
1	-2	-0.475	-0.721	0.000	-0.002	-0.001	-0.001	-0.001

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0.050	2.000	0.830	2.078	2.376	0.668	1.707	1.692	1.789
0.050	1.000	0.592	1.030	0.989	0.302	0.642	0.650	0.803
0.050	0.500	0.342	0.515	0.613	0.222	0.353	0.352	0.388
0.050	0.000	-0.002	-0.003	0.039	-0.023	0.027	0.029	-0.008
0.050	-0.500	-0.342	-0.511	-0.428	-0.322	-0.431	-0.434	-0.484
0.050	-1.000	-0.591	-1.033	-0.525	-0.427	-0.776	-0.767	-0.787
0.050	-2.000	-0.828	-2.072	-0.996	-0.649	-1.701	-1.694	-1.931
0.100	2.000	0.823	2.047	1.227	0.333	0.946	0.938	1.164
0.100	1.000	0.587	1.018	0.598	0.176	0.374	0.374	0.564
0.100	0.500	0.339	0.508	0.287	0.069	0.163	0.163	0.316
0.100	0.000	0.000	0.001	-0.015	-0.073	-0.010	-0.011	-0.034
0.100	-0.500	-0.340	-0.504	-0.167	-0.161	-0.155	-0.156	-0.376
0.100	-1.000	-0.587	-1.016	-0.255	-0.222	-0.396	-0.395	-0.683
0.100	-2.000	-0.823	-2.034	-0.456	-0.315	-0.755	-0.740	-0.951
0.250	2.000	0.781	1.762	0.007	-0.007	-0.006	-0.008	0.003
0.250	1.000	0.557	0.951	0.008	-0.018	0.007	0.007	0.128
0.250	0.500	0.321	0.480	0.009	-0.030	0.003	0.004	0.173
0.250	0.000	-0.003	0.000	0.010	-0.036	0.006	0.007	-0.004
0.250	-0.500	-0.325	-0.482	-0.008	-0.038	-0.010	-0.010	-0.190
0.250	-1.000	-0.559	-0.944	0.005	-0.020	0.008	0.009	-0.120
0.250	-2.000	-0.780	-1.768	0.038	0.015	0.039	0.041	0.032
0.500	2.000	0.666	1.240	0.000	-0.004	-0.002	-0.004	-0.004
0.500	1.000	0.471	0.752	-0.003	-0.013	-0.003	-0.003	0.000
0.500	0.500	0.269	0.400	-0.005	-0.019	-0.005	-0.004	0.056
0.500	0.000	-0.005	0.000	-0.004	-0.022	-0.004	-0.003	0.002
0.500	-0.500	-0.281	-0.410	-0.007	-0.023	-0.010	-0.009	-0.072
0.500	-1.000	-0.478	-0.759	0.010	-0.004	0.017	0.017	0.014
0.500	-2.000	-0.664	-1.239	0.010	0.001	0.009	0.009	0.009
1.000	2.000	0.414	0.592	0.002	-0.002	-0.001	-0.001	-0.001
1.000	1.000	0.293	0.421	0.000	-0.006	-0.002	-0.002	-0.002
1.000	0.500	0.168	0.245	-0.001	-0.009	-0.001	-0.001	0.003
1.000	0.000	-0.006	-0.002	-0.002	-0.011	-0.002	-0.002	-0.002
1.000	-0.500	-0.177	-0.246	0.001	-0.008	0.001	0.001	-0.003
1.000	-1.000	-0.301	-0.431	-0.007	-0.011	-0.011	-0.011	-0.011
1.000	-2.000	-0.417	-0.601	0.000	-0.002	0.003	0.003	0.003

Table 1d Bias of each estimator based on samples of size 1000. Monte Carlo used 1000 samples.
The model is overidentified. The approximate proportion of 1's in each sample is .5.

Design		Estimator						
θ	λ	ols	probit	IV probit	Linear IV	agls	tscml	pretest
0.05	2	0.817	2.007	0.873	0.276	0.649	0.650	0.953
0.05	1	0.578	1.005	0.415	0.220	0.274	0.275	0.515
0.05	0.5	0.333	0.500	0.214	0.172	0.116	0.117	0.327
0.05	0	0.000	0.000	-0.077	0.073	-0.054	-0.054	0.005
0.05	-0.5	-0.333	-0.502	-0.086	0.044	-0.088	-0.088	-0.255
0.05	-1	-0.578	-1.003	-0.282	-0.171	-0.400	-0.401	-0.684
0.05	-2	-0.815	-2.002	-0.413	-0.243	-0.694	-0.695	-0.930
0.1	2	0.811	1.966	0.270	0.094	0.171	0.171	0.208
0.1	1	0.574	0.994	0.028	0.059	0.009	0.010	0.211
0.1	0.5	0.332	0.499	-0.019	0.062	-0.007	-0.007	0.216
0.1	0	0.001	-0.001	-0.006	0.080	-0.004	-0.004	-0.007
0.1	-0.5	-0.329	-0.496	0.016	0.079	0.023	0.023	-0.198
0.1	-1	-0.572	-0.990	-0.001	0.045	0.006	0.005	-0.171
0.1	-2	-0.811	-1.968	0.041	0.044	0.075	0.074	0.040
0.25	2	0.775	1.739	0.008	0.009	0.009	0.010	0.010
0.25	1	0.548	0.927	-0.033	0.007	-0.018	-0.018	-0.017
0.25	0.5	0.319	0.476	-0.008	0.025	-0.005	-0.005	0.035
0.25	0	0.000	-0.002	0.000	0.034	0.000	0.000	0.001
0.25	-0.5	-0.315	-0.473	-0.001	0.027	-0.001	-0.001	-0.044
0.25	-1	-0.546	-0.928	-0.001	0.018	-0.001	-0.001	-0.001
0.25	-2	-0.774	-1.730	0.002	0.008	0.002	0.002	0.002
0.5	2	0.667	1.248	0.015	0.008	0.011	0.011	0.011
0.5	1	0.473	0.753	0.000	0.009	-0.001	-0.001	-0.001
0.5	0.5	0.274	0.399	0.000	0.014	0.001	0.001	0.001
0.5	0	0.003	-0.001	0.003	0.018	0.002	0.002	-0.001
0.5	-0.5	-0.269	-0.398	0.002	0.015	0.002	0.002	0.002
0.5	-1	-0.469	-0.752	-0.002	0.007	-0.004	-0.004	-0.004
0.5	-2	-0.667	-1.243	0.000	0.004	0.000	0.000	0.000
1	2	0.429	0.617	-0.004	0.001	-0.003	-0.003	-0.003
1	1	0.305	0.433	0.002	0.005	0.002	0.002	0.002
1	0.5	0.178	0.249	0.001	0.008	0.001	0.001	0.001
1	0	0.003	-0.001	-0.004	0.006	-0.003	-0.003	-0.001
1	-0.5	-0.171	-0.248	0.001	0.008	0.000	0.000	0.000
1	-1	-0.300	-0.432	0.001	0.006	0.002	0.002	0.002
1	-2	-0.428	-0.617	-0.002	0.000	-0.003	-0.003	-0.003

Table 2a The size of 10% nominal tests. Only Linear IV and agls use consistent standard errors. N=200, mc=1000, just identified.

Design		Estimator					
θ	λ	ols	probit	IV probit	Linear IV	agls	tscml
0.05	2	1.000	1.000	0.099	0.130	0.141	0.379
0.05	1	1.000	1.000	0.096	0.046	0.110	0.197
0.05	0.5	0.996	0.998	0.097	0.011	0.086	0.124
0.05	0	0.099	0.099	0.104	0.002	0.092	0.107
0.05	-0.5	0.998	0.997	0.092	0.025	0.086	0.123
0.05	-1	1.000	1.000	0.082	0.049	0.108	0.194
0.05	-2	1.000	1.000	0.096	0.115	0.121	0.365
0.1	2	1.000	1.000	0.089	0.108	0.114	0.339
0.1	1	1.000	1.000	0.092	0.045	0.102	0.193
0.1	0.5	0.999	0.999	0.103	0.032	0.105	0.137
0.1	0	0.099	0.088	0.110	0.008	0.102	0.111
0.1	-0.5	0.997	0.998	0.087	0.022	0.090	0.114
0.1	-1	1.000	1.000	0.091	0.067	0.110	0.192
0.1	-2	1.000	1.000	0.108	0.111	0.124	0.355
0.25	2	1.000	1.000	0.112	0.084	0.139	0.343
0.25	1	1.000	1.000	0.104	0.084	0.141	0.216
0.25	0.5	0.999	0.999	0.091	0.049	0.090	0.118
0.25	0	0.105	0.106	0.092	0.052	0.089	0.094
0.25	-0.5	0.999	0.999	0.089	0.060	0.098	0.125
0.25	-1	1.000	1.000	0.085	0.083	0.117	0.188
0.25	-2	1.000	1.000	0.088	0.105	0.127	0.369
0.5	2	1.000	1.000	0.085	0.085	0.114	0.348
0.5	1	1.000	1.000	0.093	0.084	0.114	0.192
0.5	0.5	0.994	0.995	0.115	0.097	0.127	0.156
0.5	0	0.097	0.101	0.113	0.094	0.111	0.114
0.5	-0.5	0.998	0.995	0.090	0.106	0.099	0.116
0.5	-1	1.000	1.000	0.099	0.098	0.122	0.193
0.5	-2	1.000	1.000	0.086	0.105	0.129	0.386
1	2	1.000	1.000	0.086	0.102	0.139	0.370
1	1	1.000	1.000	0.087	0.095	0.114	0.200
1	0.5	0.953	0.957	0.091	0.094	0.102	0.123
1	0	0.108	0.101	0.103	0.101	0.098	0.105
1	-0.5	0.976	0.966	0.095	0.111	0.104	0.132
1	-1	1.000	1.000	0.089	0.104	0.115	0.202
1	-2	1.000	1.000	0.073	0.092	0.112	0.379

Table 2b Compute rejection rate for 10% nominal t-tests. Standard errors for agls and Linear IV are consistent. N=1000, mc=1000, model is just identified.

Design		Estimator					
θ	λ	ols	probit	IV probit	Linear IV	agls	tscml
0.05	2	1.000	1.000	0.106	0.102	0.116	0.364
0.05	1	1.000	1.000	0.086	0.051	0.103	0.180
0.05	0.5	1.000	1.000	0.097	0.024	0.108	0.132
0.05	0	0.107	0.108	0.102	0.005	0.098	0.103
0.05	-0.5	1.000	1.000	0.100	0.036	0.107	0.134
0.05	-1	1.000	1.000	0.079	0.062	0.101	0.178
0.05	-2	1.000	1.000	0.085	0.110	0.124	0.348
0.1	2	1.000	1.000	0.090	0.090	0.121	0.359
0.1	1	1.000	1.000	0.080	0.062	0.101	0.173
0.1	0.5	1.000	1.000	0.091	0.044	0.096	0.115
0.1	0	0.092	0.101	0.122	0.043	0.120	0.121
0.1	-0.5	1.000	1.000	0.105	0.057	0.104	0.131
0.1	-1	1.000	1.000	0.098	0.084	0.119	0.192
0.1	-2	1.000	1.000	0.089	0.088	0.129	0.345
0.25	2	1.000	1.000	0.082	0.086	0.122	0.339
0.25	1	1.000	1.000	0.078	0.070	0.113	0.184
0.25	0.5	1.000	1.000	0.103	0.076	0.118	0.137
0.25	0	0.101	0.112	0.111	0.091	0.111	0.111
0.25	-0.5	1.000	1.000	0.095	0.089	0.112	0.130
0.25	-1	1.000	1.000	0.086	0.089	0.112	0.190
0.25	-2	1.000	1.000	0.080	0.077	0.116	0.327
0.5	2	1.000	1.000	0.077	0.086	0.130	0.343
0.5	1	1.000	1.000	0.069	0.071	0.102	0.172
0.5	0.5	1.000	1.000	0.110	0.091	0.121	0.139
0.5	0	0.094	0.099	0.106	0.097	0.104	0.106
0.5	-0.5	1.000	1.000	0.092	0.092	0.096	0.116
0.5	-1	1.000	1.000	0.087	0.102	0.110	0.198
0.5	-2	1.000	1.000	0.089	0.089	0.118	0.351
1	2	1.000	1.000	0.087	0.096	0.131	0.351
1	1	1.000	1.000	0.079	0.080	0.108	0.177
1	0.5	1.000	1.000	0.089	0.093	0.107	0.124
1	0	0.099	0.102	0.097	0.090	0.096	0.096
1	-0.5	1.000	1.000	0.098	0.092	0.107	0.134
1	-1	1.000	1.000	0.090	0.104	0.122	0.203
1	-2	1.000	1.000	0.093	0.110	0.141	0.382

Table 2c The size of 10% nominal tests. Only Linear IV and agls use consistent standard errors. N=200, mc=1000, model is overidentified.

Design		Estimator					
θ	λ	ols	probit	IV probit	Linear IV	agls	tscml
0.050	2.000	1.000	1.000	0.143	0.235	0.198	0.460
0.050	1.000	1.000	1.000	0.129	0.107	0.156	0.258
0.050	0.500	1.000	1.000	0.123	0.047	0.137	0.163
0.050	0.000	0.098	0.086	0.111	0.007	0.102	0.113
0.050	-0.500	1.000	0.999	0.122	0.052	0.125	0.159
0.050	-1.000	1.000	1.000	0.113	0.124	0.140	0.238
0.050	-2.000	1.000	1.000	0.137	0.232	0.195	0.442
0.100	2.000	1.000	1.000	0.134	0.238	0.198	0.451
0.100	1.000	1.000	1.000	0.111	0.099	0.129	0.223
0.100	0.500	0.999	0.998	0.100	0.046	0.099	0.122
0.100	0.000	0.105	0.111	0.106	0.020	0.099	0.111
0.100	-0.500	0.997	0.997	0.096	0.063	0.099	0.117
0.100	-1.000	1.000	1.000	0.095	0.118	0.124	0.204
0.100	-2.000	1.000	1.000	0.111	0.209	0.156	0.395
0.250	2.000	1.000	1.000	0.087	0.118	0.128	0.370
0.250	1.000	1.000	1.000	0.115	0.121	0.132	0.221
0.250	0.500	1.000	0.999	0.103	0.085	0.108	0.133
0.250	0.000	0.108	0.115	0.113	0.076	0.110	0.115
0.250	-0.500	0.999	0.999	0.090	0.096	0.100	0.127
0.250	-1.000	1.000	1.000	0.088	0.123	0.112	0.209
0.250	-2.000	1.000	1.000	0.092	0.144	0.132	0.361
0.500	2.000	1.000	1.000	0.090	0.098	0.124	0.370
0.500	1.000	1.000	1.000	0.094	0.091	0.108	0.188
0.500	0.500	0.994	0.996	0.106	0.098	0.111	0.134
0.500	0.000	0.124	0.117	0.096	0.110	0.097	0.101
0.500	-0.500	0.997	0.994	0.110	0.109	0.111	0.141
0.500	-1.000	1.000	1.000	0.082	0.096	0.108	0.190
0.500	-2.000	1.000	1.000	0.091	0.119	0.129	0.365
1.000	2.000	1.000	1.000	0.085	0.100	0.122	0.351
1.000	1.000	1.000	1.000	0.101	0.115	0.118	0.191
1.000	0.500	0.931	0.946	0.108	0.113	0.115	0.139
1.000	0.000	0.115	0.122	0.093	0.098	0.092	0.095
1.000	-0.500	0.955	0.951	0.089	0.100	0.095	0.121
1.000	-1.000	1.000	1.000	0.094	0.122	0.113	0.196
1.000	-2.000	1.000	1.000	0.084	0.095	0.125	0.357

Table 2d The size of 10% nominal tests. Standard errors of agls and Linear IV are consistent. N=1000, mc=1000, model is overidentified.

Design		Estimator					
θ	λ	ols	probit	IV probit	Linear IV	agls	tscml
0.05	2	1.000	1.000	0.122	0.206	0.147	0.415
0.05	1	1.000	1.000	0.108	0.133	0.117	0.184
0.05	0.5	1.000	1.000	0.096	0.054	0.110	0.130
0.05	0	0.086	0.084	0.099	0.023	0.100	0.099
0.05	-0.5	1.000	1.000	0.106	0.036	0.112	0.135
0.05	-1	1.000	1.000	0.085	0.090	0.115	0.195
0.05	-2	1.000	1.000	0.135	0.201	0.175	0.398
0.1	2	1.000	1.000	0.100	0.153	0.120	0.341
0.1	1	1.000	1.000	0.091	0.138	0.123	0.199
0.1	0.5	1.000	1.000	0.085	0.083	0.096	0.110
0.1	0	0.111	0.109	0.109	0.065	0.109	0.109
0.1	-0.5	1.000	1.000	0.099	0.042	0.104	0.119
0.1	-1	1.000	1.000	0.093	0.076	0.131	0.192
0.1	-2	1.000	1.000	0.073	0.111	0.123	0.332
0.25	2	1.000	1.000	0.095	0.116	0.155	0.378
0.25	1	1.000	1.000	0.098	0.108	0.126	0.201
0.25	0.5	1.000	1.000	0.097	0.104	0.101	0.128
0.25	0	0.102	0.109	0.095	0.100	0.095	0.095
0.25	-0.5	1.000	1.000	0.097	0.089	0.110	0.128
0.25	-1	1.000	1.000	0.108	0.112	0.125	0.207
0.25	-2	1.000	1.000	0.098	0.095	0.130	0.365
0.5	2	1.000	1.000	0.089	0.106	0.119	0.344
0.5	1	1.000	1.000	0.085	0.104	0.107	0.179
0.5	0.5	1.000	1.000	0.086	0.101	0.091	0.111
0.5	0	0.089	0.093	0.109	0.106	0.106	0.108
0.5	-0.5	1.000	1.000	0.122	0.120	0.121	0.151
0.5	-1	1.000	1.000	0.087	0.095	0.112	0.195
0.5	-2	1.000	1.000	0.060	0.071	0.094	0.311
1	2	1.000	1.000	0.081	0.097	0.128	0.335
1	1	1.000	1.000	0.095	0.108	0.116	0.187
1	0.5	1.000	1.000	0.114	0.126	0.124	0.148
1	0	0.103	0.107	0.122	0.117	0.120	0.121
1	-0.5	1.000	1.000	0.106	0.108	0.122	0.146
1	-1	1.000	1.000	0.088	0.102	0.114	0.201
1	-2	1.000	1.000	0.096	0.111	0.149	0.372

Table 3a Monte Carlo standard error each estimator based on samples of size 200, 1000 samples. The model is just identified. The approximate proportion of 1's in each sample is .5.

Design		Estimator						
θ	λ	ols	probit	IV probit	Linear IV	agls	tscml	pretest
0.05	2	0.002	0.010	7.894	1.865	2.939	2.939	1.060
0.05	1	0.002	0.005	2.063	0.715	1.086	1.086	0.712
0.05	0.5	0.002	0.004	3.382	1.599	1.876	1.876	1.116
0.05	0	0.002	0.003	12.405	7.046	8.544	8.544	0.378
0.05	-0.5	0.002	0.004	3.882	2.047	3.876	3.876	0.662
0.05	-1	0.002	0.005	1.773	1.389	3.186	3.186	0.434
0.05	-2	0.002	0.010	0.463	0.292	0.744	0.744	0.559
0.1	2	0.002	0.009	22.052	6.168	8.284	8.284	8.241
0.1	1	0.002	0.005	3.107	0.440	0.918	0.918	0.646
0.1	0.5	0.002	0.004	0.736	0.267	0.452	0.452	0.222
0.1	0	0.002	0.003	12.608	7.070	8.960	8.960	0.108
0.1	-0.5	0.002	0.004	0.214	0.113	0.284	0.284	0.086
0.1	-1	0.002	0.005	0.755	0.551	1.002	1.002	0.981
0.1	-2	0.002	0.009	0.382	0.233	0.625	0.625	0.511
0.25	2	0.002	0.008	0.154	0.044	0.138	0.138	0.139
0.25	1	0.002	0.005	0.075	0.028	0.050	0.050	0.052
0.25	0.5	0.002	0.004	0.063	0.028	0.037	0.037	0.031
0.25	0	0.002	0.003	0.064	0.027	0.045	0.045	0.033
0.25	-0.5	0.002	0.004	0.033	0.020	0.033	0.033	0.026
0.25	-1	0.002	0.005	0.057	0.043	0.085	0.085	0.087
0.25	-2	0.002	0.008	0.072	0.046	0.109	0.109	0.107
0.5	2	0.002	0.006	0.024	0.007	0.017	0.017	0.017
0.5	1	0.002	0.004	0.018	0.006	0.011	0.011	0.012
0.5	0.5	0.002	0.003	0.015	0.006	0.010	0.010	0.012
0.5	0	0.002	0.003	0.012	0.006	0.009	0.009	0.006
0.5	-0.5	0.002	0.003	0.009	0.006	0.009	0.009	0.011
0.5	-1	0.002	0.004	0.008	0.006	0.011	0.011	0.012
0.5	-2	0.002	0.006	0.011	0.007	0.017	0.017	0.017
1	2	0.001	0.003	0.011	0.003	0.008	0.008	0.008
1	1	0.002	0.003	0.008	0.003	0.005	0.005	0.005
1	0.5	0.002	0.003	0.007	0.003	0.004	0.004	0.005
1	0	0.002	0.003	0.006	0.003	0.004	0.004	0.003
1	-0.5	0.002	0.003	0.004	0.003	0.004	0.004	0.005
1	-1	0.002	0.003	0.004	0.003	0.005	0.005	0.005
1	-2	0.001	0.003	0.005	0.003	0.008	0.008	0.008

Table 3b Monte Carlo standard error each estimator based on samples of size 1000, 1000 samples. The model is just identified. The approximate proportion of 1's in each sample is .5.

Design		Estimator						
θ	λ	ols	probit	IV probit	Linear IV	agls	tscml	pretest
0.05	2	0.001	0.004	1.31	0.377	0.751	0.751	0.712
0.05	1	0.001	0.002	0.821	0.297	0.49	0.49	0.304
0.05	0.5	0.001	0.002	2.168	0.879	1.349	1.349	0.16
0.05	0	0.001	0.001	2.438	1.193	1.724	1.724	1.551
0.05	-0.5	0.001	0.002	2.122	1.279	2.089	2.089	1.981
0.05	-1	0.001	0.002	8.888	6.092	11.608	11.608	11.607
0.05	-2	0.001	0.004	1.256	0.771	1.487	1.487	1.378
0.1	2	0.001	0.004	0.368	0.1	0.243	0.243	0.243
0.1	1	0.001	0.002	3.428	1.253	1.714	1.714	0.056
0.1	0.5	0.001	0.002	0.682	0.297	0.401	0.401	0.053
0.1	0	0.001	0.001	0.195	0.099	0.138	0.138	0.129
0.1	-0.5	0.001	0.002	0.207	0.123	0.222	0.222	0.204
0.1	-1	0.001	0.002	0.038	0.029	0.051	0.051	0.049
0.1	-2	0.001	0.004	0.501	0.311	0.623	0.623	0.623
0.25	2	0.001	0.003	0.02	0.006	0.014	0.014	0.014
0.25	1	0.001	0.002	0.015	0.005	0.009	0.009	0.01
0.25	0.5	0.001	0.002	0.013	0.005	0.008	0.008	0.01
0.25	0	0.001	0.001	0.01	0.005	0.007	0.007	0.005
0.25	-0.5	0.001	0.002	0.008	0.005	0.008	0.008	0.01
0.25	-1	0.001	0.002	0.007	0.005	0.009	0.009	0.009
0.25	-2	0.001	0.003	0.009	0.006	0.014	0.014	0.014
0.5	2	0.001	0.003	0.01	0.003	0.007	0.007	0.007
0.5	1	0.001	0.002	0.007	0.003	0.004	0.004	0.004
0.5	0.5	0.001	0.001	0.006	0.003	0.004	0.004	0.004
0.5	0	0.001	0.001	0.005	0.002	0.004	0.004	0.003
0.5	-0.5	0.001	0.001	0.004	0.003	0.004	0.004	0.004
0.5	-1	0.001	0.002	0.003	0.003	0.004	0.004	0.004
0.5	-2	0.001	0.002	0.004	0.003	0.006	0.006	0.006
1	2	0.001	0.001	0.005	0.001	0.003	0.003	0.003
1	1	0.001	0.001	0.003	0.001	0.002	0.002	0.002
1	0.5	0.001	0.001	0.003	0.001	0.002	0.002	0.002
1	0	0.001	0.001	0.002	0.001	0.002	0.002	0.001
1	-0.5	0.001	0.001	0.002	0.001	0.002	0.002	0.002
1	-1	0.001	0.001	0.002	0.001	0.002	0.002	0.002
1	-2	0.001	0.001	0.002	0.001	0.003	0.003	0.003

Table 4a Comparison of agls and LIML. Sample size = 200, model just identified.
Upper panel compars the coefficient on the endogenous variable (γ=0)
Lower panel compares the percentiles to the pvalue of the corresponding t-ratio.

		λ	0.5		2		0.5		2	
		θ	0.1		0.1		1		1	
			agls	LIML	agls	LIML	agls	LIML	agls	LIML
Coefficient		1%	-44.751	-1.021	-45.860	-0.96689	-0.563	-0.371	-0.720	-0.325
		5%	-7.270	-0.947	-10.488	-0.85039	-0.347	-0.271	-0.425	-0.235
		10%	-3.649	-0.864	-5.034	-0.70906	-0.271	-0.221	-0.328	-0.195
		25%	-0.790	-0.489	-0.842	-0.27075	-0.137	-0.118	-0.173	-0.114
		50%	0.300	0.293	1.117	0.888625	-0.008	-0.008	-0.009	-0.006
		75%	1.462	1.003	2.994	1.557343	0.113	0.109	0.136	0.108
		90%	3.645	1.111	8.057	2.068173	0.221	0.219	0.246	0.212
		95%	8.198	1.166	12.735	2.246212	0.270	0.269	0.318	0.272
		99%	48.105	1.253	64.591	2.512663	0.420	0.417	0.433	0.384
	Mean		-0.368	0.235	3.462	0.703199	-0.020	-0.005	-0.029	0.001
	Std. Dev.		31.512	0.756	87.029	1.033331	0.193	0.167	0.233	0.158
	Variance		992.991	0.571	7574.060	1.067773	0.037	0.028	0.055	0.025
	Skewness		-10.139	-0.216	19.665	-0.0193	-0.341	0.155	-0.502	0.395
	Kurtosis		255.376	1.546	497.026	1.71487	3.670	3.050	3.758	3.495
p-values		1%	0.077	0.00E+00	0.004	7.46E-17	0.019	0.001	0.017	0.004
		5%	0.222	1.78E-38	0.037	1.33E-06	0.079	0.027	0.075	0.045
		10%	0.299	2.60E-16	0.105	0.001	0.129	0.083	0.126	0.097
		25%	0.479	3.92E-04	0.329	0.076	0.265	0.228	0.277	0.245
		50%	0.697	0.222	0.660	0.393	0.517	0.517	0.499	0.489
		75%	0.868	0.696	0.856	0.720	0.773	0.775	0.753	0.755
		90%	0.952	0.915	0.934	0.884	0.905	0.905	0.903	0.903
		95%	0.976	0.958	0.965	0.938	0.957	0.958	0.954	0.954
		99%	0.996	0.995	0.994	0.987	0.995	0.995	0.984	0.983

Table 4b Comparison of agls and LIML. Sample size = 1000, model just identified.
Upper panel compares the coefficient on the endogenous variable (γ=0)
Lower panel compares the percentiles to the pvalue of the corresponding t-ratio.

	λ	0.5		2		0.5		2	
	θ	0.25		0.25		1		1	
		agls	LIML	agls	LIML	agls	LIML	agls	LIML
Coefficient	1%	-1.379	-0.646	-2.295	-0.548	-0.222	-0.183	-0.261	-0.160
	5%	-0.709	-0.454	-1.212	-0.370	-0.154	-0.133	-0.168	-0.109
	10%	-0.532	-0.376	-0.901	-0.307	-0.115	-0.104	-0.128	-0.086
	25%	-0.247	-0.199	-0.439	-0.177	-0.060	-0.054	-0.074	-0.050
	50%	-0.013	-0.012	-0.006	-0.003	-0.005	-0.005	-0.001	0.000
	75%	0.218	0.210	0.338	0.187	0.051	0.049	0.063	0.048
	90%	0.411	0.410	0.601	0.388	0.102	0.099	0.125	0.096
	95%	0.534	0.533	0.736	0.505	0.130	0.128	0.158	0.127
	99%	0.787	0.748	0.961	0.731	0.201	0.199	0.220	0.177
	Mean	-0.042	0.009	-0.101	0.021	-0.005	-0.002	-0.004	0.002
	Std. Dev.	0.397	0.300	0.643	0.273	0.087	0.080	0.100	0.072
	Variance	0.158	0.090	0.414	0.075	0.007	0.006	0.010	0.005
	Skewness	-0.845	0.257	-1.243	0.455	-0.104	0.112	-0.141	0.210
	Kurtosis	5.384	2.832	6.080	3.172	3.182	3.099	2.937	2.877
p-values	1%	0.010	7.38E-05	0.004	0.004	0.006	0.003	0.009	0.008
	5%	0.069	0.006	0.050	0.050	0.040	0.031	0.042	0.042
	10%	0.114	0.037	0.129	0.108	0.090	0.079	0.094	0.091
	25%	0.255	0.215	0.288	0.261	0.232	0.234	0.245	0.236
	50%	0.506	0.498	0.509	0.494	0.505	0.501	0.488	0.484
	75%	0.757	0.760	0.736	0.734	0.753	0.754	0.724	0.724
	90%	0.907	0.907	0.896	0.895	0.910	0.910	0.886	0.887
	95%	0.959	0.959	0.946	0.946	0.955	0.955	0.941	0.941
	99%	0.995	0.995	0.989	0.989	0.988	0.988	0.992	0.992