

Testing Parameter Significance in Instrumental Variables Probit Estimators

Lee C. Adkins

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LIML

Newey

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Motivation

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

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- ▶ Does managerial compensation affect the decision to hedge using foreign exchange derivatives?
- ▶ Some of the compensation variables are endogenous.
- ▶ Stata offers 2 choices: Newey's 2 step and MLE, but produce different results.

Parameters that change significance

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

Maximum Likelihood

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

Newey's (two-step) estimator–AGLS

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- ▶ Asymptotically normally distributed
- ▶ Asymptotically efficient in 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

Which performs better in small samples?

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- ▶ Bias and MSE (Rivers and Vuong, 1988)
- ▶ Significance tests
- ▶ Power

Estimators

Estimators

- ▶ Probit and RROLS (Iwata 2001)
- ▶ RRGMM (Iwata 2001)
- ▶ Plug-in w/Murphy-Topel Covariance
- ▶ AGLS (Newey 1987)
- ▶ Pretest (for endogeneity–Probit or AGLS)
- ▶ MLE

Design Goals

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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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.

I go a few steps further. In addition to Bias and MSE I look at:

- ▶ Instrument Strength – RV consider only very strong instruments in their design.
- ▶ Different proportions of 1s and 0s are considered (no effect)
- ▶ Minimize the scaling problem
- ▶ Focus on significance test rather than bias

Probit and Reduced Form

Probit and Reduced Form

- ▶ (Probit) The underlying regression equation:

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

y_{1i}^* is latent and is observed in one of two states: coded 0 or 1

- ▶ (Reduced Form) In the just identified case, the endogenous regressor y_{2i} is determined

$$y_{2i} = \pi_1 + \pi_2 x_{2i} + \pi_3 x_{3i} + \nu_i \quad (2)$$

- ▶ and the over-identified case,

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

Design: Regressors and residuals

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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.
- ▶ The disturbances are created using

$$u_i = \lambda \nu_i + \eta_i \quad (4)$$

- ▶ 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.

Design: Parameters

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- ▶ Reduced Form: $\theta\pi$ where $\pi = \{\pi_1 = 0, \pi_2 = 1, \pi_3 = 1, \pi_4 = -1\}$ and θ is varied on the interval $[\.05, 1]$. As θ gets bigger, instruments get stronger.
- ▶ When the model is just identified, $\pi_4 = 0$.
- ▶ In the probit regression: $\gamma = 0$ and $\beta_2 = -1$.
- ▶ The intercept, β_1 takes the value $-2, 0, 2$, which corresponds roughly to expected proportions of $y_{1i} = 1$ of 25%, 50%, and 75%, respectively.
- ▶ Sample sizes: 200 and 1000

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- ▶ When there is no endogeneity, RROLS and probit work well (as expected).
- ▶ It is clear that RROLS and Probit should be avoided when you have an endogenous regressor.
- ▶ AGLS performs reasonably well, but size is too big especially as endogeneity worsens. RRGMM works a bit better when endogeneity is severe.

Instrument strength, sample size, pretesting

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- ▶ RRGMM outperforms AGLS when instruments are moderately strong.
- ▶ Larger sample sizes improves performance of AGLS and RRGMM.
- ▶ Pretesting for endogeneity is useful when samples are small and the available instruments are weak.

AGLS, MLE

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- ▶ In small samples, AGLS outperforms MLE. It also is better when instruments are weak in larger samples.
- ▶ MLE is more precise, but seriously underestimates standard errors.

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Table 2b Computed rejection rate for 10% nominal t-tests. Sample size is 1000.

The model is just identified. The approximate proportion of 1's in each sample is .5.

Design		Estimator					
θ	λ	RRrols	Probit	RRgmm	IVP	AGLS	Pretest
0.05	2	1.000	1.000	0.091	0.102	0.111	0.528
0.05	1	1.000	1.000	0.054	0.066	0.129	0.803
0.05	0.5	1.000	1.000	0.016	0.021	0.102	0.929
0.05	0	0.096	0.102	0.004	0.007	0.095	0.182
0.05	-0.5	1.000	1.000	0.036	0.021	0.105	0.929
0.05	-1	1.000	1.000	0.080	0.064	0.128	0.818
0.05	-2	1.000	1.000	0.105	0.101	0.122	0.511
0.1	2	1.000	1.000	0.059	0.065	0.101	0.136
0.1	1	1.000	1.000	0.059	0.079	0.117	0.496
0.1	0.5	1.000	1.000	0.037	0.042	0.106	0.815
0.1	0	0.094	0.095	0.055	0.038	0.107	0.183
0.1	-0.5	1.000	1.000	0.067	0.044	0.115	0.809
0.1	-1	1.000	1.000	0.097	0.074	0.101	0.521
0.1	-2	1.000	1.000	0.103	0.097	0.134	0.185
0.15	2	1.000	1.000	0.091	0.092	0.122	0.123
0.15	1	1.000	1.000	0.059	0.070	0.122	0.228
0.15	0.5	1.000	1.000	0.069	0.071	0.108	0.629
0.15	0	0.109	0.109	0.087	0.073	0.105	0.193
0.15	-0.5	1.000	1.000	0.087	0.058	0.094	0.666
0.15	-1	1.000	1.000	0.097	0.067	0.092	0.210
0.15	-2	1.000	1.000	0.103	0.095	0.120	0.120
0.25	2	1.000	1.000	0.093	0.093	0.140	0.140
0.25	1	1.000	1.000	0.090	0.086	0.127	0.127
0.25	0.5	1.000	1.000	0.088	0.078	0.113	0.348
0.25	0	0.098	0.091	0.093	0.081	0.099	0.165
0.25	-0.5	1.000	1.000	0.104	0.096	0.111	0.348
0.25	-1	1.000	1.000	0.091	0.071	0.112	0.112
0.25	-2	1.000	1.000	0.104	0.084	0.130	0.130
0.5	2	1.000	1.000	0.101	0.080	0.127	0.127
0.5	1	1.000	1.000	0.094	0.078	0.104	0.104
0.5	0.5	1.000	1.000	0.092	0.084	0.095	0.095
0.5	0	0.119	0.116	0.109	0.106	0.107	0.179
0.5	-0.5	1.000	1.000	0.099	0.087	0.102	0.102
0.5	-1	1.000	1.000	0.112	0.091	0.117	0.117
0.5	-2	1.000	1.000	0.103	0.090	0.127	0.127
1	2	1.000	1.000	0.103	0.094	0.127	0.127
1	1	1.000	1.000	0.115	0.107	0.129	0.129
1	0.5	1.000	1.000	0.110	0.099	0.112	0.112
1	0	0.103	0.091	0.093	0.083	0.083	0.124
1	-0.5	1.000	1.000	0.117	0.101	0.108	0.108
1	-1	1.000	1.000	0.113	0.093	0.126	0.126
1	-2	1.000	1.000	0.090	0.079	0.120	0.120
RMSE		0.772	0.773	0.020	0.024	0.015	0.212

Table 4a: Comparison of AGLS and ML. Sample size = 200, model just identified.

Upper panel compares the percentiles of the computed t-ratio and its summary statistics.

Lower panel compares the percentiles to the p-value of the corresponding t-ratio.

λ	-0.25		-2		-0.25		-2	
	0.15		0.15		1		1	
θ	AGLS	ML	AGLS	ML	AGLS	ML	AGLS	ML
1%	-1.854	-1.78E+01	-2.984	-7.583	-2.233	-2.666	-2.489	-2.217
5%	-1.329	-6.453	-2.189	-3.227	-1.566	-1.677	-1.686	-1.441
10%	-1.074	-2.880	-1.724	-2.203	-1.244	-1.284	-1.265	-1.108
25%	-0.534	-0.817	-0.873	-0.920	-0.599	-0.601	-0.543	-0.509
50%	0.032	0.042	-0.130	-0.157	0.098	0.099	0.163	0.168
75%	0.562	1.117	0.233	0.516	0.810	0.877	0.708	0.800
90%	0.901	2.561	0.429	1.267	1.279	1.500	1.199	1.535
95%	1.061	3.797	0.512	1.769	1.603	1.958	1.432	1.918
99%	1.425	7.130	0.688	2.583	2.166	3.173	1.792	2.801
Summary Statistics for the t-ratio and p-value for a test for normality								
Variance	0.567	13.113	0.736	3.057	0.964	1.325	0.910	1.092
Skewness	-0.304	-2.375	-1.202	-1.801	-0.123	0.204	-0.584	0.200
Kurtosis	2.578	12.801	4.013	12.317	2.606	3.755	3.326	3.584
W (p-value)	<.0001	<.0001	<.0001	<.0001	0.00432	0.00012	0.0001	0.0029
5% and 10% percentiles of the p-value for the two-sided t-test								
5%	0.154	0.000	0.029	3.74E-04	0.058	0.019	0.064	0.034
10%	0.227	0.000	0.085	1.42E-02	0.114	0.067	0.119	0.084

Table 4b: Comparison of AGLS and ML. Sample size = 1000, model just identified.

Upper panel compares the percentiles of the computed t-ratio and its summary statistics.

Lower panel compares the percentiles to the p-value of the corresponding t-ratio.

λ	-0.25		-2		-0.25		-2	
	0.25		0.25		1		1	
θ	AGLS	ML	AGLS	ML	AGLS	ML	AGLS	ML
1%	-2.327	-2.81E+00	-3.055	-2.105	-2.367	-2.413	-2.507	-2.233
5%	-1.666	-1.782	-1.922	-1.401	-1.670	-1.679	-1.619	-1.495
10%	-1.326	-1.366	-1.536	-1.190	-1.321	-1.319	-1.263	-1.183
25%	-0.631	-0.634	-0.672	-0.587	-0.599	-0.596	-0.628	-0.606
50%	0.013	0.001	0.018	0.019	0.024	0.024	0.104	0.104
75%	0.716	0.761	0.598	0.719	0.754	0.769	0.702	0.734
90%	1.216	1.434	0.979	1.423	1.317	1.380	1.227	1.337
95%	1.438	1.840	1.183	1.923	1.635	1.739	1.602	1.802
99%	1.941	2.759	1.387	2.741	2.242	2.467	2.145	2.541
Summary Statistics for the t-ratio and p-value for a test for normality								
Variance	0.926	1.266	0.968	1.032	1.041	1.107	0.963	0.996
Skewness	-0.237	0.050	-0.910	0.381	-0.104	0.009	-0.316	0.062
Kurtosis	2.732	3.665	3.956	3.386	2.957	3.160	3.202	3.139
W (p-value)	0.02905	0.0067	<.0001	<.0001	0.5446	0.8239	0.0001	0.3145
5% and 10% percentiles of the p-value for the two-sided t-test								
5%	0.055	0.023	0.055	0.037	0.046	0.040	0.058	0.048
10%	0.100	0.070	0.123	0.090	0.098	0.088	0.107	0.094