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Abstract

We consider estimation of the economic model of crime exploiting instrumental variables techniques for panel data. We extend the empirical analysis of Cornwell and Trumbull (1994) and show that their instrumental variables are very weak. We propose an alternative identification strategy based on the sequential moment conditions of Arellano and Bond (1991). The resulting GMM estimates of deterrence effects on crime are considerably more precise.

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1. Introduction

Since Becker (1968) and Ehrlich (1973) a huge empirical literature emerged analyzing the causal relationship between deterrence measures and crime rates. Central research question is whether more deterrence leads to more safety and less crime. Deterrence is often measured by probability of apprehension (conviction, sentenced), severity of punishment and number of police officers.

Cornwell and Trumbull (1994), hereafter CT94, estimate an economic model of crime using annual panel data for 90 counties in North Carolina spanning the period 1981-1987. In their empirical analysis they consider two main specification issues. First, unobserved heterogeneity in crime may be correlated with criminal justice variables leading to omitted variables bias. Therefore, they propose to estimate panel data specifications including fixed county and year effects. Second, the level of deterrence is higher in regions with relatively more crime, possibly leading to simultaneity bias. Therefore, they estimate their panel data specification with instrumental variables (IV) techniques.

CT94 is one of the many empirical crime studies relying on external instrumental variables. The validity, i.e. relevance and exogeneity, of those instruments can be questioned (Murray, 2006). CT94 note that their fixed effects 2SLS deterrence estimates, as opposed to fixed effects OLS estimates, are no longer significant. Reason is that standard errors increase radically when applying 2SLS instead of OLS. A substantial efficiency loss when applying IV estimation instead of OLS occurs more often in crime studies. For example, in Levitt (1997) IV standard errors are ten times larger than OLS counterparts. Large standard errors typically arise with weak instruments, see e.g. Bound et al. (1995), Staiger and Stock (1997) and Stock et al. (2002).

Baltagi (2006) replicates and extends the empirical analysis of CT94. Baltagi (2006) cannot replicate the fixed effects 2SLS estimates of CT94, but his alternative set of estimates results in insignificance for not only deterrent variables, but also legal opportunity regressors. Furthermore, consistency of the random effects 2SLS estimator cannot be rejected and this estimator yields plausible and significant deterrence estimates. However, Baltagi (2006) remarks that this result should be treated with care because it is based on the fact that the instrumental variables of CT94 are valid.

In the next section we further supplement the empirical results of CT94 and show that exploiting their external instruments actually leads to underidentification. This explains the large standard errors of their fixed effects 2SLS estimates. Furthermore, we use an alternative identification strategy based on the Arellano and Bond (1991) GMM estimator, which exploits lagged values of endogenous variables as instruments. The use of these internal instrumental variables is relatively scarce in empirical crime studies (for exceptions see Witt et al., 1999, and Kelaher and Sarafidis, 2011), but greatly enhances the precision of the deterrence estimates, as we shall see.

2. Empirical results

CT94 estimate the following fixed effects panel data model by OLS and IV:

$$R_{it} = X_{it}'\beta + P_{it}'\gamma + \alpha_i + \varepsilon_{it}, \tag{2.1}$$

where i denotes county, t is year, R_{it} is the (total) crime rate, X_{it} is a set of control variables and P_{it} contains a set of deterrent variables. The dimensions of the panel data are $T = 7$ years and $N = 90$ counties. Included in X_{it} are wages, population density, some demographic variables, year effects and the number of police per capita ($POLICE$). The latter is included as a measure of a county's ability to detect crime. Included in P_{it} are the ratio of arrests to offenses (P_A), the ratio of convictions to arrests (P_C), the proportion of convictions resulting in imprisonment (P_P), and average prison sentence length in days (S). Furthermore, α_i are fixed county effects and ε_{it} are idiosyncratic errors. A double log functional form has been adopted, hence coefficients are elasticities.

<Table 1 about here>

Column 1 of Table 1 replicates the Within OLS estimates of CT94.[1] The magnitude of the deterrence effects of P_A, P_C and P_P is ordered according to the economic model of crime. Contrary to other research (Levitt, 1997, 2002; Worrall and Kovandzic, 2010) police has positive correlation with crime. CT94 give as explanation that more police report more crime. An alternative explanation is

[1] Only coefficient estimates are identical. Contrary to CT94, however, we use cluster-robust standard errors allowing for arbitrary heteroscedasticity and serial correlation within counties.

that here the contemporaneous effect is included, while elsewhere often $POLICE$ only appears with a lag.

CT94 assume endogeneity of two regressors, i.e. probability of arrest (P_A) and size of police force ($POLICE$). Two external instrumental variables are used, i.e. offense mix and per capita tax revenues. The offense mix is the ratio of crimes involving "face-to-face" contact (such as robbery, assault and rape) to those that do not. Column (2) of Table 1 replicates the Within 2SLS estimates as reported by Baltagi (2006). The standard errors of the Within 2SLS estimates are many times larger than their OLS counterparts suggesting an identification problem. The Kleibergen-Paap (2006) rank statistic indeed does not reject the null hypothesis of reduced rank of the matrix of reduced form parameters. Therefore, the rank condition for identification is not satisfied.

IV estimation of the Within model can only be used when the instruments are strongly exogenous. An alternative transformation, which allows for predetermined instruments, is taking first differences. Column (3) of Table 1 reports IV estimates using the original external instruments in the First Differenced (FD) model. Again lack of identification results, i.e. the Kleibergen-Paap (2006) p-value is 0.80. Provided that the idiosyncratic errors in (2.1) are serially uncorrelated, however, lagged values of the endogenous regressors themselves are available as internal instruments for the model in first differences (Anderson and Hsiao, 1981). Column (4) of Table 1 reports FD IV estimates using two period lagged values of P_A and $POLICE$ as instruments. Here the Kleibergen-Paap (2006) rank test does reject the null hypothesis of underidentification. Reported standard errors show much higher precision resulting from using these internal instruments.

More efficient IV estimation is possible by considering more lagged values, exploiting the fact that each time period offers additional moment conditions. Column (5) of Table 1 reports FD IV estimates using two period lagged values of P_A and $POLICE$ as instruments, but now separately for each time period. In other words, we use ten instruments for two endogenous regressors.[2] Column (6) exploits all available moment conditions in IV estimation. Note that the Kleibergen-Paap (2006) rank test does not reject in this case. This may indicate that the additionally used lagged values are relatively less informative, but test power can also be low due to the relatively large degrees of freedom (29).

Compared with the IV estimates of Table 1, further efficiency gains can be achieved by considering GMM estimation (Arellano and Bond, 1991). The FD IV estimates in Table 1 do not exploit the fact that the errors of the first differenced model are serially correlated and potentially heteroscedastic.

<Table 2 about here>

Columns (1) and (2) of Table 2 reports two-step GMM estimates[3] corresponding with the IV estimates from columns (5) and (6) of Table 1. Comparing GMM and IV estimates efficiency gains are seen when a limited number of instruments is used in estimation. However, when exploiting all available lagged instruments standard errors stay more or less unchanged.

[2] The years 1981 and 1982 are used to construct the two period lagged instruments, hence the effective number of time periods used for estimation is five.

[3] We exploit Windmeijer (2005) corrected standard errors, and an initial weight matrix which is optimal under homoscedasticity and MA(1) structure of the first differenced errors.

The use of lagged internal instruments instead of external instrumental variables seems a viable alternative empirical strategy to identify deterrence effects in the CT94 data. Their validity, however, is crucially depending on absence of serial correlation in the idiosyncratic errors. In other words, in the first differenced model no higher-order residual autocorrelation should occur. Although Hansen (1982) p-values indicate that the exploited moment conditions are valid, the Arellano-Bond (1991) second-order residual autocorrelation test has a relatively low p-value. Therefore, in columns (3) and (4) of Table 2 we report estimation results of a dynamic model including one period lagged values for all three (R, P_A and $POLICE$) endogenous variables as additional regressors. Columns (3) and (4) are the first differenced two-step GMM estimates exploiting nearest and all instruments respectively. The results show that, although autoregressive dynamics are not always relevant, both Hansen and higher-order residual autocorrelation tests now have high p-values. Coefficient estimates of deterrence regressors do not change much in magnitude.[4] Finally, it is well known that in case of persistent panel data lagged values are weak predictors for changes. We therefore estimated first-order autoregressive models for the three endogenous variables. Resulting first-differenced two-step GMM estimates are 0.53, 0.44 and 0.55 for R, P_A and $POLICE$ respectively, indicating that persistence is moderately only.

[4] We also considered the additional moment conditions for the model in levels, which become available under mean stationarity (Arellano and Bover, 1995; Blundell and Bond, 1998). However, difference-in-Hansen statistics show mixed evidence on their validity. Regarding the four specifications in Table 2, difference-in-Hansen p-values are 0.17, 0.04, 0.33 and 0.02 respectively.

3. Concluding remarks

We have estimated the economic model of crime exploiting instrumental variables techniques for panel data. We extend the empirical analysis of CT94 and show that their external instrumental variables are very weak, which explains their imprecise IV deterrence estimates. We propose an alternative identification strategy based on lagged internal instruments, and apply GMM instead of IV. The resulting internal instruments are valid and reasonably strong. In magnitude coefficient estimates are in line with earlier results. However, both exploiting internal instruments and applying GMM instead of IV yields considerably more precise estimates of the deterrence effects on crime. It is interesting to investigate the effectiveness of this alternative identification strategy in other empirical crime studies too, even when strong external instruments are available. The use of strong internal and external instruments enables the researcher to test the validity of both types separately, resulting in improved credence of instrumental variables analyses.

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Table 1: OLS and IV deterrence estimates

	(1)	(2)	(3)	(4)	(5)	(6)
P_A	-0.355	-0.575	-0.400	-0.495	-0.506	-0.622
	(0.060)	(0.788)	(0.932)	(0.284)	(0.240)	(0.150)
P_C	-0.282	-0.423	-0.257	-0.281	-0.279	-0.365
	(0.049)	(0.500)	(0.688)	(0.100)	(0.097)	(0.069)
P_P	-0.173	-0.250	-0.187	-0.211	-0.211	-0.250
	(0.045)	(0.276)	(0.320)	(0.080)	(0.062)	(0.058)
S	-0.002	0.009	-0.012	-0.029	-0.009	0.010
	(0.033)	(0.055)	(0.158)	(0.043)	(0.036)	(0.033)
POLICE	0.413	0.657	0.359	0.319	0.304	0.537
	(0.084)	(0.863)	(1.890)	(0.151)	(0.182)	(0.085)
KP		0.459 (1)	0.797 (1)	0.013 (1)	0.042 (9)	0.211 (29)
HJ					0.884 (8)	0.896 (28)

Note: numbers between parentheses under coefficient estimates are cluster-robust standard errors. KP and HJ report p-values (degrees of freedom) of Kleibergen-Paap (2006) rank test and Hansen (1982) J statistic respectively.

Table 2: GMM deterrence estimates

	(1)	(2)	(3)	(4)
P_A	-0.445	-0.533	-0.474	-0.497
	(0.110)	(0.160)	(0.177)	(0.174)
P_C	-0.247	-0.293	-0.279	-0.308
	(0.044)	(0.073)	(0.103)	(0.081)
P_P	-0.171	-0.180	-0.249	-0.221
	(0.039)	(0.049)	(0.085)	(0.052)
S	0.001	0.028	-0.057	-0.011
	(0.023)	(0.030)	(0.045)	(0.042)
POLICE	0.254	0.441	0.387	0.510
	(0.119)	(0.140)	(0.226)	(0.102)
R_{-1}			0.397	0.278
			(0.227)	(0.165)
$P_{A,-1}$			-0.060	-0.049
			(0.155)	(0.077)
$POLICE_{-1}$			-0.310	-0.224
			(0.277)	(0.080)
HJ	0.896 (8)	0.885 (28)	0.748 (10)	0.850 (40)
m2	0.059	0.075	0.930	0.702

Note: see Table 1. Furthermore, m2 reports p-value of Arellano and Bond (1991) test for second order residual autocorrelation.