Urban and Regional
Analysis Group

Copycat Spending Across States:
A New Approach

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Working Paper No. 06-04
March 2006

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Abstract

This paper reexamines the extent to which each state's spending reflects mimicking the spending of other similarly situated states. Using a generalized spatial correlation model estimated with GMM, the estimates show that the previously observed strategic spending responses indicative of copycat behavior is largely the result of residual higher-order spatial correlation left uncorrected by the first-order maximum likelihood approach. The new estimates reveal a weak copycat spending effect over the early part of our sample period once the more general structure of the spatial correlation among states is taken into account. This effect disappears entirely after fundamental changes in major federal grant programs were undertaken in 1994.

JEL Classification Codes: H72, C23

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1 Introduction

One of the questions taking a prominent role in the empirical public finance literature concerns the extent to which spatial relationships affect the fiscal behavior of state and local governments. Various theoretical explanations for the spatial relationships exist in the literature. One is fiscal competition among local governments for mobile tax bases; another is the interplay of interest groups that justify their own agendas by pointing to policies adopted by similar states. Empirically, both these theories are consistent with the spatial relationships modelled as direct effects or interactions among the unmeasured or unobservable influences.

Empirical modelling of spatial relationships requires specifying the channel through which cross-sectional interdependencies occur. Brueckner (2003) defines direct fiscal effects as strategic interactions among governments and finds that this is a key feature of many empirical studies. Because it is well-known that spatial correlation among errors left uncorrected can lead to spurious estimates of strategic behavior (Case, Rosen, and Hines 1993, Anselin, et. al., 1996), prudent investigators typically try to account for both spatial strategic interaction and error correlation in their models. Much of the empirical work in this area assumes first-order spatially correlated errors.[1] While tractability and familiarity underlie this modeling choice to some extent, the approach doubtlessly also rests on the belief that the first-order error process provides a close enough approximation to purge the effects of spatially correlated errors on the strategic interaction parameter estimates. The extent to which this presumption is true, however, remains unknown.

This paper generalizes the Case, Rosen, and Hines (1993) state spending model to examine this and related questions. Our estimation strategy differs from Case, et al. They specify a first-order autoregressive spatial process to capture the direct effect of neighbor states' spending–as suggested by their theory–and also use a first-order autoregressive process for the errors. As was common at the time, they estimated their model with maximum likelihood. Hernandez-Murillo (2004) uses the same parametric spatial framework for a tax-setting model, but employ a computationally simpler

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[1] See the excellent review of the empirical literature in Brueckner (2003) for examples.

and more robust estimator, a generalized method of moments (GMM) estimator suggested by Kelejian and Prucha (1998). In contrast, while our state spending model combines a first-order process to capture the direct effect of neighbors' spending on each state, we also allow for more general error processes, estimating the model using GMM. This approach is flexible in that it allows for greater generality in the cross-sectional error dependence than assumed by Case, et al. (1993) or Hernandez-Murillo (2004). Thus, if estimates obtained from both procedures are similar, this provides some evidence that either the first order process assumed in the earlier studies adequately approximates the true spatial error structure or the error misspecification is not driving the observed spending interaction estimates.[2]

This paper contributes to the growing literature on spatial models of government behavior, casting new light on the extent to which each state's spending mimics the spending of other similarly situated states. We compare spatial interaction estimates from an updated data set under a first-order spatial error correlation regime with estimates obtained under the generalized spatial error model. We find a strong positive and significant strategic interaction effect on state spending using the Case-Rosen-Hines model but find a much weaker effect for part of the sample period using the generalized error model. The results suggest that the strategic interaction found for state spending in the first order error model is driven by the assumed error structure. In addition, estimates from the first-order error model yield smaller estimated effects of federal grants on state spending, with this result more pronounced after the fundamental changes in major federal grant programs that were undertaken in the mid-1990s. Other empirical relationships found in the state and local spending literature still pertain under the generalized spatial error structure. In particular, federal grants and resident income continue to exhibit asymmetric "flypaper" effects on state and local spending in the generalized error model across the 1977-1993 and 1994-1999 sample periods.

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[2] The first order spatial error process is a parametric formulation that allows joint estimation of the error parameters along with the spending interaction parameters. Tieing the two sets of parameters this way means that a misspecified error process can confound the spending interaction parameter estimates. Our strategy does not require joint estimation and thus our estimates of the spending interaction effects are entirely independent of the error specification.

The discussion is organized as follows. Section 2 explains the empirical models and the estimation strategy. Section 3 presents the data, the estimates, and discusses the results. The fourth section concludes.

2 The Empirical Model

The Case-Rosen-Hines (1993) model formalizes the incentive among states to adopt the copycat behavior identified earlier by Walker (1969). The underlying rationale is that residents may not wish their state to be identified as "below average" in broad spending categories like highways, education, environmental protection, and public safety, when compared with similar states. Interest groups and policy-makers exploit this, which creates a tendency for states to copy policy initiatives adopted by other states that they identify as in their cohort, where a state's relevant cohort is defined in terms of demographic similarity. Such copycat behavior can be explicit; it is not unusual for new legislation just passed or being considered in one state to be introduced for consideration in another state almost verbatim.

Letting $\mathbf{x}$ denote the vector of variables thought to directly affect state spending (including state and time period fixed effects), the structural equation describing state i's spending during time period t, y_{it}, is the jurisdiction's best response or reaction function

$$y_{it} = \mathbf{x}_{it}\beta + \lambda \sum_{j} w_{ij} y_{jt} + u_{it} \tag{1}$$

where w_{ij} are exogenous spatial weights (with $w_{ii} = 0$ and $\sum_j w_{ij} = 1$) and u_{it} is the error term. The fixed state effects and year effects are duly accounted for in the estimation, but are not central to our discussion and so are suppressed in what follows. The parameters to be estimated are $\theta = [\beta, \ \lambda]$, where $\lambda > 0$ implies strategic complementarity–the copycat spending behavior implied by the theory. The Nash equilibrium describing the vector of states' spending, $\mathbf{y}_t$, is found from (1) as

$$\mathbf{y}_t = (I - \lambda \mathbf{W})^{-1} \mathbf{x}_t \beta + u_{it} \tag{2}$$

for the spatial weight matrix $\mathbf{W} = [w_{ij}]$.

The spending determinants in $\mathbf{x}$ include Case, et al.'s variables (grants, income, income squared, and demographic variables). In addition, we include a state government wage index in order to control for differences in production costs across states. We anticipate that our wage variable is likely to be correlated with the error term not only because public sector wages are jointly determined with state and local government spending, but also because the wage variable is a proxy, which raises concerns about measurement error. The estimation strategy that we adopt yields instruments that work well in this regard, but as we shall see our estimates are quite similar whether instruments are used for wages or not. The procedure is described later.

The Case-Rosen-Hines empirical approach adopts the Cliff-Ord (1981) type of first-order spatial error correlation model widely used in the regional and environmental literatures,

$$\mathbf{u}_t = \rho \mathbf{W} \mathbf{u}_t + \varepsilon_t \tag{3}$$

where $E[\varepsilon_{it}\varepsilon_{jt}] = 0$ for $i \neq j$.

The model assumes that the expenditures of state i in time period t depend on a weighted average of its cohorts' expenditures, with the relative weights in $\mathbf{W}$ known *a priori*. We use their preferred weight matrix, where the similarity between two jurisdictions depends upon the differences between their respective sample period mean demographic features, here, the proportion of black population, or

$$w_{ij} = \frac{1/|\overline{Black_i} - \overline{Black_j}|}{\sum_j 1/|\overline{Black_i} - \overline{Black_j}|}$$

This weight matrix defines neighboring states as those with similar proportions of blacks in their populations.

We are persuaded by the arguments that states look beyond their own boundaries when determining the levels of provision of public goods and services. It also seems entirely plausible to expect that random shocks do not stop at state borders, but instead exhibit some cross-sectional dependence. There is no need, however, to restrict this cross-sectional dependence to a first order process. Consider that in the vast majority of empirical studies, researchers make few parametric assumptions about the error process, even though they make strong assumptions about functional form and the choice of explanatory variables for the conditional mean of the dependent variable. Advances in econometric method are making it easier to avoid specific parametric forms for a model's stochastic structure. Such a nonparametric approach is particularly useful for the copycat problem studied here. Misspecifying the spatial error structure can lead to an inconsistent variance/covariance matrix estimate and yield invalid test statistics. In addition, the maximum likelihood procedure estimates the first order error parameter jointly with the conditional mean parameters, an error misspecification can affect estimates of λ, the spending interaction effect.[3] Thus, we find GMM estimation combined with a robust covariance matrix estimator especially attractive; this alternative approach allows us to remain agnostic about the form of the spatial relationship among the unobservable error terms in the spending model.

Our empirical model for a panel of n states is based on the assumption that the error structure is given by

$$E(\mathbf{u}_t\mathbf{u}_t') = \Omega_n = D_n D_n'. \tag{4}$$

This implies that $\mathbf{u}_t = D_n\boldsymbol{\varepsilon}_t$. We assume that the matrix $\mathbf{D}_n$ is nonsingular and the error vector, ε, is independent and identically distributed with covariance matrix $\mathbf{I}_n$. These assumptions imply that each state's structural disturbance u_{it} is a weighted sum of all state's disturbances; however, the weights are unknown. With the elements of $\mathbf{D}$ unknown, we cannot estimate the disturbance covariance matrix since n (the number of states) is greater than T (the number of years) and thus cannot use a fully efficient estimator such as maximum likelihood or a best IV estimator. Nonetheless, the general form of the spatial correlation implicit in $\mathbf{D}$ does not inhibit our ability to estimate the coefficient vector $\theta = [\beta,\ \ \lambda]$; we use an efficient GMM method and construct a robust covariance estimator for inference. Note that the usual first order error process sets $\mathbf{D} = (\mathbf{I}-\rho\mathbf{W})^{-1}$.

We estimate the model by an efficient GMM method that identifies θ by the moment conditions, $E[\mathbf{H}_t'\mathbf{u}_t] = 0$, where $\mathbf{H}_t$ is the instrument matrix suggested by

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[3] It is well known that the information matrix is not block diagonal between ρ and λ. However, complete asymptotic results have not been established for this model, even under correct specification. Recently, Lee (2003) found that in a simplified version of this model, rates of convergence depend on properties of the weight matrices.

Kelejian and Prucha (1998). The matrix $\mathbf{H}_t$ is defined as the p linearly independent columns of $(\mathbf{x}_t^*, \mathbf{W}\mathbf{x}_t^*, \mathbf{W}^2\mathbf{x}_t^*)$. Here, x_t^* represents the exogenous columns of x_t. This ability to treat some of the explanatory variables as endogenous marks another difference between our approach and that taken by Case, Rosen and Hines. The GMM estimator is based on p sample moments that are averaged over both n and T, that is, $\sum_{i=1}^{n}\sum_{t=1}^{T} H_{ti}' u_{ti}/nT$.

To define the resulting GMM estimator, it is convenient to write model (2) and (4) stacked by observation.

$$\begin{aligned} \mathbf{y} &= (\mathbf{x}, (\mathbf{I}_T \otimes \mathbf{W}_n)\mathbf{y})\theta + \mathbf{u} = \mathbf{Z}\theta + \mathbf{u} \qquad (5) \\ \mathbf{u} &= (\mathbf{I}_T \otimes \mathbf{D}_n)\varepsilon \end{aligned}$$

The efficient GMM estimator can then be written as,

$$\widehat{\theta} = (\mathbf{Z}'\mathbf{H}\mathbf{S}^{-1}\mathbf{H}'\mathbf{Z})^{-1}\mathbf{Z}'\mathbf{H}\mathbf{S}^{-1}\mathbf{H}'\mathbf{y} \qquad (6)$$

where

$$\mathbf{S} = \lim_{n\to\infty, T\to\infty} \sum_{t=1}^{T}\sum_{i=1}^{n}\left(\frac{\mathbf{H}_t'\mathbf{D}_n\mathbf{D}_n'\mathbf{H}_t}{nT}\right)$$

The estimator's limiting distribution is $\sqrt{nT}(\widehat{\theta}-\theta) \to N(0,V)$ where $V = \overline{Q_{ZH}}\mathbf{S}^{-1}\overline{Q_{HZ}}$ and $plim_{n,T\to\infty}\sum_{t=1}^{T}\sum_{i=1}^{n}\mathbf{Z}_t'\mathbf{H}_t/nT = \overline{Q_{ZH}}$. We estimate the covariance matrix in the obvious way by replacing the probability limits with their sample counterparts and replacing $\mathbf{D}_n\mathbf{D}_n'$ with $\sum_{t=1}^{T}\widehat{\mathbf{u}}_t\widehat{\mathbf{u}}_t'/T$, where $\widehat{\mathbf{u}}_t = \mathbf{y}_t - \mathbf{Z}_t\widehat{\theta}$.[4]

2.1 Data and Variables

Table 1 presents the variable definitions and summary statistics. The sample period extends over 1977–1999. With the exception of the wage index, the variables follow those used by Case, Rosen, and Hines (1993). The dependent variable is defined as annual expenditures by state and local governments (net of expenditures for insurance, interest, and state-run liquor and utility firms). These data come from the U.S. Bureau of the Census, Government Finance Series, General Revenue Tables. In

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[4] This covariance estimator follows the general form suggested by Driscoll and Kraay (1998) for spatially dependent errors in panel data models and is based on both n and T asymptotics.

order to obtain real, per capita expenditure figures, we use population figures from the Bureau of the Census and a state deflator from the Bureau of Economic Analysis.

The real per capita income (*Income*) is obtained from U.S. Census publications; the square of this variable is also included in the empirical models. The *Grants* variable represents real federal grants to state and local governments per capita. Population density (*Density*) is measured as the ratio of state population to land area in square miles.

The demographic variables are the proportion of the states' populations that is over 65 years of age (*Over65*), the proportion that is school-age (*SchoolAge*), and the proportion that is black (*Black*). These variables are also obtained from U.S. Department of Census publications.

We construct our government real wage index using data from the Bureau of Labor Statistics. We sum payments to workers at the state and local levels, then divide by the number of full-time equivalent workers. The computed variable, *Wage*, represents average real monthly wages for full-time workers measured in thousands of dollars.

The demographic variables changed by relatively small amounts over the period under consideration. The largest change was in *Over65,* which increased by about 10 percent. Population growth in the entire U.S. from 1977 to 1999 was about 24 percent, much higher than the average increase in population density of about eight percent.

None of the variables in the spending model is controversial. It is common to include variables associated with the median voter model, like median income and voter tax share, in spending models. While there is evidence that the median voter model provides a good framework for modeling public spending demand in small and medium size local governments, there is strong evidence that it is not appropriate for higher level governments (Turnbull and Mitias, 1999; Fischel, 2001). Given that we are modeling the aggregate state and local spending, there is even less reason to restrict the specification to variables identified with the median voter in each state–which is fortunate, given that they are not available for non-census years. In our model, the *Income* and *Grants* variables measure state and local governments' resources. *Density* has been identified with a variety of influences in the local spending literature, from consumption congestion to effects on production costs. The variable *Wage* is included to pick up unit cost effects on the budget, but is also a component of the voters' tax price of publicly provided services (Bergstrom and Goodman, 1973). The demographic variables are used as ad hoc controls for voter preferences or interest group effects in this study. These variables have been found to be significant determinants of government spending in some cases (Poterba, 1997; Merrifield, 2000).

2.2 Results

Our sample period runs from 1977 to 1999. We selected the ending date to avoid the post-technology bubble recession, the 9/11 terrorist attacks, and the aftermath. The 23 year sample period covers several potential turning points in federal policy that can influence state spending patterns. It turns out that the revision of welfare and other grant programs undertaken in the mid-1990s led to fundamental changes in the federal-state fiscal relationship and, not surprisingly, to substantial differences in the estimated state spending equations. To take those changes into account, we partition the sample period into the 1977-1993 and 1994-1999 subsamples reported in Tables 2-3.

The columns labeled [1a] and [1b] in Table 2 report the ML estimates of the Case-Rosen-Hines model (2) and (3). These models treat *Grants* as exogenous. We note that the 1977-1993 results are largely consistent with the original Case, et al. estimates for the sample period 1970-85 in terms of signs and significance of coefficients. *Grants*, *Income*, *Over65* are all significant, as in the earlier paper. In addition, *Density* is significant in our sample while it was not in the earlier study. Of greatest interest to us, the spending interaction effect, measured by λ, is positive and significant while the spatial error correlation parameter, ρ, is negative and significant. The size of the spatial interaction parameter, at 0.76, is very close to the original Case, et al. estimate of 0.70.

Comparing the two periods in our sample, we find clear evidence of the expected structural change. The *Grants* effect declines dramatically in the later period. *Income* remains important, but the relationship with spending is concave instead of convex.

Further, the estimated impacts of the demographic factors fall substantially in the later sample. The variable we added to the Case-Rosen-Hines model, *Wage*, is not important in determining state spending in either sample. For a \$1000 increase in real average monthly wages, we find a reduction in per capita spending of at most \$5. What is surprising in light of the other differences reported in the table is how stable the copycat and spatial correlation parameters, λ and ρ, respectively, are over time.

The columns labeled [2a] and [2b] report the GMM estimates of the spending model (2) with the generalized spatial error correlation (4). The new estimates for *Grants*, *Income*, *Over65*, and *Density* replicate the signs and significance of the ML models in [1a] and [1b], respectively. The income-spending relationship also shifts from convex to concave over the two samples as in the MLE models. Nonetheless, some systematic differences are evident. *Black* is not significant in the ML model for the early sample while it is significantly positive in the GMM model. In addition, the *Grants* estimates are similar in magnitude in the first period, but fall less dramatically in the second period in the GMM models than in the ML models. Finally, looking at the parameters of central importance, the GMM spending interaction or copycat effect is quite small and is not significantly different from zero in either subsample. (Recall that there is no parameter in the GMM models that corresponds to the spatial error correlation parameter, ρ, in the ML models.) Referring to columns [3a] and [3b] in Table 2, dropping *Wage* from the model has no appreciable impact on these conclusions.

The calculated marginal effect of per capita income on spending at the sample mean is 0.063 in the early period model [2a] and 0.045 in the later period [2b], spending effects that are considerably below those observed for grants (1.285 and 0.599 in [2a] and [2b], respectively). This is not a surprising pattern. Studies of local governments often find this so-called flypaper effect, where marginal grants effects exceed income effects on spending (Hines and Thaler, 1995; Roemer and Silvestre, 2002). Theoretical explanations for this type of income-grants asymmetry on spending range from the side-effects of interjurisdictional tax competition (Turnbull and Niho, 1986) to voter fiscal illusion or uncertainty (Turnbull, 1998). From the empirical side, Megdal (1987) and Knight (2002) suggest that grant endogeneity can create an upward bias on the estimated grant effect. Many federal grants programs require state or local matching spending, particularly in the earlier sample period here. Other grants are only awarded to governments that apply. More broadly, Knight (2002) suggests that because political processes determine both federal grants and state spending, these variables are correlated with unobservable components of voters' preferences, hence grants will be endogenous in a spending equation. In sum, there is good reason to expect *Grants* to be endogenous in our models. The question is, does this affect our conclusions, especially those pertaining to the copycat effect?

Table 3 reports the model estimates treating *Grants* as endogenous. Comparing models [4a] and [4b] in Table 3 with [2a] and [2b] in Table 2, we find that correcting for the endogeneity of grants has few effects on the 1977-93 estimates. The grant coefficient is slightly lower, but not significantly so. The copycat coefficient λ increases in magnitude and becomes significant at the 10% level–but its magnitude is still less than one fifth of that estimated in the MLE model [1a]. Correcting for endogeneity in the 1994-99 sample reveals a much larger and significant decline in the marginal grant effect of approximately 0.20. In this sample, however, the copycat effect remains small and insignificant regardless of whether *Grants* are exogenous or endogenous in the model.

Table 3 also includes estimates without the *Wage* variable in columns [5a] and [5b] for comparison purposes. The results do not change qualitatively. We also estimated the GMM models treating *Wage* as endogenous. For brevity, we do not report the results but merely note that none of our conclusions are affected when *Wage* is endogenous in the model.

In sum, we find no consistent evidence of spending interaction among states with similar racial composition when not imposing the more restrictive spatial error structure. The only significant estimate (at the 10% level) is for the early sample when *Grants* are endogenous, and that effect is less than one fifth the size of the ML estimate. There is no evidence of any copycat spending effect in the later sample. A comparison of the ML and GMM estimates reveals that the previously observed interaction effect is driven in whole or in part by the first-order spatial error specification. Our results do not mean that there is no overlapping spending effects among similar states. These effects, however, appear to be largely felt through the spatially correlated errors rather than through explicit copycat behavior. What this most likely means is that the underlying political structure is correlated with the racial composition of state populations, and that those unmeasured effects are correlated with spending patterns. The copycat model is intuitively appealing and we have no doubt that copycat behavior exists at some level in many states. Nonetheless, our estimates indicate that such behavior is not sufficiently pervasive throughout the fiscal decision-making process to surface as a key determinant of state and local spending.

3 Conclusion

This paper reexamined Case, Rosen, and Hines (1993) model of state and local government spending, generalizing the spatial error model and correcting for endogenous federal grants. Using a generalized spatial correlation model estimated with GMM, the results show that the previously observed strategic state spending responses indicative of copycat behavior appears to be largely an artifact of a residual higher-order spatial correlation left uncorrected by the popular first-order maximum likelihood approach. The new estimates reveal no evidence of pervasive copycat effects in state spending once the more general structure of the spatial correlation among states is a taken into account. Although taking possible grants endogeneity into account removes the upward bias in the grant coefficient estimates, it does not alter our conclusions regarding the spending interaction or copycat effect.

In addition to the main results, this paper also contributes to the methodology used in estimating and interpreting spatial models. We combine an instrumental variable estimator for the model's structural parameters with a robust covariance matrix estimator. We maintain the assumption of a first order spatial dependence model to capture copycat spending effects, but we allow for a more general spatial error correlation than the first order model used previously. Our instruments are those suggested by Kelejian and Prucha (1998). This estimation strategy yields more instruments than are needed to account for the endogeneity of other states' expenditures, thus we are also able to take into account the endogeneity of the unit cost and federal grants, which has not often been done in previous empirical studies of expenditure or tax spatial interaction.

Our results raise questions about other models of spending interaction. In his review of the empirical literature, Brueckner (2003) notes that most studies find significant positive spending or taxing interaction effects. Those models tend to rely on the same type of parametric first-order spatial error correlation model as examined here. We believe that the methodology employed in this paper can be useful in other panel data applications where such spatial relationships are important.

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Table 1: Summary Statistics

Variables	1977-1993		1994-1999	
	Mean	Std. Dev	Mean	Std. Dev
real per capita expenditures	3005.370	710.937	4201.582	611.137
grants	654.942	171.787	905.167	242.923
income	187.468	41.075	236.935	35.353
over 65	11.913	1.918	12.851	1.721
school age	19.876	2.120	19.560	9.851
black	9.663	9.268	10.360	9.566
density	163.511	230.148	176.467	240.116
wage	2.407	0.474	2.313	0.399
population	4.905	5.092	5.495	5.839

$*$ Grants, expenditures and income are in real dollars per capita terms. Income is scaled to $100s. The wage variable represents real average monthly wages for full time workers. State population is in millions.

Table 2: MLE and GMM Spending Equation Estimates: Exogenous Grants and Wages

Model	[1a]	[1b]	[2a]	[2b]	[3a]	[3b]
Period	1977-1993	1994-1999	1977-1993	1994-1999	1977-1993	1994-1999
grants	1.226* (0.059)	0.336	1.285* (0.079)	0.599* (0.036)	1.287* (0.081)	0.568* (0.040)
income	-6.687* (1.963)	20.660	-3.405 (1.869)	24.905* (1.688)	-3.541 (1.847)	25.823* (1.758)
income^2	0.030* (0.004)	-0.033	0.026* (0.003)	-0.043* (0.002)	0.026* (0.003)	-0.045* (0.002)
over 65	-57.500* (12.575)	26.490	-73.815* (18.380)	45.280* (16.578)	-76.710* (18.770)	42.120* (17.356)
school age	7.930 (6.539)	-0.320	9.902 (8.435)	0.228 (0.155)	10.596 (8.519)	0.070 (0.201)
black	18.170 (13.491)	-0.507	35.419* (14.774)	12.098 (8.692)	39.951* (14.655)	12.485 (8.811)
density	-2.798* (0.667)	-3.066	-4.081* (0.588)	-1.815 (1.064)	-4.244* (0.602)	-0.818 (1.111)
wage	-5.066 (11.757)	-0.664	0.435 (14.850)	5.447 (12.129)		
λ	0.762* (0.066)	0.862	0.051 (0.067)	0.146 (0.107)	0.026 (0.070)	0.172 (0.104)
ρ	-1.122* (0.060)	-1.248				
n	816	288	816	288	816	288
Method	MLE	MLE	GMM	GMM	GMM	GMM

Note: Standard error in parentheses. (*) statistically significant at 5% or better. We do not report standard errors for the ML estimates in the second period because the Hessian matrix evaluated at the point estimates was not positive definite.

Table 3: GMM Spending Equation Estimates:
Endogenous Grants and Exogenous Wages

Model	[4a]	[4b]	[5a]	[5b]
Period	1977-1993	1994-1999	1977-1993	1994-1999
grants	1.129* (0.158)	0.384* (0.086)	1.076* (0.160)	0.361* (0.103)
income	-2.112 (2.245)	28.907* (2.803)	-1.669 (2.220)	29.456* (2.722)
income^2	0.024* (0.004)	-0.051* (0.004)	0.024* (0.004)	-0.052* (0.004)
over 65	-64.944* (18.400)	59.224* (14.946)	-66.409* (17.605)	58.688* (16.370)
school age	4.235 (8.798)	-0.087 (0.164)	11.096 (9.050)	-0.152 (0.198)
black	38.839* (15.537)	-3.342 (11.963)	40.085* (15.441)	-3.127 (13.323)
density	-4.374* (0.605)	-1.990 (1.129)	-4.517* (0.622)	-1.620 (1.224)
wage	1.232 (15.065)	-11.036 (15.004)		
λ	0.142 (0.080)	0.067 (0.514)	0.133 (0.080)	0.075 (0.157)
n	816	288	816	288
Method	GMM	GMM	GMM	GMM

Note: Standard errors in parentheses. (*) statistically significant at 5% or better.