Testing for Strategic Interaction Among Local Governments: The Case of Growth Controls*

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This paper helps to fill a gap in the public economics literature by providing empirical evidence on strategic interaction among local governments. Using the methodology of Case et al. (Journal of Public Economics, 52, 285-307 (1993)), the paper focuses on the adoption of growth-control measures by cities in California and looks for evidence of policy interdependence in these choices. The data are drawn from an elaborate survey of growth control practices in California cities, conducted by Glickfeld and Levine (“Regional Growth . . . Local Reaction,” Lincoln Institute of Land Policy, Cambridge, MA, 1992). The survey results are used to compute an index of the stringency of growth controls in each city, which serves as the dependent variable for the study.

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1. INTRODUCTION

Strategic interaction is a key element in recent models of local government behavior. Interaction occurs because the market environment in which local policy decisions are made is affected by the actions of other local governments. Policy choices are thus interdependent, and the resulting interaction must be taken into account in characterizing the public sector equilibrium.

Models with strategic interaction have found their widest use in the tax competition literature. In the basic tax competition model, communities finance public spending with a tax on mobile capital. Since capital migrates to equalize after-tax returns across communities, the allocation of capital (as well as the level of the common after-tax return) depends on tax rates in all communities. Treating other tax rates as fixed, each community chooses its own rate taking account of this dependence. This model was

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first analyzed by Mintz and Tulkens [31], Wildasin [39], and Bucovetsky [11], building on earlier studies by Zodrow and Mieszkowski [44] and Wilson [41] (they treated the competitive case, where strategic interaction is absent). The key feature of the Nash equilibria in tax competition models is underprovision of public goods. This occurs because the capital flight accompanying a higher tax rate dampens the incentive to raise taxes, even though the fleeing capital is not lost to the economy as a whole.

Following these early papers, models of strategic interaction have become commonplace in local public economics. Bucovetsky and Wilson [12], Hoyt [27], Wilson [42], and Wildasin [40] explore variants of the basic tax competition model. Hoyt [26, 28], Henderson [23, 24], and Wilson [43] add consumer mobility as well as a richer menu of tax instruments to the tax competition framework, building on earlier work by Epple and Zelenitz [19]. Using models of strategic interaction, Scotchmer [35, 36], Helsley and Strange [21], and Hochman et al. [25] analyze the provision of public goods by profit-maximizing club developers. Myers [32], Myers and Papageorgiou [33], and Burbidge and Myers [13] study the efficiency-enhancing properties of voluntary intercommunity transfers, again using a strategic interaction framework. Finally, Brueckner [7] and Helsley and Strange [22] study strategic interaction in the choice of urban growth control measures.

Despite the widespread recognition of policy interdependence in theoretical work, Case et al. [14] and Besley and Case [5] present the only existing empirical studies of strategic interaction among governmental units. Case et al. [14] investigate interdependence in the determination of spending by state governments in the United States, using a “spatial lag” framework adapted from the literature on spatial econometrics (Anselin [1]). In their model, a weighted average of spending levels in neighboring states (computed by applying a predetermined weight matrix to the data) appears as a right-hand side variable in the regression. The estimation results show that a given state's spending responds positively to higher spending in “competing” states. Besley and Case [5], using a different empirical approach, find similar interdependence in state taxes.

1Oates and Schwab [34] offer a parallel analysis of the choice of environmental policies by competitive communities in an economy with mobile firms.

2Kolstad and Wolak [29] conduct a “quasi-empirical” analysis of tax competition between state governments, focusing on tax rates charged by Western states on the coal they produce. Kolstad and Wolak generate supply elasticities from engineering data and combine these with independent estimates of demand elasticities to simulate the competitive behavior of the Western states.

3In contrast to the models discussed above, policy interdependence in Case et al. [14] comes from benefit spillovers across states rather than from interjurisdictional resource flows. In both cases, however, the implied empirical specification is the same: a given jurisdiction's policy choice depends in part on the choices of its competitors.
More empirical evidence on policy interdependence is clearly needed, and the present paper helps to fill this gap. It uses the methodology of Case et al. [14] to study strategic interaction among local (rather than state) governments. The paper focuses on the adoption of growth control measures by cities in California and looks for evidence of policy interdependence in these choices. The data are drawn from an elaborate survey of California growth control practices conducted by Glickfeld and Levine [20]. The survey results are used to compute an index of the stringency of growth controls in each city, which serves as the dependent variable for the study.

Under the spatial lag specification, the growth control index depends on city characteristics and on a variable measuring the stringency of controls in competing cities. The coefficient on this “competing controls” variable, which indicates how a given city responds to tighter controls in nearby jurisdictions, gives the slope of its reaction function. If the estimated slope is nonzero, then growth control choices are interdependent across cities, and strategic interaction occurs. If, by contrast, the slope coefficient is zero, then the reaction functions are, respectively, flat and vertical in the two-city case. In this situation, one city’s growth control choice is unaffected by the position of the other city’s reaction function, which depends on that city’s characteristics and objectives. The absence of such an effect means that strategic interaction is not present.

As in other models with strategic interaction, theoretical reaction functions in the growth controls case can slope up or down. Thus, the appropriate alternative hypothesis in testing for strategic interaction is that the reaction function has a nonzero slope, which requires a simple significance test on the slope coefficient. While the sign of the estimated slope is therefore of secondary interest, this sign does determine how the Nash equilibrium shifts in response to a change in city characteristics. This fact is illustrated in a simulation exercise based on the estimated reaction functions.

Strategic interaction arises in theoretical growth control models through a mechanism similar to that found in the tax competition literature. In the models of Brueckner [7] and Helsley and Strange [22], the city government attempts to enrich local landowners by restricting the amount of developable land, which raises land rent both locally and in nearby cities. The models show that the optimal degree of restriction in the given city depends on the overall tightness of the regional housing market. This tightness, in turn, depends on the growth control choices made by other jurisdictions.

Lenon et al. [30] estimate a model of local zoning decisions that is meant to capture interdependence among jurisdictions. However, their empirical procedures fail to account for the endogeneity of the choices of competing jurisdictions. The same criticism applies to Shroder [37], who studies interaction in the choice of state welfare benefits.
Thus, as in the tax competition framework, a given city’s policy decision depends on the choices of other cities, generating strategic interaction.

To motivate the empirical work, the next section of the paper illustrates these principles by presenting a simple theoretical model of the choice of growth controls. Sections 3 and 4 discuss the data and the estimation problem, Section 5 presents the empirical results, and Section 6 discusses the simulation exercise.

2. THEORETICAL MODEL

As explained above, growth control models portray city governments as restricting their land areas to raise total land rents, thereby benefiting landowners. In the models, individual cities are large relative to the urban system, consumers are mobile across cities, and preferences embody a negative population externality (people prefer small to large cities). Land rent escalation then comes from two sources: supply restriction and amenity creation. The first effect arises because one city’s land area restriction appreciably limits the supply of urban land, driving up land rents throughout the system. In addition, the smaller population achieved by the restriction makes the city more attractive to consumers, and this amenity gain is partly capitalized in local rents.

The amenity creation motive for growth controls was first analyzed by Brueckner [6] and Engle et al. [18]. The supply restriction motive was explored by Brueckner [7], and both effects were combined in the model of Helsley and Strange [22]. Because of its simplicity, the Helsley-Strange framework is used in the following discussion. Their model is based on a number of restrictive assumptions, and it has the additional drawback that the implied reaction functions are necessarily downward sloping. Brueckner’s [7] model, by contrast, is based on less restrictive assumptions, and it generates reaction functions that have both upward and downward sloping ranges. However, since the reaction functions do not have closed-form representations, and since the intuitive workings of the model are not especially transparent, Brueckner’s framework is less suitable than that of Helsley and Strange for illustrating the logic of strategic interaction in the choice of growth controls. This makes the Helsley-Strange model preferable as a vehicle for motivating an empirical study, even though the empirical findings presented below are inconsistent in some respects with the model.

Note that despite use of the term “growth,” the model described above is static. Rather than limiting a city’s rate of growth, controls are meant to restrict its size in a static environment. The conclusions of the analysis are similar in a dynamic setting.
The detailed assumptions of the model are as follows. Each city in the economy is occupied by a class of mobile renters, who commute to work in the CBD, earning wage income $y$. Commuting cost from a residence $x$ miles from the CBD is given by $tx$. Renters consume land, whose amount is fixed at one unit per household, and a numeraire nonland commodity, denoted $c$. Utility also depends negatively on the population $P$ of the city, with the utility function written $c - \beta P$, where $\beta \geq 0$ is the externality parameter. Since land consumption is fixed, it can be suppressed in writing this function. Note that in the presence of a negative population externality, some countervailing agglomeration force must be present for cities to exist. This force is not explicitly modeled. Finally, it is assumed that the land in the region containing each city is owned by absentee landowners.\(^6\)

The budget constraint of a renter household living at distance $x$ from the CBD is $c + r = y - tx$, where $r$ is rent per unit of land. Rearranging yields the bid-rent function,

$$r = y - tx - c,$$

which shows land rent conditional on a particular consumption level. As usual, the bid-rent function is downward sloping, indicating a rent premium for CBD accessibility, and it is linear, a consequence of fixed land consumption. In the ensuing discussion, the income and consumption terms in (1) differ across cities.

For simplicity, let the economy contain three cities, denoted 0, 1, and 2. Note that each city has its own CBD, which means that the cities should not be viewed as suburban communities in a large metropolitan area. Cities 0 and 1 (the “controlling” cities) impose growth controls, while city 2 (the “passive” city) never adopts a control and absorbs the population expelled from the controlling cities. A passive city is needed because, with fixed land consumption, not all cities can restrict their spatial sizes without violating the requirement that everyone has a place to live. In contrast, all cities can impose growth controls when individual land consumption is flexible, as in Brueckner [7]. However, flexible consumption leads to a more complex model and rules out simple closed-form solutions.

To derive the equilibrium conditions for the urban system, observe first that in the absence of a growth control, a city expands until land rent at the boundary equals the agricultural rent, assumed to be zero. Since this boundary condition must hold in the passive city, the first requirement of

\(^6\)To focus on the interests of landowners as a class, the absentee owners are assumed to share the rental income from the developed land within the city and the undeveloped land around it. Owners of undeveloped land, who are likely to oppose growth controls, are thus not recognized as a separate interest group.
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\[ y_2 - f_2 - c_2 = 0. \]  

(2)

In (2), \( \bar{x}_2 \) is the distance to the boundary of the passive city, and \( y_2 \) and \( c_2 \) are the city’s income and consumption levels. In contrast to (2), the boundary distances \( \bar{x}_0 \) and \( \bar{x}_1 \) are not determined by equilibrium conditions, but instead are decision variables of the controlling cities.

The additional equilibrium conditions require that the urban system fits its population and that renter utilities are the same in all cities, a consequence of free mobility. To simplify these conditions, let cities in the economy be linear with unit width. Then, given unitary land consumption, it follows that a city’s population is equal to the distance to its boundary, \( \bar{x} \). Letting \( N \) denote the size of the economy’s renter population, the remaining equilibrium conditions are then

\[ \bar{x}_0 + \bar{x}_1 + \bar{x}_2 = N \]  

(3)

\[ c_0 - \beta \bar{x}_0 = c_1 - \beta \bar{x}_1 \]  

(4)

\[ c_0 - \beta \bar{x}_0 = c_2 - \beta \bar{x}_2. \]  

(5)

Equation (3) says that the total population \( N \) fits in the three cities, and (4) and (5) indicate that renter utility is equal across the cities.

To analyze city 0’s growth control choice (its choice of \( \bar{x}_0 \)), the system (2)-(5) is solved, yielding

\[ c_0 = y_2 + (t + 2\beta)\bar{x}_0 + (t + \beta)(\bar{x}_1 - N) \]  

(6)

as the consumption value in city 0 and

\[ u = c_0 - \beta \bar{x}_0 = y_2 + (t + \beta)(\bar{x}_0 + \bar{x}_1 - N) \]  

(7)

as the common renter utility level. The consumption and utility values in (6) and (7) depend positively on \( \bar{x}_0 \), and to see the reason, suppose that the population externality is absent, with \( \beta = 0 \). Then, as city 0’s population falls in response to a decline in \( \bar{x}_0 \), population rises in city 2, leading to an increase in its land rents and a decline in utility for its residents. Since the same utility loss must occur in city 0, the consumption level \( c_0 \) must fall, an outcome that is achieved via an increase in land rents. When \( \beta \) is positive, these supply restriction effects are augmented by an amenity creation effect. In this case, city 2’s expansion generates an additional loss for its residents via the population externality, while city 0’s residents benefit from a smaller population. Therefore, the decline in \( c_0 \) required to match city 2’s utility loss is more substantial than in the absence of the exter-
nality, as can be seen in (6). The effect of \( x_1 \) in (6) and (7) is explained similarly.

The objective function of city 0's government depends on the welfare of landowners, as reflected in total land rents. However, following Brueckner [7], the welfare of renters is also assumed to matter. City 0's objective function is then

\[
\lambda_0 u + (1 - \lambda_0) \int_0^{x_0} (y_0 - t x - c_0) dx,
\]

where \( \lambda_0 \) is a welfare weight satisfying \( 0 \leq \lambda_0 \leq 1 \). Thus, the city government seeks to maximize a weighted average of renter utility and total land rent, given by the integral in (8). This is done by appropriate choice of \( x_0 \).

To see the trade-off involved in this decision, recall from (7) that renter utility is increasing in \( x_0 \). Then observe that city 0's landowners benefit from a restriction in \( x_0 \), as follows. On the one hand, a reduction in \( x_0 \) lowers \( c_0 \) and thus raises land rent \( (y_0 - t x - c_0) \) at each location, as seen above. The lower \( x_0 \) also leads to a loss of rent at the urban boundary, where land is returned to agricultural use. Since this rent loss is negligible as long as the restriction on \( x_0 \) is mild (ensuring that the boundary rent is near zero), it follows that total rent rises initially as the city's size is restricted. Total rent reaches a maximum when the gain from rent escalation equals the lost boundary rent.

The city government balances the gain to landowners and the loss to renters in choosing the optimal \( x_0 \). The problem is solved by first substituting the \( c_0 \) and \( u \) solutions from (6) and (7) into (8). Then, the derivative with respect to \( x_0 \) is computed and set equal to zero, and the resulting equation is solved for \( x_0 \).\(^8\) This yields

\[
x_0 = \frac{t + \beta}{3t + 4\beta} \left( \frac{\lambda_0}{1 - \lambda_0} + \frac{y_0 - y_2}{t + \beta} + N - x_1 \right).
\]

Equation (9) constitutes city 0's reaction function, which gives its optimal growth control choice \( x_0 \) conditional on the choice of the other controlling city \( x_1 \). City 1 has an analogous reaction function, which comes from reversing the 0 and 1 subscripts in (9). Both reaction functions are downward sloping, as shown in Fig. 1, indicating that \( x_0 \) and \( x_1 \) are "strategic substitutes." The intersection of the functions constitutes the Nash equilibrium of a growth control game. In the symmetric case, which is illustrated.

\(^7\)Note that while declines in \( x_0 \) and \( x_1 \) have the same effect on utility, \( x_1 \) has a smaller impact on \( c_0 \). The reason is that city 0's population is unaffected when \( x_1 \) falls, which means that adjustment in \( c_0 \) need not offset the benefit from a smaller local population.

\(^8\)Since (8) is a strictly concave function of \( x_0 \), the second-order condition for a maximum is satisfied.
in Fig. 1, the presence of controls is reflected in the fact that both \( \pi_0 \) and \( \pi_1 \) are smaller than \( N/3 \), the equilibrium \( \pi \) value under symmetry in the absence of controls. 9

Estimation of the slope of city reaction functions is the main goal of the subsequent empirical work. Therefore, it is important to understand the reason for the negative slope of these functions in the present model, and to note whether this finding is robust. To begin, observe that city 0’s function slopes down because the marginal benefit from a reduction in \( x_0 \) is greater the larger is \( x_1 \), which leads to a smaller optimal value when \( x_1 \) is large. To understand why the marginal benefit behaves this way, note first that the marginal effect of \( x_0 \) on renter utility is independent of \( x_1 \) (from (7), the marginal effect equals \( t + \beta \)). In addition, the marginal effect of \( x_0 \) on \( c_0 \), and hence on the level of city 0’s land rent, is independent of \( x_1 \) (using (6), the marginal effect on rent equals \( -\beta x_0 + 2\beta \)). However, the boundary rent lost when \( x_0 \) is reduced equals \( y_0 t - \beta x_0 c_0 \), which is smaller the larger is \( x_1 \) (see (6)). Thus, by lowering the level of rents in both cities, growth controls are inefficient. The appropriate welfare function is total utility plus total land rent in the economy, and it can be shown that this function is maximized at the market equilibrium, where \( \pi_0 = \pi_1 = \pi_2 = N/3 \). Furthermore, to better understand the nature of the equilibrium, it should be noted that all points on the reaction functions in Fig. 1 are not feasible (see Brueckner [7] for a fuller discussion). To see this, observe that for a given \( x_1 \), city 0 cannot expand beyond the \( \pi_0 \) value at which boundary rent equals zero. This value is found by substituting (6) into \( y_0 t - \beta x_0 c_0 = 0 \) and solving for \( \pi_0 \), which yields

\[
\pi_0 = \frac{1}{2} \left( y_0 - y_1 \frac{t}{\beta} + N - x_1 \right).
\] (f1)

City 0’s best response to a given \( \pi_1 \) is then the minimum of the \( \pi_0 \) values in (9) and (f1). Since the line corresponding to (f1) is steeper than city 0’s reaction function in Fig. 1, the upper range of that function (which then has the smaller of the two \( \pi_0 \) values) is relevant. The relevant range expands as \( \lambda_0 \) falls, which shifts the reaction function downward. A similar discussion applies to city 1. As long as \( \lambda_0 \) and \( \lambda_1 \) are small, most of the range of the reaction functions shown in Fig. 1 remains relevant, and the equilibrium is unaffected by this complication. On the other hand, if the \( \lambda \)’s are large, the intersection of the modified reaction functions lies on the range corresponding to (f1), and growth controls are not imposed. These conclusions can be seen by computing the value of \( \pi \) at the intersection point for the symmetric case shown in Fig. 1. Setting \( y_0 = y_1 = y_2 \) and \( \lambda_0 = \lambda_1 = \lambda \), and solving (9) with \( \pi_0 = \pi_1 = \pi \) yields

\[
\pi = \frac{t + \beta}{4t + 5\beta} \left( \frac{\lambda}{1 - \lambda} + N \right).
\] (f2)

When \( \lambda = 0 \), so that renter welfare carries no weight, \( \pi \) in (f2) is less than \( N/3 \), indicating the presence of controls. However, when \( \lambda \) is close to unity, (f2) exceeds \( N/3 \), which is infeasible. In this case, \( \pi \) is instead given by the intersection of (f1) and the analogous function for city 1, which yields \( \pi = N/3 \) in the symmetric case. A final observation is that, because the reaction function slope in (9) is less than unity in absolute value, the Nash equilibrium in Fig. 1 is stable.
a larger $x_1$ reduces the boundary rent loss from a reduction in $x_0$, raising the overall marginal benefit from the reduction. Since the other marginal effects are independent of $x_1$, it follows that a smaller $x_0$ is optimal when $x_1$ is large.\(^{10}\)

As noted above, the behavior of reaction functions is generally sensitive to model specification, and this rule applies in the present case. For example, in Brueckner's [7] growth control model, where land consumption is flexible and consumers have Leontief preferences, reaction functions are upward sloping over much of their range. This follows because the marginal effect of $x_0$ on the level of rent is no longer independent of $x_1$, overturning the above argument. This shows that no prior prediction is possible regarding the slope of empirically estimated reaction functions.

The position of the reaction functions in Fig. 1 depends on city characteristics. For example, if renter income ($y_0$) or the renter welfare weight ($\lambda_0$) falls in city 0, then the city's reaction function shifts down. This shift

\(^{10}\)Note that the form of the reaction function is unchanged if the population externality is suppressed by setting $\beta = 0$. Thus, a pure supply restriction model is sufficient to generate strategic interaction in the choice of growth controls.
moves the Nash equilibrium to the southeast along city 1’s function, with \( x_0 \) falling and \( x_1 \) rising. Alternatively, if the amenity parameter \( \beta \) increases, indicating a stronger preference for small cities, then both reaction functions shift. Provided that \( y_2 \) is not large relative to \( y_0 \) and \( y_1 \), the shift is downward, leading to tighter controls in both cities.

While the effects of \( \lambda_0 \) and \( \beta \) on the position of the reaction function are intuitively clear, the impact of income \( y_0 \) requires further explanation, along the lines of the slope discussion above. The marginal effects of \( x_0 \) on utility and the level of rent are independent of \( y_0 \), but the lost boundary rent from a reduction in \( x_0 \) is larger when \( y_0 \) (and hence the level of rent) is high. As a result, a weaker restriction in \( x_0 \) is optimal for any given \( x_1 \), shifting the reaction function up. It should be noted that in Brueckner’s [7] model, where reaction functions slope up instead of down, an increase in \( y_0 \) or \( \lambda_0 \) also leads to an upward shift in city 0’s function. 11

To make this simple model more representative of real cities, the absentee landowners could be replaced by a class of resident owners, following Brueckner and Lai [9] and Brueckner [8]. These immobile individuals own all of the city’s land, rent out a portion to a class of mobile renters, and occupy the remainder themselves. For empirical purposes, this model has the additional implication that an increase in the population of resident owners shifts the reaction function toward tighter controls. 12 This outcome reflects the stronger market power of large cities, whose growth control choices substantially affect land prices in the regional economy.

Another modification would be to introduce exogenous differences in city amenities by adding \( \delta_0 \) and \( \delta_1 \) terms in (4) and (5) (with \( \delta_2 = 0 \)). With this modification, the term \( y_0 \) in (9) is replaced by \( y_0 + \delta_0 \), indicating that exogenous amenities play the same role as city income. In particular, by raising land rents, better amenities increase the loss from growth controls at the city boundary, making a weaker control optimal.

Empirically, this discussion suggests that city characteristics help determine the level of the reaction function. Characteristics such as income, amenities, and the size of the immobile portion of the population matter. Any characteristics that affect the relative weights of landowners and renters in the government’s objective function are important as well. Since a host of variables may play a role in determining these weights, it is desirable to include an exhaustive list of city characteristics in the empirical model.

11 In contrast to the case shown in Fig. 1, both \( x_0 \) and \( x_1 \) rise in response to such a shift.

12 Formally, this follows because a given increase in the population of resident owners leads to a less than one-for-one upward shift in the \( x \) value on reaction function, indicating a shrinkage in the size of city’s renter area.
3. DEPENDENT VARIABLE AND EMPIRICAL MODEL

3.1. Dependent Variable

Information on growth controls is drawn from the results of a survey of California cities and counties conducted by Glickfeld and Levine [20]. A remarkable feature of their monograph is that the actual survey results are tabulated and presented in an appendix, ready for use by other researchers. The survey, conducted in 1988, asked each jurisdiction a variety of questions regarding the types of growth control measures in place at that date. In practice, growth control efforts are multifaceted, in contrast to the previous model’s simple spatial restriction. The following measures covered by the survey were viewed as best reflecting a city’s growth control efforts:

- Population growth limitations
- Housing permit limitations
- Use of an urban limit line or greenbelt
- Square-footage limitations for commercial construction
- Square-footage limitations for industrial construction
- Rezoning of residential land to agriculture or open space
- Rezoning of commercial or industrial land to another use
- Reduction of permitted residential density via rezoning
- Commercial building height limitations

Because they directly limit urban development, the first seven measures correspond roughly to the model’s representation of growth controls. The last two measures, by contrast, limit the density of development without constraining its extent.

The survey tabulation indicates a value of 1 if a city had adopted a given measure as of 1988 and a value of 0 if it had not. To compute an index of the stringency of growth controls, these 0-1 values are summed across the above nine measures, yielding the total number of measures adopted by the city as of 1988. The resulting variable is denoted MEASURES.13

Note that in contrast to the model, where the decision variable $x$ is inversely related to growth control effort, the MEASURES variable increases as a city’s growth control becomes more stringent. In the model, a variable analogous to MEASURES would be $M = N/3 - x$, which equals the reduction in city size below the market equilibrium value. The reaction function in (9) is easily rewritten in terms of this variable.

13 Missing responses in the data are treated as zeros, indicating that a given measure is not in place. Ned Levine agreed that since a nonresponse probably indicates the absence of a measure, this recoding is justified. Glickfeld and Levine [20] perform statistical analysis using a similar variable that includes several additional types of measures.
The sample is restricted to cities with a population of at least 25,000 in 1990. After deletion of a handful of observations with incomplete census data, the resulting sample contains 173 cities. Table 1 shows the frequency distribution of MEASURES across the sample cities. A value of 0, indicating no growth control effort, is most common, but values of 1, 2, and 3 are well represented. The mean value is 1.35. Among the individual policies that comprise the MEASURES index, the most common are residential density restrictions (present in 37% of the cities) and commercial building height limitations (24%). Less common are urban limit lines (17%), housing permit limitations (15%), rezoning of commercial or industrial land (14%), population growth limitations (12%), rezoning of residential land (8%), and commercial and industrial square-footage limitations (6% and 5%).

Glickfeld and Levine [20] present information on the date of adoption of growth controls, although nonresponses make the information less than complete. The data show that most of the growth control measures in place in 1988 were adopted during the 1980s. Among measures for which the date of adoption was available, 70% were enacted after 1980, while 50% were enacted after 1985.

Use of the MEASURES variable to represent the stringency of growth controls may be inappropriate if the extent of enforcement of the underlying restrictions varies appreciably across the sample. However, since enforcement is unobservable, there is no remedy for such a problem. In any case, it could be argued that the existence of a range of growth control

\[\text{TABLE 1} \]

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<td>1</td>
</tr>
<tr>
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<td>173</td>
</tr>
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</table>

Mean = 1.35
measures in a city itself indicates a serious attitude toward enforcement.\textsuperscript{15} The \textsc{Measures} variable then remains an appropriate indicator of the stringency of controls.\textsuperscript{16}

3.2. \textit{Empirical Model}

The reaction function (9) indicates that city 0’s growth control depends on its characteristics and on the control chosen by city 1. Empirically, the interaction phenomenon cannot be this simple. A given city is likely to interact with many competing cities in a regional housing market, and the challenge is to allow for such interaction in the empirical specification.

To see how this is done, let the \textsc{Measures} variable for city \(i\) be denoted \(z_i\), and let \(S_i\) denote the vector of city \(i\)’s characteristics. Then, the empirical version of (9) is written

\[
   z_i = \phi \sum_{j \neq i} w_{ij} z_j + S_i \theta + \epsilon_i, \tag{10}
\]

where the \(w_{ij}, j \neq i\), represent a set of weights that aggregate the growth control choices of other cities into a single “competing controls” variable, which has a scalar coefficient \(\phi\). This coefficient represents the slope of the reaction function.\textsuperscript{17} The vector \(\theta\) in (10) contains city characteristics coefficients, and \(\epsilon_i\) is the error term, which is assumed to be normally distributed, homoscedastic, and independent across observations. Equation (10) can be rewritten in matrix form as

\[
   z = \phi W z + S \theta + \epsilon, \tag{11}
\]

where \(W\) is the weight matrix, \(S\) is the matrix of city characteristics, and \(\epsilon\) is the error vector. In the spatial econometrics literature, a specification such as (11) is known as a “spatial lag” model (see Anselin [1]).

The weight matrix \(W\) has zero diagonal elements, and a representative off-diagonal element is \(w_{ij}\). The values of the \(w_{ij}\)’s are specified arbitrarily to reflect prior expectations regarding the spatial pattern of interaction. For example, \(W\) could reflect the assumption that competing cities are those located within 50 miles of a given city. In this case, the \(j\)th element of the \(i\)th row of \(W\) equals 1 if the distance from city \(i\) to city \(j\) is less than 50 miles and equals 0 otherwise. The competing controls value for city \(i\),

\textsuperscript{15}Ned Levine holds this view.

\textsuperscript{14}Instead of imposing land area restrictions, cities can instead restrict their spatial sizes by charging development fees (see Helsley and Strange [22]). Such fees are widely used in California, but no systematic data on them are available. A more complete empirical study that would investigate the joint choice of land use restrictions and development fees must await such data.

\textsuperscript{17}Recall that since \(z\) is an increasing measure of growth control effort while \(x\) is a decreasing measure, the reaction function (9) must be rewritten as described above to match (10).
which equals the inner product of the $i$th row of $W$ and $z$, is then the sum of the MEASURES variable across cities within 50 miles of city $i$. Other weighting schemes are also used, as explained below.

Referring to Fig. 1, it is clear that $x_0$ and $x_1$ are simultaneously determined by the intersection of the two reaction functions. Since the values of $z$ in the sample are jointly determined in exactly the same fashion, the competing controls variable $Wz$ on the right-hand side of (11) is endogenous. As a result, ordinary least-squares estimates of the parameters of (11) are affected by simultaneity bias. To overcome this problem, (11) can be rearranged to solve for the equilibrium $z$ vector, which is given by the reduced-form equation

$$z = (I - \phi W)^{-1}S\theta + (I - \phi W)^{-1}\epsilon.$$  \hspace{1cm} (12)

The model parameters are estimated by applying maximum likelihood techniques to this reduced form. The estimation uses SpaceStat, a statistical package for spatial econometrics written by Luc Anselin [2].

A noteworthy feature of the growth control equilibrium can be seen in (12). In particular, because the $(I - \phi W)^{-1}$ matrix premultiplies $S$ in (12), the equilibrium $z$ for any given city depends on the characteristics of all cities in the sample, not just its own. This conclusion can also be seen in Fig. 1, where the characteristics of both cities jointly determine the intersection point of the reaction functions. This interdependence is illustrated below in a simulation exercise based on the estimated reaction functions.

As noted above, the variance-covariance matrix of the error vector $\epsilon$ is assumed to be proportional to the identity matrix, indicating that errors are independent across jurisdictions. Suppose this assumption were violated and that the errors exhibit spatial dependence, satisfying the relationship

$$\epsilon = \lambda W\epsilon + v,$$  \hspace{1cm} (13)

where $v$ is a well-behaved normal error vector. Such spatial dependence can arise when $\epsilon$ includes omitted variables not captured in $S$, which are themselves spatially dependent. If spatial error dependence is ignored, estimation of (12) may yield a misleading estimate of the reaction function slope $\phi$. For example, suppose that the true value of $\phi$ is zero but the errors are positively correlated across nearby cities. In this case, the true model is the “spatial error” model, which consists of $z = S\theta + \epsilon$ and (13), with $\lambda > 0$. Then, when (12) is estimated using a distance-based $W$, the $\phi$ estimate is likely to be positive and significant, indicating that growth con-

\hspace{1cm} 18Another means of estimating (11) is to use an instrumental variables approach to generate fitted values of $Wz$, which may be uncorrelated with the error vector. However, given the availability of the maximum likelihood procedure, there is little justification for using this approach.
trols in nearby cities move together. Thus, uncorrected error dependence can give a false impression of strategic interaction when none in fact is occurring. Moreover, once the spatial lag model is estimated, a test for spatial error dependence may show its absence. The effects of error dependence may therefore be “hidden” in a spurious spatial lag parameter.

There are several approaches to this problem. One is to estimate an expanded model consisting of (11) and (13), as is done by Case et al. [14]. However, some authors claim that reliable estimation of the separate parameters $\phi$ and $\lambda$, which perform similar roles in the model, may be difficult (see Anselin [1], Anselin and Bera [3], and Anselin et al. [4]). A another approach is to separately test the hypotheses $\phi = 0$ and $\lambda = 0$ by using the robust Lagrange multiplier tests developed by Anselin et al. [4]. The robust test on $\phi$ adjusts the usual test statistic, which assumes $\lambda = 0$, for bias due to uncorrected spatial error dependence. Similarly, the robust test on $\lambda$ adjusts the usual test statistic, which assumes $\phi = 0$, for bias due to an overlooked spatial lag. The tests are computed using the weight matrix $W$ in conjunction with ordinary least-squares estimates from the equation $z = S\theta + \epsilon$. If the robust tests show that $\phi$ is nonzero and $\lambda$ is zero, then the possibility of a spurious estimate of $\phi$ from uncorrected spatial error dependence is discounted. A third approach is to test the “common factor hypothesis,” which must hold if the spatial error model is correct. Rejection of this hypothesis again suggests that evidence of strategic interaction is not spurious. Finally, the likelihood value for the spatial lag model can be compared to the value for the spatial error model. The last three approaches are pursued below.

Several final points concern the unusual nature of the MEASURES variable, which is discrete and ranges between 0 and 8 (recall Table 1). Although it would be natural to use an ordered probit model to describe the generation of such a variable, the econometric theory for using this approach in a spatial lag context has not been developed. The same problem prevents any attempt to handle censoring of the MEASURES variable at zero in the case where it is treated as continuous. In any event, with MEASURES treated as continuous, the unusual nature of the variable may lead to violation of the normality and homoscedasticity assumptions on $\epsilon$. As this identification problem is eased if the weight matrices in (11) and (13) are different. However, it is difficult to justify such a difference on theoretical grounds. In any case, this estimation approach was not available because it is not programmed in SpaceStat.

To see how the test is carried out, suppose the true model is the spatial error model, which consists of (13) and $z = S\theta + \epsilon$. Then, solving for $\epsilon$ and substituting its value in the previous equation yields the equivalent model, $z = \lambda Wz + v$, known as the spatial Durbin model. This equation can be rewritten as $z = \lambda Wz + S\theta + WS\theta + v$, and if the spatial error model is correct, the restriction $\delta = -\lambda \theta$ (known as the common factor hypothesis) must be satisfied. This restriction can be tested to indicate whether a spatial error model is appropriate.
a result, close attention must be paid to the regression diagnostics. Initial results showed that use of the straight MEASURES variable generated heteroscedastic residuals. This problem was solved by replacing MEASURES with a transformed variable equal to the natural log of \( \text{MEASURES} + 1 \). This transformation also generates residuals that are consistent with the assumption of normal errors, as will be seen below.

4. CITY CHARACTERISTICS

As noted above, it is desirable to include a large number of city characteristics in the empirical model to fully capture the motivations for growth controls. In addition, this strategy helps to eliminate spatial error dependence, which arises when spatially dependent variables are omitted from the model. The characteristics variables are listed and defined in Table 2, and their mean values are given. The list includes variables measuring a city's population and density (POP80 and DENS); racial mix (BLK and HISP); age structure (KIDS and OLD); education, skill levels, and unemployment (EDUC, SKILLED, UNEMP); household crowding (PERHOUS and ONEPERS); and income (MEDINC). Additional variables measure the extent of commercial activity (RETSALES and SVCSALES), as well as the city's tax burden (TOTTAX), its total expenditures (TOTEXP), capital expenditures (CAPEXP), and debt level (DEBT) (all of these variables are expressed on a per capita basis). DEMVOTE measures the percentage Democratic vote in the 1988 presidential election, OWNOCC equals the city's percentage of owner-occupiers, and HVAL80 gives the median house value in 1980. MIGRANTS equals net 1980–1986 migration into the county containing the city, expressed as a percentage of 1980 county population. DELAY equals 1992 daily vehicle-hours of congestion delay on freeways in the county containing the city, expressed on a per capita basis. Finally, OCEAN is a dummy variable indicating that the city borders the Pacific Ocean.

Predictions can be stated for the effects of some of these variables. First, since the model suggests that a high level of income lowers the incentive to impose growth controls, the effect of MEDINC on the MEASURES index should be negative. In addition, exploitation of market power by big cities should lead to more stringent controls, as explained above. Thus, the effect of POP80 on MEASURES should be positive. Similarly, since a large share of owner-occupiers in the population may diminish renters' influence in the formulation of policy, leading to tighter controls, the effect of OWNOCC should be positive.\(^1\) DEMVOTE may measure the interventionist attitude

\(^1\)Because the model has absentee landowners, it cannot directly generate such a prediction. The claim can be demonstrated, however, in the resident landowner model described above.
TABLE 2
Variable Definitions and Means

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>POP80</td>
<td>88,164</td>
<td>City population in 1980</td>
</tr>
<tr>
<td>DENS</td>
<td>1,968</td>
<td>Population density (persons per square kilometer)</td>
</tr>
<tr>
<td>BLK</td>
<td>5.5</td>
<td>Black population percentage</td>
</tr>
<tr>
<td>HISP</td>
<td>24.9</td>
<td>Percent Hispanic</td>
</tr>
<tr>
<td>KIDS</td>
<td>26.0</td>
<td>Percent 17 years and younger</td>
</tr>
<tr>
<td>OLD</td>
<td>10.4</td>
<td>Percent 65 years and older</td>
</tr>
<tr>
<td>EDUC</td>
<td>23.4</td>
<td>Percent with 16 years or more of education</td>
</tr>
<tr>
<td>SKILLED</td>
<td>11.2</td>
<td>Precision production, craft and repair workers per 1000 employees</td>
</tr>
<tr>
<td>UNEMP</td>
<td>6.2</td>
<td>Unemployment rate</td>
</tr>
<tr>
<td>PERHOUS</td>
<td>2.8</td>
<td>Persons per household</td>
</tr>
<tr>
<td>ONEPERS</td>
<td>21.9</td>
<td>Percent of households with one person</td>
</tr>
<tr>
<td>MEDINC</td>
<td>38,702</td>
<td>Median household income (in $)</td>
</tr>
<tr>
<td>RETSALES</td>
<td>0.0088</td>
<td>1987 retail sales per capita (in $ million)</td>
</tr>
<tr>
<td>SVCSALES</td>
<td>0.0049</td>
<td>1987 service sales per capita (in $ million)</td>
</tr>
<tr>
<td>TOTTAX</td>
<td>333</td>
<td>City tax revenue per capita (in $)</td>
</tr>
<tr>
<td>TOTEXP</td>
<td>691</td>
<td>City expenditure per capita (in $)</td>
</tr>
<tr>
<td>CAPEXP</td>
<td>141</td>
<td>City capital expenditure per capita (in $)</td>
</tr>
<tr>
<td>DEBT</td>
<td>1119</td>
<td>City debt per capita (in $)</td>
</tr>
<tr>
<td>DEMVOTE</td>
<td>0.46</td>
<td>Democratic vote share in 1988 presidential election</td>
</tr>
<tr>
<td>OWNOCC</td>
<td>56.0</td>
<td>Percent of housing units owner-occupied</td>
</tr>
<tr>
<td>HVAL80</td>
<td>89,439</td>
<td>Median house value in 1980 (in $)</td>
</tr>
<tr>
<td>MIGRANTS</td>
<td>0.062</td>
<td>1980-86 net migration into city's county, as a share of 1980 population</td>
</tr>
<tr>
<td>DELAY</td>
<td>0.0088</td>
<td>Per capita vehicle-hours of delay on freeways in city's county in 1992</td>
</tr>
<tr>
<td>OCEAN</td>
<td>0.13</td>
<td>Dummy variable indicating that city borders Pacific Ocean</td>
</tr>
</tbody>
</table>

Note: Unless otherwise indicated, variables are measured in 1990.
Sources: Slater and Hall [38], California Department of Transportation [15], California Secretary of State [16].

of city residents in setting government policy, and thus their willingness to impose growth controls. DEMVOTE should thus have a positive effect on the MEASURES index. Since a high level of education may also make a city's population more willing to use government policy to serve its interests, a positive coefficient for EDUC is also likely. As explained above, an increase in a city's exogenous amenities has the same effect as an increase in income. Thus, the coefficient of OCEAN should be negative.

DEN, MIGRANTS, DELAY, and HVAL80 are meant to capture the pressure from regional population growth. To see how such an effect fits into the model, suppose that the externality parameter $\beta$ were to differ across cities, being higher in cities with strong disamenity effects from population pressure. A high value of $\beta$ would shift the city's reaction function
downward, indicating a greater preference for growth controls.\textsuperscript{22} By measuring county migration, MIGRANTS is a direct measure of the population pressure felt by a city, and its effect on the MEASURES index should be positive. DEN is an indirect measure, reflecting the presumption that dense cities have little additional room for growth, and its effect should be negative. DELAY captures a symptom of population pressure, namely freeway congestion, and it should have a positive effect on MEASURES. HVAL80 measures house prices, another symptom of population pressure. Since a high median house value for the city in 1980 may indicate substantial population pressure over the 1970s, the coefficient of HVAL80 should be positive. Although the effects of the remaining variables are hard to predict, they are included in the model to capture unexpected influences in the choice of growth controls.\textsuperscript{23}

With the exception of POP80 and HVAL80, the city-specific variables above are measured using 1990 census data. Since the goal is to explain growth control decisions over the 1980s, as represented by the 1988 MEASURES variable, use of 1980 city characteristics values would have been preferable. However, since attention is restricted to cities with populations above 25,000 (for which more data are available), this choice would have appreciably reduced the sample size. The reason is that many cities with 1990 populations above 25,000 were below this limit in 1980. Use of \textit{ex post} 1990 characteristics seemed preferable to such a shrinkage in the sample.

One concern in using \textit{ex post} city characteristics is that they could be endogenous, being influenced by the very growth control decisions that are to be explained. A city's 1990 population and house prices seem most likely to be affected by the controls imposed in the 1980s, and as a result, 1980 values for these variables are used (fortunately, these are available for cities below 25,000). Endogeneity seems not to be an issue for many other city characteristics, although growth control decisions may have some effect on RETSALES, SVCSALES, TOTTAX, TOTEXP, DEBT, and CAPEXP.\textsuperscript{24} Note, finally, that avoidance of endogeneity is the reason for using a county-

\textsuperscript{22}It is awkward to incorporate such an effect into the model of Section 2 in a rigorous manner. Doing so would require $\beta$ to be a function of the city's $x$ value, and this would greatly complicate the algebra. Another complication from different $\beta$'s is that the slope of the reaction function then differs across cities, in contrast to (11).

\textsuperscript{23}Although speculation regarding the impact of CAPEXP and DEBT is possible, their net effects appear ambiguous. To see this, observe that high levels of city debt per capita (DEBT) and current capital expenditure per capita (CAPEXP) could reflect extensive infrastructure spending in response to urban growth. On the one hand, this may reflect a willingness to accommodate growth. Alternatively, high spending on infrastructure may spur a desire to restrict further growth.

\textsuperscript{24}Unlike POP80 and HVAL80, 1980 values for these variables are not available for cities below 25,000.
level population pressure variable, MIGRANTS, rather than a city-level variable. Migration into a county should only be weakly influenced by any one city’s growth control efforts.25

At this point, it is useful to note the close connection between this study and the earlier empirical study of Dubin et al. [17]. These authors studied precinct-level voting returns for a growth control referendum in San Diego county. As is done here, they used the 1988 Democratic vote as an explanatory variable, along with a measure of local traffic congestion, analogous to the DELAY variable. Their results are discussed further below.

5. RESULTS

Results based on four different weighting schemes are presented. To understand these schemes, let \( d_{ij} \) denote the distance from city \( i \) to city \( j \), let \( P_j \) denote city \( j \)’s population, and let \( d^* \) denote the critical distance beyond which weights are set equal to zero. Then, \( w_{ij} \) (the \( i-j \)th element of \( W \)) is set equal to zero if \( d_{ij} > d^* \), and \( W \)’s diagonal elements are also set equal to zero. For off-diagonal elements where \( d_{ij} \leq d^* \), \( w_{ij} \) is given by one of the following expressions:

\[
\begin{align*}
w_{ij} &= 1 \quad (14) \\
        &= 1/d_{ij} \quad (15) \\
        &= P_j \quad (16) \\
        &= P_j/d_{ij} \quad (17)
\end{align*}
\]

Equations (14) and (15) represent the “population-unweighted” scheme, while (16) and (17) give the “population-weighted” scheme. In (15) and (17), the weights exhibit an inverse distance decay, while in (14) and (16), there is no distance decay.26 Recalling from (10) that city \( i \)’s response to a change in \( z_j \) equals \( \phi w_{ij} \), the above weighting schemes make the magnitude of this response depend on both the distance to the competing city and its population. Because own population also appears as a city characteristic, it follows that both the intercept and the effective slope of the reaction function depend on population sizes. After the weights in (14)–(17) are computed, the elements of each row of \( W \) are normalized so that they sum to unity (this follows the conventional practice in the literature).

25Although 1992 freeway congestion (as measured by DELAY) is also potentially endogenous, the fact that the variable is computed at the county level should mitigate this problem (an analogous variable is not available at the city level in any case).

26Great-circle distances between cities are computed from latitude and longitude measures.
Estimates for the population-weighted scheme are presented in Table 3 (asymptotic normal statistics are in parentheses). The results without distance decay are found in the first column, which uses a $d^*$ value of 50 miles. Distance decay results, which are computed for $d^*$ values of 50, 100, and 150 miles, are presented in columns 2-4. The most important finding from Table 3 is that the estimated coefficient on $Wz$, the competing-controls variable, is positive and statistically significant at the 5% level, regardless of

<table>
<thead>
<tr>
<th>Variable</th>
<th>$d^* = 50$</th>
<th>Distance decay $d^* = 50$</th>
<th>Distance decay $d^* = 100$</th>
<th>Distance decay $d^* = 150$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Wz^{**}$</td>
<td>2.29 E − 1 (2.50)</td>
<td>2.05 E − 1 (2.28)</td>
<td>4.02 E − 1 (1.76)</td>
<td>3.91 E − 1 (3.08)</td>
</tr>
<tr>
<td>CONST:</td>
<td>2.06 E + 0 (1.63)</td>
<td>2.14 E + 0 (1.69)</td>
<td>2.02 E + 0 (1.61)</td>
<td>2.12 E + 0 (1.68)</td>
</tr>
<tr>
<td>POPB**</td>
<td>4.30 E − 7 (2.67)</td>
<td>4.42 E − 7 (2.62)</td>
<td>4.63 E − 7 (2.87)</td>
<td>4.46 E − 7 (2.75)</td>
</tr>
<tr>
<td>DENSP</td>
<td>−9.42 E − 5 (1.68)</td>
<td>−1.01 E − 4 (1.80)</td>
<td>−1.06 E − 4 (1.90)</td>
<td>−1.02 E − 4 (1.82)</td>
</tr>
<tr>
<td>BLK</td>
<td>−7.79 E − 3 (1.09)</td>
<td>−8.22 E − 3 (1.15)</td>
<td>−9.54 E − 3 (1.31)</td>
<td>−9.31 E − 3 (1.27)</td>
</tr>
<tr>
<td>HISP</td>
<td>6.58 E − 3 (1.26)</td>
<td>6.43 E − 3 (1.23)</td>
<td>5.49 E − 3 (1.04)</td>
<td>5.43 E − 3 (1.02)</td>
</tr>
<tr>
<td>KIDS</td>
<td>−1.22 E − 2 (0.55)</td>
<td>−1.28 E − 2 (0.57)</td>
<td>1.41 E − 2 (0.64)</td>
<td>1.20 E − 2 (0.54)</td>
</tr>
<tr>
<td>OLD</td>
<td>5.95 E − 3 (0.36)</td>
<td>7.55 E − 3 (0.46)</td>
<td>7.08 E − 3 (0.44)</td>
<td>7.24 E − 3 (0.66)</td>
</tr>
<tr>
<td>EDUC**</td>
<td>2.77 E − 2 (2.72)</td>
<td>2.67 E − 2 (2.62)</td>
<td>2.63 E − 2 (2.60)</td>
<td>2.52 E − 2 (2.47)</td>
</tr>
<tr>
<td>SKILLED**</td>
<td>8.41 E − 2 (3.19)</td>
<td>8.08 E − 2 (3.06)</td>
<td>7.94 E − 2 (3.02)</td>
<td>7.57 E − 2 (2.86)</td>
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<tr>
<td>UNEMP</td>
<td>−3.35 E − 5 (1.10)</td>
<td>−3.60 E − 2 (0.99)</td>
<td>−2.36 E − 2 (0.65)</td>
<td>−2.70 E − 2 (0.74)</td>
</tr>
<tr>
<td>PERHOUS</td>
<td>−4.11 E − 1 (1.17)</td>
<td>−4.04 E − 1 (1.15)</td>
<td>−4.22 E − 1 (1.21)</td>
<td>−4.35 E − 1 (1.24)</td>
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<tr>
<td>ONEPERS**</td>
<td>−5.37 E − 2 (3.13)</td>
<td>−5.46 E − 2 (3.17)</td>
<td>−5.54 E − 2 (3.24)</td>
<td>−5.69 E − 2 (3.31)</td>
</tr>
<tr>
<td>MEDINC**</td>
<td>−3.45 E − 5 (2.32)</td>
<td>−3.15 E − 5 (2.31)</td>
<td>−3.03 E − 5 (2.24)</td>
<td>−3.09 E − 5 (2.07)</td>
</tr>
<tr>
<td>RETSALES**</td>
<td>−2.10 E + 1 (1.65)</td>
<td>−2.13 E + 1 (1.67)</td>
<td>−2.31 E + 1 (1.83)</td>
<td>−2.22 E + 1 (1.75)</td>
</tr>
<tr>
<td>SWCSALES</td>
<td>8.85 E − 6 (0.61)</td>
<td>8.68 E + 0 (0.79)</td>
<td>7.75 E + 0 (0.72)</td>
<td>8.37 E + 0 (0.77)</td>
</tr>
<tr>
<td>TOTTAKE</td>
<td>6.20 E − 5 (0.11)</td>
<td>7.37 E − 5 (0.13)</td>
<td>1.65 E − 4 (0.29)</td>
<td>1.12 E − 4 (0.20)</td>
</tr>
<tr>
<td>TOTEXP</td>
<td>3.36 E − 4 (1.06)</td>
<td>3.47 E − 4 (1.09)</td>
<td>3.28 E − 4 (1.04)</td>
<td>3.63 E − 4 (1.14)</td>
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<tr>
<td>CAPEXP</td>
<td>−9.13 E − 5 (0.19)</td>
<td>−9.60 E − 5 (0.20)</td>
<td>−1.32 E − 4 (0.28)</td>
<td>−1.36 E − 4 (0.28)</td>
</tr>
<tr>
<td>DEBT</td>
<td>−5.17 E − 5 (0.94)</td>
<td>−5.96 E − 5 (1.08)</td>
<td>−6.32 E − 5 (1.15)</td>
<td>−6.42 E − 5 (1.16)</td>
</tr>
<tr>
<td>DEMVOTE**</td>
<td>1.21 E − 2 (2.56)</td>
<td>1.26 E − 2 (2.67)</td>
<td>1.27 E − 2 (2.68)</td>
<td>1.29 E − 2 (2.67)</td>
</tr>
<tr>
<td>OWNOC</td>
<td>−2.62 E − 3 (0.33)</td>
<td>−4.38 E − 3 (0.55)</td>
<td>−5.12 E − 3 (0.65)</td>
<td>−5.11 E − 3 (0.64)</td>
</tr>
<tr>
<td>HVAL80°</td>
<td>6.14 E − 6 (1.80)</td>
<td>5.66 E − 6 (1.65)</td>
<td>5.60 E − 6 (1.65)</td>
<td>5.83 E − 6 (1.70)</td>
</tr>
<tr>
<td>MIGRANTS</td>
<td>1.40 E − 0 (1.16)</td>
<td>1.39 E + 0 (1.16)</td>
<td>1.39 E + 0 (1.17)</td>
<td>1.14 E + 0 (0.95)</td>
</tr>
<tr>
<td>DELAY</td>
<td>−4.24 E + 0 (0.53)</td>
<td>−3.15 E + 0 (0.39)</td>
<td>−2.25 E + 0 (0.28)</td>
<td>−2.53 E + 0 (0.32)</td>
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<tr>
<td>OCEAN</td>
<td>7.07 E − 3 (0.05)</td>
<td>−6.25 E − 3 (0.05)</td>
<td>−3.30 E − 2 (0.25)</td>
<td>−1.94 E − 2 (0.15)</td>
</tr>
</tbody>
</table>

Test for:

<p>| | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
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</thead>
<tbody>
<tr>
<td>Heterosced.</td>
<td>1.30 E + 1 (96%)</td>
<td>1.36 E + 1 (96%)</td>
<td>1.33 E + 1 (96%)</td>
<td>1.32 E + 1 (96%)</td>
</tr>
<tr>
<td>Normality</td>
<td>4.22 E + 0 (12%)</td>
<td>4.51 E + 0 (10%)</td>
<td>4.98 E + 0 (8%)</td>
<td>4.90 E + 0 (9%)</td>
</tr>
<tr>
<td>Sp. err. dep.</td>
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<td></td>
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</tr>
<tr>
<td>Conditional</td>
<td>1.14 E − 1 (73%)</td>
<td>9.55 E − 4 (98%)</td>
<td>6.84 E − 1 (41%)</td>
<td>8.05 E − 2 (78%)</td>
</tr>
<tr>
<td>Robust</td>
<td>8.00 E − 6 (99%)</td>
<td>4.17 E − 2 (84%)</td>
<td>1.27 E + 0 (26%)</td>
<td>1.59 E − 2 (90%)</td>
</tr>
<tr>
<td>Sp. Lg(robust)</td>
<td>1.41 E + 0 (23%)</td>
<td>1.43 E + 0 (23%)</td>
<td>3.94 E + 0 (5%)</td>
<td>1.88 E + 0 (17%)</td>
</tr>
<tr>
<td>Com. factor</td>
<td>5.55 E + 1 (0%)</td>
<td>4.55 E + 1 (1%)</td>
<td>4.74 E + 1 (0%)</td>
<td>4.03 E + 1 (2%)</td>
</tr>
<tr>
<td>LIKELHD</td>
<td>−115.24</td>
<td>−115.58</td>
<td>−114.56</td>
<td>−115.51</td>
</tr>
</tbody>
</table>

Note: $z = \ln(M E A S U R E S + 1)$. Absolute normal statistics are in parentheses. Asterisks indicate variables whose coefficients are significant at the 10% (*) and 5% (**) levels. Diagnostic tests are described in the text.
which distance formulation is used. This finding provides evidence of spatial interaction in the choice of growth controls. The positive coefficients indicate that, in contrast to Fig. 1, cities’ reaction functions are upward sloping, so that the decision variables are strategic complements. It is important to realize that this finding is not inconsistent with the general conceptual approach underlying the previous analysis. As noted above, another version of the theoretical model generates upward-sloping reaction functions. In addition to being positive, the $W_z$ coefficient is less than 1 in each of the specifications shown in Table 3, indicating that an increase in the competing controls variable elicits a smaller increase in a given city's control effort.27

The first two diagnostic tests in Table 3 show that, despite the unusual nature of the MEASURES variable, use of the log transformation yields an error structure that satisfies the maintained assumptions. In each case, the Bruesch-Pagan test for heteroscedasticity indicates its absence (probability values are over 95%). Moreover, based on the Kiefer-Salmon test for normal errors, the null hypothesis of normality cannot be rejected at the 5% level in any case (probability values range between 8% and 12%).

The estimates from the population-unweighted scheme, which are reported in Table 4, tell a different story. In contrast to the population-weighted results, the competing controls coefficient is insignificantly different from zero in each column of the table. Therefore, regardless of how distance is handled, the population-unweighted estimates show no evidence of strategic interaction in the determination of growth controls. Note that results for the two regression diagnostics are similar to those in Table 3.

To evaluate this discrepancy in the findings, it should be realized that the population weighted scheme is more plausible a priori than the unweighted scheme. As seen in the model of Section 2, the growth control choices of competing cities affect a given city's choice by altering the tightness of the regional housing market. If a competing city is small, then its impact on the regional market will be negligible. For this reason, a scheme that assigns more weight to large cities is preferable to one that does not distinguish between cities of different sizes. In view of this conclusion, the failure to find evidence of strategic interaction under the population-unweighted scheme is understandable.28 Tables 3 and 4 also show that the log likelihood is uniformly higher under the population-weighted scheme, suggesting its superiority on statistical grounds.

While the overall results thus appear consistent with the existence of strategic interaction in the choice of growth controls, the possibility that the $\phi$ estimates are spurious must still be considered. The first step is to note that the conditional Lagrange multiplier test for spatial error depen-

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27This is required, in fact, for stability of the equilibrium.

28In contrast to the present results, Case et al. [14] found significantly positive interaction coefficients under a wide variety of weighting schemes.
<table>
<thead>
<tr>
<th>Variable</th>
<th>No distance decay</th>
<th>Distance decay $d^* = 50$</th>
<th>Distance decay $d^* = 100$</th>
<th>Distance decay $d^* = 150$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$W_x$</td>
<td>1.29 E − 1 (0.88)</td>
<td>1.44 E − 1 (1.14)</td>
<td>1.72 E − 1 (0.87)</td>
<td>2.36 E − 1 (1.03)</td>
</tr>
<tr>
<td>CONST*</td>
<td>2.30 E + 0 (1.80)</td>
<td>2.30 E + 0 (1.80)</td>
<td>2.32 E + 0 (1.81)</td>
<td>2.28 E + 0 (1.78)</td>
</tr>
<tr>
<td>POP80**</td>
<td>4.12 E − 7 (2.53)</td>
<td>4.09 E − 7 (2.52)</td>
<td>4.10 E − 7 (2.52)</td>
<td>4.06 E − 7 (2.50)</td>
</tr>
<tr>
<td>DENS*</td>
<td>−9.18 E − 5 (1.62)</td>
<td>−9.48 E − 5 (1.68)</td>
<td>−9.26 E − 5 (1.64)</td>
<td>−9.28 E − 5 (1.64)</td>
</tr>
<tr>
<td>BLK</td>
<td>−7.95 E − 3 (1.10)</td>
<td>−8.05 E − 3 (1.12)</td>
<td>−7.64 E − 3 (1.05)</td>
<td>−7.11 E − 3 (0.97)</td>
</tr>
<tr>
<td>HISP</td>
<td>6.85 E − 3 (1.30)</td>
<td>6.77 E − 3 (1.28)</td>
<td>7.06 E − 3 (1.33)</td>
<td>7.30 E − 3 (1.37)</td>
</tr>
<tr>
<td>KIDS</td>
<td>−1.00 E + 2 (0.45)</td>
<td>−1.14 E − 2 (0.51)</td>
<td>1.00 E − 2 (0.44)</td>
<td>1.00 E + 2 (0.45)</td>
</tr>
<tr>
<td>OLD</td>
<td>8.72 E − 3 (0.53)</td>
<td>8.71 E − 3 (0.53)</td>
<td>8.70 E − 3 (0.53)</td>
<td>8.90 E − 3 (0.54)</td>
</tr>
<tr>
<td>EDUC**</td>
<td>2.42 E − 2 (2.36)</td>
<td>2.40 E − 2 (2.35)</td>
<td>2.40 E − 2 (2.34)</td>
<td>2.44 E − 2 (2.38)</td>
</tr>
<tr>
<td>SKILLED**</td>
<td>7.15 E − 2 (2.68)</td>
<td>7.18 E − 2 (2.70)</td>
<td>7.17 E − 2 (2.70)</td>
<td>7.26 E − 2 (2.73)</td>
</tr>
<tr>
<td>UNEMP</td>
<td>−3.81 E − 2 (1.04)</td>
<td>−3.58 E − 2 (0.98)</td>
<td>−3.76 E − 2 (1.02)</td>
<td>−3.90 E − 2 (1.06)</td>
</tr>
<tr>
<td>PERNOS</td>
<td>−4.28 E − 1 (1.20)</td>
<td>−4.20 E − 1 (1.18)</td>
<td>−4.36 E − 1 (1.23)</td>
<td>−4.30 E − 1 (1.22)</td>
</tr>
<tr>
<td>ONEPERS**</td>
<td>−5.47 E − 2 (3.15)</td>
<td>−5.47 E − 2 (3.16)</td>
<td>−5.52 E − 2 (3.18)</td>
<td>−5.52 E − 2 (3.18)</td>
</tr>
<tr>
<td>MEDINC**</td>
<td>−3.05 E − 5 (2.21)</td>
<td>−2.92 E − 5 (2.12)</td>
<td>−2.94 E − 5 (2.13)</td>
<td>−2.98 E − 5 (2.16)</td>
</tr>
<tr>
<td>RETSALES*</td>
<td>−2.16 E + 1 (1.68)</td>
<td>−2.17 E + 1 (1.69)</td>
<td>−2.24 E + 1 (1.74)</td>
<td>−2.24 E + 1 (1.75)</td>
</tr>
<tr>
<td>SVCSALES</td>
<td>1.02 E + 1 (0.94)</td>
<td>1.01 E + 1 (0.92)</td>
<td>1.04 E + 1 (0.96)</td>
<td>1.08 E + 0 (0.98)</td>
</tr>
<tr>
<td>TOTAX</td>
<td>5.81 E − 5 (0.10)</td>
<td>5.92 E − 5 (0.10)</td>
<td>5.72 E − 5 (0.10)</td>
<td>4.91 E − 5 (0.09)</td>
</tr>
<tr>
<td>TOTEXP</td>
<td>3.34 E − 4 (1.06)</td>
<td>3.41 E − 4 (1.06)</td>
<td>3.58 E − 4 (1.11)</td>
<td>3.65 E − 4 (1.14)</td>
</tr>
<tr>
<td>CAPEXP</td>
<td>−1.31 E − 4 (0.27)</td>
<td>−1.26 E − 4 (0.26)</td>
<td>−1.66 E − 4 (0.34)</td>
<td>−1.77 E − 4 (0.36)</td>
</tr>
<tr>
<td>DEBT</td>
<td>−5.31 E − 5 (0.95)</td>
<td>−5.72 E − 5 (1.03)</td>
<td>−5.82 E − 5 (1.05)</td>
<td>−5.92 E − 5 (1.07)</td>
</tr>
<tr>
<td>DEMVOTE**</td>
<td>1.31 E − 2 (2.71)</td>
<td>1.31 E − 2 (2.74)</td>
<td>1.27 E − 2 (2.60)</td>
<td>1.22 E − 2 (2.45)</td>
</tr>
<tr>
<td>OWNOCO</td>
<td>−4.70 E − 3 (0.58)</td>
<td>−5.28 E − 3 (0.66)</td>
<td>−5.28 E − 3 (0.65)</td>
<td>−5.23 E − 3 (0.65)</td>
</tr>
<tr>
<td>HVAL8O*</td>
<td>5.95 E − 6 (1.72)</td>
<td>5.67 E − 6 (1.64)</td>
<td>5.80 E − 6 (1.68)</td>
<td>5.73 E − 6 (1.66)</td>
</tr>
<tr>
<td>MIGRANTS</td>
<td>1.32 E + 0 (1.08)</td>
<td>1.34 E + 0 (1.11)</td>
<td>1.30 E + 0 (1.07)</td>
<td>1.27 E + 0 (1.05)</td>
</tr>
<tr>
<td>DELAY</td>
<td>−3.69 E + 0 (0.45)</td>
<td>−3.16 E + 0 (0.39)</td>
<td>−3.31 E + 0 (0.41)</td>
<td>−3.39 E + 0 (0.42)</td>
</tr>
<tr>
<td>OCEAN</td>
<td>−7.20 E − 3 (0.05)</td>
<td>−1.32 E − 2 (0.10)</td>
<td>−1.45 E − 2 (0.11)</td>
<td>−3.38 E − 3 (0.02)</td>
</tr>
</tbody>
</table>

Test for:

- Heterosced. 1.44 E + 1 (94%) | 1.44 E + 1 (94%) | 1.43 E + 1 (94%) | 1.44 E + 1 (94%) |
- Normality 4.86 E + 0 (9%)  | 4.79 E + 0 (9%)  | 4.91 E + 0 (9%)  | 4.86 E + 0 (9%)  |

Sp. err. dep.:

- Conditional 1.82 E − 2 (89%) | 4.72 E − 1 (49%) | 1.05 E − 2 (92%) | 1.56 E − 2 (90%) |
- Robust 2.53 E − 1 (61%)  | 9.30 E − 1 (33%) | 2.59 E − 1 (61%) | 1.56 E − 1 (69%) |

Sp. lag(robust) 6.71 E − 1 (41%) | 1.77 E + 0 (18%) | 4.09 E − 1 (52%) | 6.24 E − 1 (43%) |

Com. factor 5.31 E − 1 (0%)  | 4.95 E + 1 (0%)  | 5.22 E + 1 (0%)  | 5.22 E + 1 (0%)  |

LIKELIHD −116.89  | −116.66  | −116.88  | −116.74

Note: $z = \ln(\text{MEASURES} + 1)$. Absolute normal statistics are in parentheses. Asterisks indicate variables whose coefficients are significant at the 10% (*) and 5% (**) levels. Diagnostic tests are described in the text.


dence, which is based on the estimates of the spatial lag model, shows its absence (probability values in Table 3 exceed 40%). To see that this test may be misleading, suppose that the spatial error model, which has a zero spatial lag coefficient and spatial error dependence, were estimated instead. When this is done, the estimate of $\lambda$ in (13) is significantly positive for each of the specifications in Table 3, and the test for a spatial lag shows its absence (i.e., $\phi = 0$). Therefore, the data appear to be consistent with
either the spatial lag model or the spatial error model, a common outcome in spatial econometric analysis. The spatial error model, however, does not yield strategic interaction in the choice of growth controls.

The robust tests, which are computed from the OLS results without estimating either the spatial lag or the spatial error model, can be applied to deal with this indeterminacy. As seen in Table 3, the robust test shows the absence of spatial error dependence, with probability values usually near 90%. In contrast, the robust test shows that the spatial lag parameter is significantly different from zero for the third specification in Table 3. The test, however, shows the absence of a spatial lag in the remaining cases, although the probability values are lower than for the test of error dependence. While these results provide some evidence in favor of the spatial lag model, further support comes from the test of the common factor hypothesis. This hypothesis, which must hold if the spatial error model is correct, is strongly rejected under each specification in Table 3. A final piece of evidence in favor of the spatial lag model comes from comparing likelihood values, which are uniformly higher for the lag model than for the spatial error model. Note that the test results in Table 4 are similar, except for the higher probability values on the robust spatial lag test, which mirror the insignificance of the estimated lag coefficient. Taken together, these results suggest that the nonzero estimates of $\phi$ in Table 3 are not due to uncorrected spatial error dependence, but instead reflect the existence of strategic interaction. In other words, the true model has $\lambda = 0$ and a positive $\phi$.29

Turning to the city characteristics coefficient estimates, a number of conclusions emerge from the preferred results in Table 3. Under each specification, the coefficients of POP80, EDUC, SKILLED, DEMVOTE, and HVAL80 are positive and significant at the 10% level or better. Conversely, the coefficients of DENS, ONEPERS, MEDINC, and RETSLSPC are negative and significant, again using the 10% level. The POP80, DEMVOTE, EDUC, and HVAL80 coefficients show that, as expected, tight controls are preferred when a city is large, highly Democratic, highly educated, and has

29If the four cities with populations over 500,000 (Los Angeles, San Diego, San Francisco, and San Jose) are deleted from the sample, the case for strategic interaction weakens. Using the population-weighted scheme with distance decay, the last two specifications in Table 5 yield positive $Wz$ coefficients that are significant at only the 10% and 13% levels, respectively. The second-column specification, as well as the distance decay specifications in Table 3, all yield inferior significance levels (never higher than 21%). The reason for the weaker results appears to lie in the fact that the deleted cities have relatively large values of MEASURES (equal to 4, 2, 4, and 6, respectively, using the above city order). This, together with the cities’ large populations, may lead to greater scope for interaction under the population-weighted scheme. However, since there is no sound justification for deleting the big cities, the results in Tables 3 and 5 remain credible.
high house values. The DENS and MEDINC coefficients show that loose controls are preferred in dense, high-income cities, again as predicted. The results also show that cities with high skill levels prefer tight controls, a finding that mirrors the education effect. Conversely, cities with a large share of one-person households prefer loose controls, as do cities with a high level of retail sales per capita. The negative impact of ONEPERS may indicate that the disamenities from growth are most strongly felt by families.\(^{30}\)

None of the remaining city characteristics in Table 3 have a statistically significant effect on a city's growth control effort. In many cases, this finding is natural because no prior prediction was made regarding the effect of the variable. For example, the racial mix and age structure of the population have no effect on a city's preference for controls (BLK, HISP, KIDS, and OLD have insignificant coefficients), and the impacts of PERHOUS, UNEMP, SVCSALES, TOTTAX, TOTEXP, CAPEXP, and DEBT are also insignificantly different from zero.

Insignificant coefficients are also found for some variables where an effect was expected. Contrary to expectations, the owner-occupier share in the city's population (OWNOCC) has no effect on the preference for growth controls. The same conclusion applies to the level of traffic congestion, as measured by DELAY, and to the county migration variable, MIGRANTS, both of which have insignificant coefficients. An explanation for the latter results is that these two variables may serve as poor proxies for the effects of interest.\(^{31}\) Since DELAY is computed at the county level and covers freeways but not city streets, it represents a very imperfect measure of local traffic congestion. Similarly, because MIGRANTS is also computed at the county level, it may be an imperfect measure of the population pressure felt by a city. Finally, the OCEAN dummy variable has an insignificant coefficient, indicating no effect on a city's preference for growth controls. Note that the population-unweighted results in Table 4 show exactly the same pattern of effects for the city characteristics variables.\(^{32}\)

\(^{30}\) The fact that EDUC and SKILLS have positive coefficients while the MEDINC coefficient is negative is noteworthy, given that the variables typically move together. One explanation is that EDUC and SKILLS might capture the demand for environmental quality, as reflected in a subjective part of the externality parameter $\beta$, while MEDINC captures the effect of money income, which determines a city's willingness to impose controls through the boundary rent effect discussed above.

\(^{31}\) Using a somewhat smaller sample, MIGRANTS can be replaced with a variable measuring city growth over the 1970-80 period, which is properly treated as exogenous. However, the coefficient of this variable is also insignificant, which may indicate that 1988 controls are mainly affected by population pressure during the 1980s.

\(^{32}\) As in the present case, the results of Dubin et al. [17] show that a precinct-level version of DEMVOTE has a positive effect on the number of votes cast in favor of growth controls. Unlike in Table 3, however, high local traffic congestion and a high share of owner-occupiers also raise the pro-control vote.
Table 5 shows estimates based on a smaller set of city characteristics, using the preferred population-weighted scheme and the same distance formulations. The variables with significant coefficients in Table 3 are retained, as is the MIGRANTS variable (the case for its inclusion is strong, despite the absence of an effect in Table 3). RETSALES is deleted because its coefficient becomes insignificant in a more parsimonious specification. Referring to Table 5, the competing controls coefficient is once again significant in all cases, and the heteroscedasticity and normality tests again are satisfactory.  

The empirical findings can be summarized as follows. Most importantly, the results provide convincing evidence of strategic interaction among California cities in the choice of growth controls. Confirming the suspicion of many observers, it appears that California cities are indeed playing a "growth controls game." The results also show that a number of other factors affect city choices. A large population, high education and skill levels,
a liberal political stance, and high house prices increase a city’s preference for controls. Conversely, dense, high-income cities that contain many one-person households have a weaker preference for controls. A noteworthy aspect of the results is the poor performance of variables explicitly intended to measure population pressure, which may partly reflect imperfect measurement. HVAL80 is the only such variable that performs as expected.34

In appraising the paper’s findings, it is natural to wonder whether a positive competing controls coefficient is virtually “guaranteed,” given the popularity of growth controls in California. To see why the answer is negative, imagine a situation where communities are “inward looking” in their growth control decisions, responding only to internal growth pressures. In this case, the community’s decision will depend only on its own characteristics, being unrelated to the growth control choices of other communities. This model, which is perfectly consistent with the widespread adoption of controls, implies a zero coefficient for the competing controls variable in (11). Although the inward-looking model is logically defensible, the finding of a nonzero \( \phi \) suggests that it is unrealistic.

6. SIMULATION EXERCISE

As explained above, strategic interaction implies that the growth control choices of a given city depend on the characteristics of all of the cities in the sample. To illustrate the consequences of this fact, suppose that the characteristics of a single city change in such a way as to shift its reaction function upward. Redrawing Fig. 1 to show upward-sloping reaction functions, and recalling that the axes now represent MEASURES instead of \( x \), the result of the shift in the two-city case is tighter controls in both cities. This outcome generalizes to the many-city case, with growth controls becoming tighter everywhere when a single city’s reaction function shifts up.

To illustrate this principle using the empirical results, suppose that Sacramento’s median house value in 1980 had been $40,000 higher than the actual value of $54,600, equal to $94,600. Since HVAL80’s coefficient is positive, with high house values raising the incentive for controls, this change causes an upward shift in Sacramento’s reaction function. Using the distance decay estimates from the third column of Table 5 (where \( d^* = 100 \)), the reaction function shifts up by 0.11. To compute the predicted change in the \( z \) vector for the sample resulting from this shift, let \( S_0 \) and \( S_1 \) give the \( S \)

34Goodness of fit for the estimated equations can be evaluated by computing an \( R^2 \) value, using \( z - \phi Wz \) as the dependent variable. For the models in Tables 3 and 4, these \( R^2 \) values closely bracket 0.30. While this number is not substantial, it suggests that the city-characteristics variables do a reasonable job of capturing growth control variation in the sample.
matrix before and after the change, with \( h_1 \) and \( h_0 \) denoting the vectors of \textsc{HVAL80} values (these differ only in the Sacramento element). Then, using (12), the predicted change in \( z \) is given by

\[
(I - \hat{\phi}W)^{-1}(S_1 - S_0)\hat{\theta} = (I - \hat{\phi}W)^{-1}\hat{\theta}_h(h_1 - h_0) = (I - \hat{\phi}W)^{-1}k, \tag{18}
\]

where \( \hat{\cdot} \) denotes estimated values, \( W \) is the relevant weight matrix, \( \theta_h \) is the \textsc{HVAL80} coefficient, and \( k \) is a vector with 0.11 as the Sacramento element and zeros elsewhere. Recalling that \( z \) comes from a log transformation of \textsc{MEASURES}, the change in \textsc{MEASURES} itself is found by applying the inverse transformation to (18).

Table 6 shows the elements of the transformed (18) for sample cities near Sacramento, where the predicted changes are largest. The third column shows the change in \textsc{MEASURES}, while the first and second columns show the predicted values before and after the change. As can be seen, the \textsc{HVAL80} increase in Sacramento raises its \textsc{MEASURES} value by 0.19, from 0.59 to 0.78.\textsuperscript{35} The largest changes among nearby cities occur in Davis and Chico, where changes are nearly half as large as Sacramento’s, lying between 0.07 and 0.08. Impacts on other nearby cities are smaller, while changes in more distant cities (not shown in the table) are of a lower order.

\textsuperscript{35}The actual \textsc{MEASURES} value for Sacramento is zero.
of magnitude. These results show that in the presence of strategic interaction, a change in the characteristics of a single city can generate a spatial cascade of impacts, altering growth control choices over a wide area.36

7. CONCLUSION

Strategic interaction among local governments has been a major focus of recent theoretical work in public economics. This paper has presented the first empirical evidence on this important issue. By showing evidence of strategic interaction in the choice of growth controls, the paper suggests that important local policy decisions of this type are not taken in a vacuum. When nearby cities impose stringent growth controls, a given city is likely to do the same. When nearby growth controls are mild, the city is likely to adopt mild controls as well.

The model suggests that policy interdependence arises because a city’s growth control decision is sensitive to the tightness of the regional housing market, which depends on the control choices of other cities. It is important to note that, while the results provide evidence of interaction, they do not prove that this particular mechanism is the source of it. For example, cities could instead be naive followers of localized policy “fads” in a setting of generalized hostility toward growth, which would generate results like those that have been found. Further research is needed to settle this issue.

A final point is that the paper’s methodology could be applied to the study of strategic interaction in the choice of other policy variables. Brueckner and Saavedra [10] use the current approach to investigate interaction in the choice of property tax rates by local governments, a natural extension given that this policy instrument is the focus of the large tax competition literature. Using data on cities in the Boston metropolitan area, Brueckner and Saavedra again find evidence of strategic interaction, with their estimates again showing upward-sloping reaction functions. This same methodology could be used to investigate interaction in the choice of income tax rates or welfare benefits at the state level.

REFERENCES


36 The fact that impacts in some competing cities are relatively large is a consequence of the sparseness of cities in the Sacramento region. If the exercise is repeated for Irvine, located in populous Orange county, the growth control changes in nearby cities (of which there are many) are more modest.


