Effects of urban growth controls on intercity commuting

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Abstract

This paper presents an empirical study of the effects of urban growth controls on intercity commuting of workers. Growth controls (land use regulations that attempt to restrict population growth and urban sprawl) have increased housing prices and diverted population growth to uncontrolled cities. Ogura (*2005, Journal of Urban Economics 57, 371-390*) suggests that resulting changes in local labor supply might stimulate intercity commuting from uncontrolled to controlled cities. To test this hypothesis, a gravity model of commuting flows between places in California is estimated using alternative econometric methods (OLS, Heckman selection, and count-data). The possibility of spatial dependence in commuting flows is also taken into consideration. Results suggest larger commuting flows to destination places that restrict residential growth.

Keywords: Urban growth controls, land use regulation, intercity commuting, jobs-housing mismatch, local labor supply.

JEL Classification Numbers: R14, R21, R31, R52.

1 Introduction

Many jurisdictions in the US have adopted land use regulations to restrict population growth and urban sprawl. These regulations, known as urban growth controls (UGC), have been advocated to prevent problems from excessive population growth and urban sprawl like greater congestion in the use of government provided services and infrastructure, loss of open space, and pollution. In the U.S., UGC have been adopted in areas that have experienced fast population growth like California, Portland-OR, Boston-MA, New York-NY, Boulder-CO, New Jersey, Maryland, etc.

The widespread adoption of UGC has prompted many studies on this issue. Fischel (1990) reviews earlier empirical evidence that UGC raise housing prices. Brueckner (1990) and Engle et al. (1992) show how UGC can theoretically increase housing prices by reducing future negative externalities from population growth. Brueckner (1995) and Helsley and Strange (1995) present alternative models where housing price increases because the adoption of UGC by one or more cities restricts the supply of developable land in the region. Population growth diverted to neighboring places increases the demand for land there, but ultimately raises land rents everywhere in the region due competition for land by mobile households. Levine (1999) provides empirical evidence that UGC causes housing supply displacement.

Because population growth is diverted from controlled to uncontrolled cities, Ogura (2005) suggests that theoretically UGC could induce workers to live in an uncontrolled city but to work in the controlled one. Vermeulen and Rowendal (2008) also consider intercity commuting (IC) in a model of UGC, but with the restricting assumption that all jobs in the region are located in the central city, so that UGC there necessarily leads to IC. On the empirical side, however, there is no rigorous study on this issue. In a related work, Cervero (1989) finds that jobs-housing mismatches in the California Bay Area in 1980 are partially explained by restricted supply of housing. His study, however, lacks a direct measure of residential restriction, employing the proportion of land area zoned for residential use as a proxy. Aivalotis et al. (2001) also report jobs-housing mismatches in the San Francisco Bay Area, suggesting that newcomers are induced to commute to work from homes in the outskirts due to lack of housing available in interior areas. There is also anecdotal evidence that UGC stimulate IC. For instance, Kelley and Rabin (2006) suggest in a news article that UGC in Santa Barbara have induced high traffic of commuters on roads that connect the city to nearby places where housing supply is less restricted. Therefore, existent empirical evidence suggests that UGC divert traffic growth from local roads to intercity roads. Aivalotis et al. (2001) add that longer intercity commuting increase overall pollution and loss of labor productivity. Because the effects of UGC and of commuting on society are important policy issues, it is important to better understand how UGC impact IC.

The work presented here attempts to provide a rigorous analysis of the effects of UGC on IC. To do so, a gravity model of IC flows between California cities is estimated, controlling for distance, number of workers in the home place, job availability in the work place, and other characteristics of the places involved, including the adoption of UGC by the work place. Data on place-to-place commuting flows is obtained from the U.S. Census Bureau (1990), while UGC indicators are based on data from the 1989 survey of growth-control practices adopted by jurisdictions in the state of California conducted by Glickfeld and Levine (1992). As a proxy for the stringency of residential growth controls, an index is computed taking into consideration the number of different types of residential regulations existent in each place. The justification for the use of this index is that jurisdictions should adopt more types of regulations if they want to make it harder for developers to produce more housing (similar growth-control indexes were used by Brueckner (1998) and Levine (1999) to test other hypothesis). In the estimation of IC flows, however, one of the problems is the existence of large number of zero-valued observations, requiring the use of alternative estimation methods (Heckman selection and count-data models are employed for this purpose). Moreover, the empirical analysis also takes into account the possibility of spatial dependence between IC flows. Overall, the results of the estimations indicate greater IC flow when the destination place adopts residential growth-control measures.

A possible implication of this result is that UGC increase overall commuting costs. It is not completely clear, however, whether this increase in commuting is socially inefficient. While greater commuting directly hurts workers and businesses, UGC are adopted to avoid negative externalities from excessive development, thus the net effect on society's welfare can be ambiguous.[1] On the other hand, if UGC are adopted without coordination by local jurisdictions, it is likely that regulations can become too strict because negative effects on workers and firms in neighboring places are not considered (Glaeser et al., 2006, and Glaeser, 2007, suggest the need for regional coordination to avoid excessive construction regulations).

The remainder of this paper is organized as follows. The next section discusses Ogura's (2005) model of how UGC might affect IC. Section 3 presents an empirical analysis of this issue based on the estimation of IC flows. Concluding remarks are presented in Section 4.

2 Theoretical analysis

Ogura (2005) presents a theoretical analysis of the relationship between UGC adoption and IC of workers. On one hand, his model suggests that the adoption of UGC depends on how price elastic the local labor supply is, which is affected by how easily commuting from other places can occur. On the other hand, the model also shows that UGC might eventually stimulate the intensity of IC between close cities. In the model, IC emerges solely due to the adoption of UGC, i.e., other factors are ignored. In practice, however, Hamilton (1982) notes that jobs-housing mismatches are expected due to the existence of households composed by couples who work in different areas and to the higher frequency of job turnover relative to residential mobility. Moreover, White (1988) suggests that workers belonging to minority groups may face restricted housing choices due to discrimination, thus having to incur greater commuting. While these and other factors are not considered in the theoretical model, they are included in the empirical analysis presented in this paper.

A simplified version of Ogura's (2005) model is presented next. Because the objective of this paper is to test whether UGC affect IC, the model presented here focuses on this relationship.

2.1 Setup

Consider a closed economy with two regions indexed by i=0,1. There is a linear city in each region, with width one and length $\bar{x}_i$. The central business district (CBD), where production takes place, is located at one of the extremes of the city. Thus, the length of the city corresponds to the distance between the boundary of the urban area and the CBD. The distance between the CBDs of the two cities is D. Urban land is occupied by mobile renters, who demand one unit of land each. Thus, $\bar{x}_i$ equals the city population P_i, and $\bar{x}_0 + \bar{x}_1 = P_0 + P_1 = P$, where P is the total population of workers in this economy.

Renters also consume a numeraire private good with income obtained from the supply of labor (one unit is supplied by each renter), which is exchanged for a wage w_j, where j denotes the city of work. In order to work in the CBD of her own city, a renter residing at a distance x_i from the CBD incurs a commuting cost tx_i, where t represents the commuting cost per unit of distance. However, if she is employed in the CBD of the other city, she incurs an additional cost tD. This setting implies that every renter in one city would incur the same additional commuting cost if she decided to work in the other city.[2]

The land rent paid by a renter residing at x_i is $r_i(x_i)$, which is a decreasing function of x_i because individuals are willing to bid more to live closer to their work place in order to avoid commuting. In equilibrium, land rents offset all utility differentials related to where individuals live, equalizing renters' utilities everywhere. To simplify, assume that utility is derived from the consumption of the numeraire private good. Thus, the indirect utility function of a renter who lives in city i and works in city j can be written as

$$u_{i,j}(x_i)=\begin{cases} w_i - tx_i - r_i(x_i) & if j=i \\ w_j - tD - tx_i - r_i(x_i) & otherwise. \end{cases} \qquad (1)$$

Land ownership in each region is shared among absentee landowners.[3] To avoid dealing with conflict of interests, assume that each landowner receives rents from only one of the regions. Normalizing non-urban land rent to zero, total land rent in each region (denoted by R) equals $R_i\left(\bar{x}_i\right)=\int_0^{\bar{x}_i} r_i(x_i)dx_i$. Regions are symmetric in all aspects, except that landowners are politically dominant only in one of the cities, adopting UGC to maximize total land rents R.[4]

Last, production in each city follows the aggregate function $F(N_i)$, where N_i is the number of workers in city i, with $F'(N_i)>0$ and $F''(N_i)<0$ (i.e., production exhibits decreasing returns to labor). In addition, $F(0)=0$ and $F'(0)=+\infty$. Therefore, in equilibrium, profit maximization by competitive firms implies

$$w_i=F'(N_i), \qquad (2)$$

resulting in positive total profits. To simplify, assume that profits are shared among absentee firm-owners, who are neither workers nor landowners.[5]

2.2 Effects of UGC

To understand how the adoption of UGC affects this economy, consider first the case without controls. Then, there are three equilibrium conditions. First, land rent at the boundary of each city must equal the opportunity cost of land outside the city, which was assumed to be zero, i.e., $r_i(\bar{x}_i) = 0$. Second, rents at other places in city i are determined by utility equalization: $u_{i,h}(x_i) = u_{i,h}(\bar{x}_i)$ for all x_i and for any $h \in \{i,j\}$. Consequently,

$$r_i(x_i) = t\left(\bar{x}_i - x_i\right), \tag{3}$$

which implies that land rent offsets the commuting cost differential with respect to the boundary resident in the city. Third, utility must be equalized across cities due to free mobility. Thus, the following equality must hold in equilibrium: $u_{0,0}(\bar{x}_0) = u_{1,1}(\bar{x}_1)$. Substituting (2), (3), and the population constraint $\bar{x}_1 = \left(P - \bar{x}_0\right)$ in (1), the utility equalization condition becomes $F'(N_0) - t\bar{x}_0 = F'(P - N_0) - t(P - \bar{x}_0)$, which is satisfied when $\bar{x}_0 = \frac{1}{2}P$, i.e., with a symmetric population distribution and no IC of workers.[6] Intuitively, symmetric population and production are optimal because regions are symmetric in their geographical and economic characteristics and production exhibits decreasing returns to labor.

Now, turn to the case where one city, say city 0, adopts UGC (i.e., $\bar{x}_0$ is restricted below $\frac{1}{2}P$). Since growth in city 1 is uncontrolled, the land rent function (3) still applies to that city. City 0's land rent function is, however, affected. Recall that residents must be equally well-off everywhere and suppose for the moment that IC does not occur, meaning that the first expression in (1) is valid. Noting that $u_{1,1}(\bar{x}_1) = w_1 - t\bar{x}_1$ and setting this expression equal to $u_{0,0}(x_0) = w_0 - tx_0 - r_0(x_0)$, the resulting land rent function for city 0 is

$$r_0(x_0) = t\left(\bar{x}_1 - x_0\right) + w_0 - w_1. \tag{4}$$

In words, this function implies that land rents in the controlled city offset two utility differentials: $t\left(\bar{x}_1 - x_0\right)$ is the commuting cost differential with respect to the boundary resident in city 1 and

$w_0 - w_1$ represents the wage differential between cities. Then, note that when stricter UGC are adopted ($\bar{x}_0$ is reduced), both differentials go up at interior locations of the controlled city. The commuting cost differential increases because city 1's size $\bar{x}_1$ is expanded as population growth is relocated to that city. The wage advantage for workers in city 0 widens because the local labor supply in the city is restricted relative to city 1.

The effects of UGC on land rents in each city are illustrated in Figure 1. In the figure, note that the slopes of the land rent curves is $-t$ because the decrease in land rent due to greater distance is determined by the additional commuting cost t. As UGC become stricter, city 0's size is reduced from $\bar{x}_0$ to $\bar{x}_0^{'}$ and rents in city 0 increases for the two reasons mentioned above. Areas B and B_1 depict the increase in land rents in each city due to the higher demand for land in city 1 (city 1's size expands from $\bar{x}_1$ to $\bar{x}_1^{'}$). Area C represents the gain in land rents in city 0 due to the widened wage advantage. There is also a boundary rent loss (represented by area A) because the number of renters in city 0 is reduced by the stricter UGC. The rent loss ensures that there is an optimal stringency of UGC.

[FIGURE 1]

Consider now the possibility of IC. Then, local labor supply becomes more elastic as long as the wage differential between cities is high enough to cover the cost of IC (which equals tD in the model), making it advantageous for workers to live in one place and work in the other. As UGC become stricter, the wage differential widens, but only until IC starts to occur. At that point, inflow of commuters from the nearby city offsets further population restriction in the controlled place.[7] Formally, once IC starts, the equilibrium size of the controlled city's workforce $\hat{N}_0$ is determined by the equilibrium equality of the wage differential between cities to the IC cost, i.e.,

$$F'(\hat{N}_0) - F'(P - \hat{N}_0) = tD. \qquad (5)$$

Since the number of workers remains fixed at $\hat{N}_0$ as long as IC occurs, the number of outside workers commuting to the controlled place increases with the stringency of growth controls. In other words, the adoption of stricter UGC increases IC flows of workers.

Notice that condition (5) implies that $\frac{d\hat{N}_0}{dD}<0$. Consequently, the magnitude of IC flow (given by $\hat{N}_0 - \bar{x}_0$) decreases with D, holding the strictness of UGC fixed. In other words, the greater the distance between cities, the smaller is the IC flow.[8]

Last, recall that the stringency of UGC in this model is chosen to maximize land rents only. In practice, the adoption of UGC is determined by additional factors like environmental quality. Moreover, landowners' share of political power varies across cities. Because both renters and firm-owners tend to lose under stricter controls, these groups should oppose UGC, leading to different stringency levels depending on the distribution of political power (Brueckner, 1999, presents a UGC model where political power is shared among landowners and renters). In any case, because cities are different in practice, UGC strictness differs across places. Accordingly, the empirical analysis presented next takes the intensity of UGC as given. Then, noting that the local labor supply $\hat{N}_0$ is determined by D, the theoretical implication to be tested is that, when controlled for distance between cities and for other characteristics of the cities involved, IC flow increases with the stringency of UGC adopted in the destination place.

3 Empirical model

According to the theoretical model, IC from the residence place i to the work place j should be positively affected by the stringency of UGC measures that restrict labor supply in the destination place j. To test this hypothesis, IC flows are estimated using an origin-destination gravity model. The conventional gravity model for spatial interaction is specified in analogy to Newton's law of gravity (see Batten and Boyce, 1986). In its simplest form, the model predicts that spatial interactions are negatively affected by distance and positively related to the gravitational masses of the interacting places. In the case of IC flows, workers commute for employment, so that the gravitation mass of the origin place must be the number of workers while the mass of the destination place is the number of jobs available. Of course, other characteristics of each place may reinforce or restrain spatial interaction (other control variables used in the estimation are discussed later).

The following linearized version of the gravity model is used to estimate IC flows:[9]

$$ln(IC_{ij})=\beta_d ln(d_{ij})+\beta_{M_i} ln(M_i)+\beta_{M_j} ln(M_j)+ \sum_{s=1}^{S} \beta_{si} ln(X_{si})+ \sum_{v=1}^{V} \beta_{vj} ln(X_{vj})+\varepsilon_{ij}, \tag{6}$$

where IC_{ij} represents the intensity of the commuting flow of workers from place i to place j, d_{ij} is the distance between cities, M_i is the gravitational mass of place i (represented by i's labor force) and M_j is the gravitational mass of place j (represented by j's job availability). Variables X_{si} and X_{vj} are respectively characteristics of place i and place j that might affect IC between places. As usual, βs are the parameters of the model and ε_{ij} is the unexplained residual.

To test the hypothesis that UGC stimulate IC flows, a variable for the presence or intensity of UGC is included as one of the characteristics of place j, with a positive expected estimated coefficient.

Other characteristics of places i and j included in model (6) are factors that should impact workers' willingness to commute between places: unemployment, ethnicity, income, education, age, gender, marital status, homeownership, occupation, and density. Two dummy variables are also included: the first for origin and destination places located in the same county and the second for destination places that are attractive job-center. These additional factors are discussed in the Appendix, including comments on expected and estimated effects.

3.1 Data

Information about UGC measures adopted by each jurisdiction is drawn from the 1989 survey conducted by Glickfeld and Levine (1992). The survey (answered by local public officials) consisted of a questionnaire on the types of land use restrictions existent in each jurisdiction at the end of 1988 approximately.[10] For the purposes of this work, only regulations that should greatly affect local labor supply are considered, i.e., regulations that restrict housing construction. Table 1 summarizes the frequency of adoption of the types of regulations considered. While adoption of regulations does not imply enforcement, it is plausible that there is a positive correlation between a greater number of regulations and how concerned the jurisdiction is about restricting growth (this view is suggested by Glickfeld and Levine, 1992). Accordingly, the stringency of growth controls can be measured through an index that counts the number of different types of residential regulations adopted in each place based on the list of types in Table

1.[11] The resulting index is denoted *hc* and can vary from 0 to 3. Alternatively, a dummy variable *dhc* is created, taking value one when the jurisdiction adopted at least one type of residential regulation (true for 41% of jurisdictions in the sample that answered the survey).

[TABLE 1]

For IC patterns, journey-to-work flows between places in California are obtained from the 1990 Census Transportation Planning Package (CTPP) assembled by the US Census Bureau (1990). The intensity of IC from residence place *i* to the work place *j* is measured by the flow of workers who commute from *i* to *j*, denoted by *ICij*. In the original dataset, there are 668 places with population over 2,500 in 1990, while other places are categorized as "remainder of the county" areas. In the estimations, only flows between the 668 identified places are considered (excluded flows represent 21.63% of all workers who commute between Californian cities). Moreover, the CTPP does not report eventual flows to or from other states. The final sample used in the estimations also disregards flows to places for which there was no information on UGC (that was the case for 310 of the 668 places identified in the CTPP; IC flows to these 310 places represent 17.01% of the total flows between the 668 places).

Additional geographic and socio-economic characteristics of the 668 places were obtained from the 1990 Decennial Census (US Census Bureau, 1990b, 1990c).

Table 2 presents all variables used in the empirical work. Descriptive statistics are shown in Table 3. Besides *ICij*, *hc*, and *dhc*, which were discussed before, all other variables listed in Tables 2 and 3 are used as control variables in the estimations.[12]

[TABLE 2]

[TABLE 3]

3.2 Methodology

The gravity model (6) is first estimated using ordinary least square (OLS) method.[13] One problem, however, is that *ICij* equals zero too often (91.4% of the observations in the final sample used are zero-valued). To deal with this issue, several approaches are suggested in the literature. The simplest one just ignores zero-valued observations. Taking this procedure as a first attempt, relevant results are presented in Table 4. Results are in accordance with theoretical expectations, but further discussion will be left to the next subsection when results based on other estimation methods will be compared.

Another simple alternative suggested is to replace zero values by a small ad hoc number, but neither this nor the procedure of ignoring zero-valued observations are satisfactory because information is either dismissed or altered (Linders and de Groot, 2006, discuss these procedures in the case of trade flows).

In cases where the lack of spatial interaction between places might be caused by a selection process, the use of a sample selection model is recommended. Linders and de Groot (2006) and Helpman et al. (2008) apply this method to estimate trade flows. To better understand this approach, a brief explanation is presented next. First, consider the regression equation

$$y_h = x_h'\beta + \mu_h, \tag{7}$$

where y is the dependent variable, x is the vector of covariates, β is the vector of parameters of the model, and μ is the vector of errors. In the case of IC flows, this equation can be rewritten as model (6). Suppose that y_h in (7) is observed only under a selection condition determined by the equation

$$s_h^* = z_h'\gamma + e_h. \tag{8}$$

However, only the sign of the selection variable s_h^* can be observed. Hence, taking s_h=1 if s_h^*>0 and 0 otherwise, the dependent variable in the regression model (7) is observed only if s_h=1 (in the case of IC flows, a possible interpretation is that a strictly positive flow between places only happen if, for instance, there is an easy way to commute between these places). If μ_h and e_h are correlated, the OLS method becomes inadequate to estimate the regression model. One option is to estimate both the selection and the regression equations together using the maximum likelihood method. An easier way is to follow the two-step estimation procedure called Heckit, named after Heckman's (1976, 1979) seminal works. The first-step is to estimate the probability that s_h^*>0 using the Probit method (i.e., estimate $Prob(s_h=1)=\Phi(z_h'\gamma)$, where Φ is the normal c.d.f.) and then to use the result to compute the corresponding inverse Mills ratio for each observation (the ratio is given by $\hat{\lambda}_h=\phi(\hat{\gamma}z_h)/\Phi(\hat{\gamma}z_h)$, where ϕ is the normal p.d.f.). In the second-step, the OLS method can be used to regress y_h on x_h and $\hat{\lambda}_h$. It is typically suggested that the selection model should also include an exclusion restriction, i.e., a variable that helps determining the selection process, but not the outcome.[14] The problem is to find a restriction variable that satisfies this requirement. In the case of IC flows, the restriction variable must affect the likelihood of a strictly positive IC flow, but not the intensity of the flow. A justification for such variable might be that there is a maximum commuting cost that workers are willing to incur. In practice, however, factors that affect this threshold IC cost are likely to also affect the intensity of IC because individual workers have heterogeneous threshold IC costs (thus, as the cost increases, fewer and fewer workers commute, until the threshold is reached). Nonetheless, the estimations suggest that the variable *unemployrtj* (unemployment in the work place *j*) satisfy the restriction requirement, i.e., *unemployrtj* is statistically significant in the first-step Probit estimation, but not in the second-step estimation, thus allowing us to exclude it from the regression model. Results from Heckit estimations are presented in Table 4. Note that the inverse mills ratio ($\hat{\lambda}$) is statistically significant, indicating that the error terms in the selection equation are in fact correlated to error terms in the regression equation. While the results for the UGC variables are in accordance with theoretical expectations, comparison to the results of other estimations is presented in the next subsection.

For comparison, a third method will be used to estimate IC flows. Because an IC flow is the number of workers commuting between places, count data estimation methods might be appropriate. For instance, Flowerdew and Aitkin (1982) estimate migration flows with a Poisson model, while Silva and Tenreyro (2006) use that model to estimate trade flows. In the current work, IC flows are estimated using the zero-inflated negative binomial (ZINB) model because of the large variance relative to the mean (Poisson distribution requires that variance equals mean) and large number of zero-valued observations. Results based on the ZINB model are presented in Table 4. In the table, *ln(α)* gives the natural log of the dispersion parameter α of the count model, which is statistically different than zero, indicating that the ZINB model is more appropriate than the Poisson model (see Stata, 2008). The Vuong test statistic (Vuong, 1989) shows that the zero-inflated model is better than the standard negative binomial model (the null hypothesis is that the standard model is appropriate; see Stata, 2008). As shown in the table, results from this method are qualitatively to the others. Quantitative comparison is discussed next.

3.3 Results

Results from the OLS, Heckit, and ZINB estimations are presented in Table 4. Standard errors presented there are robust White standard errors, employed to correct for heteroscedasticity. Specifications in columns (1), (3), and (5) include *hcj* as the growth-control variable, while specifications in (2), (4), and (6) include *dhcj*. OLS results are in columns (1) and (2), Heckit results are in columns (3) and (4), and ZINB results are in columns (5) and (6).

[TABLE 4]

The estimated coefficients of *distanceij*, *laborforcei*, and *jobsj* are similar in the OLS and ZINB estimations, but approximately 1.5 times greater in the Heckit estimations. Regarding the growth-control variables *hcj* and *dhcj*, estimated coefficients are much larger in the ZINB estimations, while Heckit estimates indicate smaller effects. Most importantly, however, these estimates are positive and statistically significant in all estimations. Therefore, places that adopt stricter UGC attract relatively more IC workers. Although it is not the concern of this work, the following quantitative effects can be noted: one-unit increase in the *hcj* index stimulates the flow of intercity commuters by 7.6% to 13.7% depending on the method used; in addition, the existence of residential growth controls, measured by the dummy variable *dhcj*, increases IC flows by 7% to 18.9%. Social welfare effects are hard to evaluate as they depend on which groups of workers are more affected, mode of transportations, negative externalities from increased commuting, etc. Attempts to study welfare effects will be left for future research.

Results for other explanatory variables included in the estimations are generally consistent with expected effects, thus supporting the proposed empirical model. Those results are discussed in the Appendix.

One potential problem with the empirical analysis presented so far is that there might be spatial correlation between flows from neighboring origin or neighboring destination places. If that is the case, estimation of IC flows must be controlled for spatial dependence. The next subsection discusses how spatial autocorrelation are tested and taken into account. Heckit estimations will be used for this purpose (OLS and ZINB methods were used before for the sake of comparison only).

3.4 Spatial autocorrelation

Spatial dependence between observations is common when there are spillover effects. For instance, property crime is likely to be spatially correlated across neighboring areas because criminals are mobile (Anselin, 1988). Local public expenditure and taxation also experience spatial dependence (see Case et al., 1993, Revelli, 2002, and Mattos and Rocha, 2008).

In the case of spatial interactions, LeSage and Pace (2005) discuss empirical models that take spatial autocorrelation into account, using them to estimate migration flows across U.S. states. Based on the two simplest empirical models suggested by them, which can be implemented with the statistical software Geoda™, Figure 2 depicts the patterns of spatial autocorrelation tested here. Diagram (a) depicts the case where all commuting flows from place i to places in the neighborhood of j are considered to be correlated with the flow from i to j, i.e., there is destination-based spatial dependence (DSD). Diagram (b) presents the case where all flows from the neighborhood of place i with destination to place j are considered to be correlated with the flow from i to j, i.e., there is origin-based spatial dependence (OSD). The neighborhood definition adopted here is ad hoc: jurisdictions are considered to be neighbors if their geographical centers are less than 15 miles (24 km) apart. Under this definition the average number of neighbors in the sample is 20 (the median is 12, with 22 places having no neighbors). For the sake of robustness, estimations were also performed with thresholds of 10 or 20 miles, without changes in the relevant results (these additional results are available upon request). An alternative neighborhood definition commonly suggested in the spatial econometrics literature is based on the existence of common borders, but that might be inadequate here due to the incomplete sample and the existence of unincorporated areas between jurisdictions.

[FIGURE 2]

Two main types of spatial autocorrelation are discussed in the spatial econometrics literature: spatial lag dependence and spatial error dependence. An overview of these types of autocorrelation is presented next (for further details, see Anselin, 1988, 2005). In the spatial lag case, each observation is directly correlated to neighboring observations. In the spatial error case, the error term is correlated with error terms of the estimations of neighboring observations (the assumption is that unmodeled effects spill over across observations, resulting in spatially correlated errors).

Formally, the spatial lag model can be written as

$$y = \rho Wy + X\beta + u, \quad (9)$$

where y is the vector of origin-destination independent variable, W is the spatial weight matrix (to be explained soon), X is the matrix of other explanatory variables, and u represents the vector of i.i.d. error terms. ρ and β give the estimated parameters. In the DSD case, when the flow from place i to j is estimated, the weight matrix W produces the weighted average of IC flows originated in i with destination to places in the neighborhood of j. In the OSD case, W produces the weighted average of flows destined to place j that are originated in the neighborhood of i. The weight matrix is computed so that neighbors' influences are standardized, with equal weight for each neighbor (for instance, if place i has two neighbors, each neighbor's weight is 0.5; thus, the sum of weights in each row of W is one).

The spatial error model can be formally represented by a system of two equations:

$$y = X\beta + u \quad (10)$$

$$u = \delta Wu + v, \quad (11)$$

where the first equation is the regression model to be estimated and the second represents the residual autocorrelation process. δ denotes the autocorrelation parameter and v is a vector of i.i.d. error terms. W is the weight matrix computed as before.

To assess whether IC flows are subject to spatial dependence, diagnostic tests are performed for the regression model of the Heckit estimation method.[15] Resulting statistics are presented in Table 5 (spatial diagnostic tests and estimations are performed using Geoda™; for further discussion on the interpretation of tests and estimation results, see Anselin, 1988, 2005). The first two columns in the table show tests for DSD, while remaining columns show tests for OSD. Note that Moran's I scores are statistically significant (the null hypothesis of zero score indicates absence of spatial autocorrelation). However, Moran's I test detects misspecification in general (not only spatial autocorrelation), thus not indicating which alternative model should be used. To this end, Lagrange Multiplier (LM) test statistics are helpful. The LM-Lag and Robust LM-Lag test statistics assume spatial lag models as alternatives, while the LM-Error and Robust LM-Error test statistics take spatial error models as alternatives. All LM statistics reported in Table 5 are significant. High significance reinforces the view of spatial dependence between IC flows. When tests for both spatial lag and spatial error models reject the null hypothesis, Anselin (2005) suggests the selection of the model that produces the largest test statistic value, although misspecification might be due to other reasons. According to such approach, spatial error models are appropriate. Alternatively, Revelli (2002) and Mattos and Rocha (2008) compare the log-likelihood in the estimation of lag and error models, although doing so also provide support for the spatial error model. For comparison, estimation results for both the spatial lag and spatial error models are presented (in Table 6).

[TABLE 5]

[TABLE 6]

In Table 6, first notice that the inverse Mills ratio ($\hat{\lambda}$) is statistically significant in all estimations, justifying the use of the selection model. Second, both the spatial lag and spatial error variables (*Wy* and *Wu*) are statistically significant, reinforcing the results of previous diagnostic tests that suggest spatial dependence in IC flows. Third, estimates for the variables *distanceij*, *laborforcei*, and *jobsj* are not very different relative to the non-spatial estimations (shown in columns (3) and (4) of Table 4). Finally, regarding the estimates for the growth-control variables *hcj* and *dhcj*, coefficients remain positive and statistically significant as theoretically expected, but the magnitude of the coefficients is smaller compared to the non-spatial estimations. For instance, according to the DSD-error model, a one unit increase in the *hcj* variable has a 3.2% impact on IC flows, much lower than the 7.6% impact suggested by the non-spatial Heckit model.

In summary, results of estimations that take into consideration spatial dependence still suggest that UGC stimulate greater IC flows, although estimated effects are smaller compared to results from non-spatial estimations.

4 Concluding remarks

This work attempts to empirically analyze how the adoption of urban growth controls (UGC), a policy that has become widespread in fast growing areas, has affected intercity commuting (IC) of workers. To do so, a gravity model of IC flows between California places in 1990 is estimated with a measure of UGC included as one of the explanatory variables. Because of the large proportion of zero-valued IC observations, the two-step Heckman selection method is used (a count data method is also employed alternatively). Moreover, spatial dependence in IC flows is taken into account.

Regardless of the estimation method used in this work, results indicate greater IC flows to places with stricter residential controls, supporting the hypothesis that UGC induce jobs-housing mismatches. A possible implication of this result is that UGC make overall commuting longer and therefore more costly. This does not necessarily imply that there is inefficient commuting because controls are originally adopted by local governments to improve communities and in the long-run households and firms should try to move around to adjust to UGC. However, distortions from longer commuting (e.g., more congestion on intercity roads and increased overall pollution and loss of worker productivity) are likely to be socially inefficient because UGC are typically imposed by local jurisdictions without considering the location of workers and firms in nearby places, thus restricting residential development where it might be socially optimal in the regional point of view. Market oriented policies like development fees are often proposed as better alternatives to UGC, but when UGC adoption is unavoidable it should regard the effects on commuting patterns and on workers and firms in neighboring communities.

For future research, updated data on land use regulations in California might allow to explore changes in the effects of UGC on commuting since 1990 (as people and firms relocate over time and in face of increasing housing demand). Local governments might also be interested in knowing which commuting areas have been more affected by UGC (this would require to look at smaller geographical units like census track or traffic analysis zones). Also, studying individual commuting data might allow one to figure out whether commuting patterns of different groups of people have been affected differently by UGC.

Appendix: Other control variables

As explained in Section 3, besides distance, labor force, job availability, and a variable related to UGC, additional explanatory variables are included in the estimations of IC flows. The additional variables are measures of unemployment (*unemployrt*), population ethnicity (*minoritypc*), age distribution (*age25pc* and *age45pc*), median household income (*income*), homeownership rate (*homeownerpc*), marriage rate (*marriedpc*), gender (*femalepc*), college education rate (*bapc*), occupation of resident workers (*manufpc* and *tradepc*), and land area (*area*). Two dummy variables were also included: one for IC flows with origin and destination in the same county (*D_county*) and another for flows destined to job-centers (*D_jobcenterj*). For exact definitions of these variables and descriptive statistics, refer to Tables 2 and 3. Expected and estimated effects of those variables are discussed next (estimated parameters are not presented here due to space constraint, but are available upon request). In the following discussion, the suffix *i* refers to the residence place while *j* refers to the work place.

First, unemployment rate is included to capture the difficulty in finding jobs. Hence, *unemployrti* should have a positive impact on IC flows while *unemployrtj* should have a negative impact holding everything else constant. Estimation results, however, indicate that the latter has no impact on the intensity of IC flows, although it positively affects the probability that IC occurs (recall, from Section 3, that for this reason *unemployrtj* is used as the exclusion restriction in the Heckit estimations).

Demographic characteristics should also be relevant because workers differ in their willingness to commute longer distances. First, workers belonging to minority groups tend to cluster in residency due to housing discrimination (see Cutler, Glaeser, and Vigdor, 1999, for a study of the formation of ghettos) or preferences (see Gonzales, 1998, for a study of Mexican neighborhoods). Thus, job-housing mismatches should be more likely for these workers.[16] On the other hand, if minority workers are clustered and poor, they may not be able to afford commuting to other places (this is the spatial mismatch hypothesis; see Gobillon, Selod, and Zenou, 2007, for a recent review of the literature). In fact, estimations indicate that both *minorityi* and *minorityj* negatively affect IC.

Clustering based on income is also common (for instance, poorer households cannot afford better neighborhoods, thus becoming trapped in bad areas). Accordingly, IC flows should be greater between places with high *incomei* and *incomej*. Estimation results confirm this prediction.

Matching job and housing locations should be particularly difficult for married workers and homeowners. Married workers are constrained by the locational needs of the spouse. For homeowners, home ownership implies high moving costs, preventing them from moving close to work as they change jobs.[17] Indeed, results confirm that *marriedpc* and *homeownerpc* (for both the origin and the destination places) positively impact IC flows.

On the other hand, lower mobility of workers in certain age groups should negatively affect IC flows. Older workers are more likely to be professionally established (with less frequent job changes and thus residing closer to work). Moreover, workers with children should prefer to commute less far due to greater need to be closely available during the day. Younger workers should also work closer to home because their skills are not specialized, they do not earn much to afford longer commuting, and many of them might be part-time students (with high opportunity cost of commuting time). Therefore, IC flows should be smaller between places with larger *age25pci*, *age25pcj*, *age45pci*, and *age45pcj*, which is confirmed by the results.

Female workers might also prefer shorter journeys because of their greater household responsibilities (Lee and McDonald, 2003, present a literature review and an empirical assessment on this hypothesis). Hence, *femalepci* and *femalepcj* should have negative estimated coefficients. Results, however, indicate that *femalepcj* has a positive effect, although not always significant. One possibility is that a larger proportion of female workers in a place must be complemented by male workers from other cities because women are not always perfect substitutes for male workers.

Educated workers should also want to avoid IC due to high marginal opportunity cost of commuting time. On the other hand, they might be clustered for services that better satisfy their needs (school quality for their children, for instance), implying longer commuting. Education also indicates specialized skill, implying that educated workers might need to commute more to find jobs that match their skills. Estimations indicate that IC flows are larger from places with greater *bapci* and to places with smaller *bapcj*, although estimates for the latter were not always statistically significant. These results suggest that educated workers commute more often between cities, with places that have fewer of such workers demanding more of them from outside.

Effects are harder to predict for the explanatory variables related to job occupation. Large proportion of workers in the same sector could imply that there are activities in these sectors nearby, although it might be in neighboring places. Because the two activities that employ the largest proportions of workers are trade and manufacture, the proportions of resident workers in these sectors are included in the estimations. Results indicate that IC flows are smaller when the residence and work places have large proportion of manufacture workers (*manufpc*), suggesting that workers in this sector live closer to where they work than workers in other sectors. However, in the case of trade workers, flows are greater from places with high proportion (high *tradepci*) or to places with low proportion (low *tradepcj*). A possible explanation is that trade activities exist in most places, but not exclusively, thus requiring that trade workers need to find job elsewhere if there is a surplus, commuting to places where trade workers are scarcer.

The geographical variables added have more predictable effects. Land area is included as a proxy for density of workers and jobs. Greater area (lower density) should make it harder for jobs-housing matches to occur, inducing greater IC flows. In fact, both *areai* and *areaj* have positive and significant coefficients. Last, the effects captured by the two geographical dummies are obvious. Flows between places in the same county are likely to be greater due to better transportation and greater economic integration, while large availability of jobs or high jobs-to-workers ratio should increase flows to such places. In fact, both *D_county* and *D_jobcenterj* have large positive estimated coefficients.[18]

In summary, results for the additional control variables do not contradict economic intuition, thus supporting the empirical model adopted.

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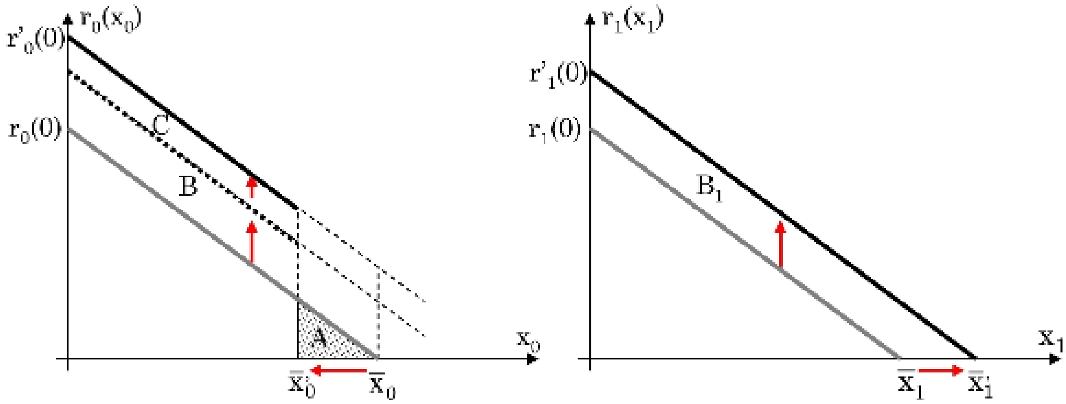
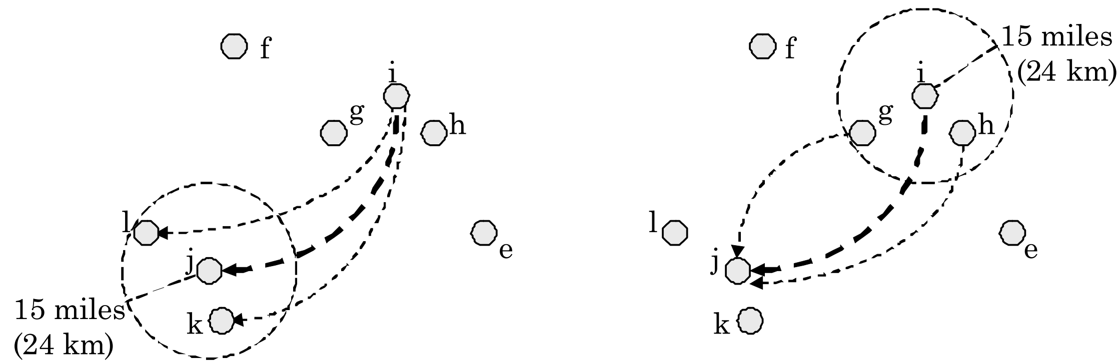
Figure 1: Change in land rents due to growth controls



(a) city 0' land rent curve (b) city 1' land rent curve

Figure 2: Spatial patterns of autocorrelation



(a) destination-based spatial dependence (DSD)

(b) origin-based spatial dependence (OSD)

Table 1: Growth controls and percentage of jurisdictions adopting

Type of measure	Percentage[a]
Restriction on the number of residential building permits	11.17
Housing infrastructure requirements for new residential development	29.32
Urban limit line beyond which development is not permitted	14.80

[a] Proportions refer to the 358 jurisdictions in the sample that provided information through the growth-control survey. The sum is not 100 % because some jurisdictions did not adopt measures, while others adopted more than one type of measures.

Table 2: Description of Variables

Variable	Description[a]
ICij	number of workers commuting from place *i* to the work place *j*, from CTPP
hc	index of intensity of residential growth controls, 1988
dhc	dummy variable, value 1 if $hc>0$
distanceij	distance between geographical centers of residence *i* and work place *j*
laborforce	labor force, in thousand workers
jobs	employees, in thousand workers, based on CTPP data
unemployrt	total labor force 16 years and over, percent unemployed
minoritypc	population by origin, percent non-Hispanic black or Hispanic
age25pc	population by age, percent under 25 years
age45pc	population by age, percent 45 years and over
marriedpc	persons 18 years and over, percent married
homeownerpc	housing units, percent owner-occupied
femalepc	civilian labor force, percent female
bapc	persons 25 years and over, percent with bachelor's degree or higher
income	median household income
tradepc	labor force, percent working in trade industry
manufpc	labor force, percent working in manufacture industry
area	land area in square kilometers (1 square km ≈ 0.39 square mile)
D_county	dummy variable, value 1 if residence place *i* is in the same county of work place *j*
D_jobcenter	dummy variable, value 1 if $jobs>50$ or $\frac{jobs}{laborforce}>1.5$

[a]Observations are for 1990 and refer to the residence place, unless otherwise noticed.

Table 3: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Minimum	Maximum
ICij	445556	14.3	275.2	0	45321
hc	358	0.6	0.8	0	3
dhc	358	0.4	0.5	0	1
distanceij	445556	223.6	152.6	0.6	789.8
laborforce	668	18338.7	71790.1	423	1622423
jobs	668	18278.4	82555.5	1	1831531
unemployrt	668	7.0	4.5	0.4	33.9
minoritypc	668	27.6	24.0	2.4	98.5
age25pc	668	36.8	8.5	7.7	82.4
age45pc	668	29.9	9.8	0.9	80.7
marriedpc	668	56.0	10.3	10.5	88.3
homeownerpc	668	58.1	16.1	0.7	93.8
femalepc	668	43.2	3.8	11.7	51.4
income	668	37897.1	16008.5	14215	130734
bapc	668	21.7	15.4	0.7	90.9
tradepc	668	21.1	3.7	7.6	39.3
manufpc	668	14.9	7.7	1.6	41.7
area	668	31.2	70.5	1.1	1215.6
D_county	445556	0.1	0.2	0	1
D_jobcenter	668	0.1	0.3	0	1

Table 4: Estimation results: OLS, Heckit, and ZINB

Dependent variable: *lnICij*[a]

Explanatory Variable[b]	OLS (1)	OLS (2)	Heckit (3)	Heckit (4)	ZINB (5)	ZINB (6)
hcj	0.082 ***		0.076 ***		0.137 ***	
	(0.009)		(0.009)		(0.017)	
dhcj		0.070 ***		0.067 ***		0.173 ***
		(0.014)		(0.013)		(0.034)
lndistanceij	-1.627 ***	-1.623 ***	-2.259 ***	-2.258 ***	-1.453 ***	-1.451 ***
	(0.012)	(0.012)	(0.017)	(0.017)	(0.051)	(0.049)
lnlaborforcei	0.435 ***	0.435 ***	0.616 ***	0.617 ***	0.412 ***	0.411 ***
	(0.014)	(0.014)	(0.013)	(0.013)	(0.019)	(0.019)
lnjobsj	0.667 ***	0.673 ***	0.910 ***	0.916 ***	0.671 ***	0.676 ***
	(0.016)	(0.016)	(0.015)	(0.015)	(0.019)	(0.019)
$\hat{\lambda}$			1.007 ***	1.011 ***		
			(0.021)	(0.021)		
Obs	20635	20635	238786	238786	238786	238786
Nonzero obs	20635	20635	20635	20635	20635	20635
R^2	0.68	0.68	0.72	0.72		
F-stat	1018.2 ***	1014.07 ***	1782.09 ***	1773.58 ***		
Wald chi^2					21860.3 ***	21979.7 ***
ln(α)					-0.268 ***	-0.264 ***
					(0.051)	(0.050)

[a] The dependent variable in ZINB estimations is *ICij*. The interpretation of the effects of the covariates is, however, the same for all three methods.

[b] Other control variables were also included in the estimations. See Appendix.

Robust White standard errors are reported in parentheses.

***, **, and * indicate 1, 5, and 10% significance levels respectively.

Table 5: Diagnostics for spatial dependence

Statistics for second-step Heckit estimations

Dependent variable: *lnICij*

	DSD				OSD			
	(hcj)		(dhcj)		(hcj)		(dhcj)	
Moran's I score	0.274		0.275		0.270		0.271	
Moran's I z-value	69.9	***	70.3	***	76.5	***	76.9	***
LM-lag	1494.1	***	1499.4	***	2619.6	***	2630.1	***
Robust LM-lag	54.1	***	51.3	***	234.7	***	230.9	***
LM-error	4837.1	***	4899.2	***	5787.5	***	5841.0	***
Robust LM-error	3397.0	***	3451.2	***	3402.6	***	3441.8	***

DSD: destination spatial dependence

OSD: origin spatial dependence

LM test statistics are distributed as χ^2 with one degree of freedom.

***, **, and * indicate 1, 5, and 10% significance levels respectively.

Table 6: Estimation results: spatial models

Results for second-step Heckit estimations

Dependent variable: *lnICij*

Explanatory	DSD-Lag		DSD-Error		OSD-Lag		OSD-Error	
Variables[a]	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
hcj	0.071***		0.032***		0.070***		0.049***	
	(0.008)		(0.008)		(0.008)		(0.017)	
dhcj		0.063***		0.023**		0.070***		0.051*
		(0.012)		(0.011)		(0.012)		(0.026)
lndistanceij	-2.063***	-2.062***	-2.162***	-2.161***	-1.945***	-1.943***	-2.048***	-2.047***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)
lnlaborforcei	0.551***	0.551***	0.575***	0.575***	0.650***	0.651***	0.766***	0.767***
	(0.012)	(0.012)	(0.018)	(0.018)	(0.011)	(0.011)	(0.011)	(0.011)
lnjobsj	0.904***	0.910***	0.949***	0.952***	0.764***	0.769***	0.775***	0.779***
	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.027)	(0.027)
$\hat{\lambda}$	1.071***	1.075***	0.915***	0.916***	1.064***	1.068***	0.848***	0.849***
	(0.018)	(0.018)	(0.017)	(0.017)	(0.017)	(0.017)	(0.018)	(0.018)
Wy	0.201***	0.201***			0.295***	0.296***		
	(0.005)	(0.005)			(0.006)	(0.006)		
Wu			0.546***	0.547***			0.651***	0.653***
			(0.008)	(0.008)			(0.007)	(0.007)
Obs	20635	20635	20635	20635	20635	20635	20635	20635
R^2	0.74	0.74	0.78	0.78	0.75	0.75	0.79	0.79
Log likelihood	-24774.9	-24791.1	-23699.2	-23703.4	-24328.6	-24343.0	-23383.1	-23384.3
Akaike	49613.7	49646.2	47460.4	47468.9	48721.1	48750.0	46828.2	46830.7
Schwarz	49867.6	49900.2	47706.4	47714.9	48975.0	49003.9	47074.2	47076.7
LR test	1414.5***	1419.1***	3565.8***	3594.5***	2307.1***	2315.4***	4198.0***	4232.7***

DSD: destination spatial dependence

OSD: origin spatial dependence

[a] Other control variables were also included in the estimations. See Appendix.

Standard errors are reported in parentheses.

***, **, and * indicate 1, 5, and 10% significance levels respectively.

Notes

[1] Excessive commuting has been discussed before in a different context by Hamilton (1982, 1989), White (1988), Cropper and Gordon (1991), Small and Song (1992), and others. Their studies generally find that commuting costs are not minimized when considering actual employment and residential locations or locations assumed in the monocentric city model. However, these works cannot answer whether commuting patterns are optimal because locations chosen by workers and firms are not only based on employment. The adoption of UGC might be one of the other factors that determine location choices, thus leading to longer commuting patterns.

[2] This setting keeps the analysis simple, restricted to the case of a monocentric city with identical individuals.

[3] An extension with resident landowners shows that the effects of UGC on IC are similar compared to the absentee landowners case (see Ogura, 2005).

[4] In practice, UGC has been advocated for other reasons, but since land rents offset utility advantages across locations, maximization of land rents implies that the total pre-rent utility advantage obtained by local residents is maximized.

[5] Ogura (2005) extends the model by considering the case where landowners and firm-owners share political power. Because labor supply restriction reduces profits, the optimal population size tends to be greater, but the way UGC affects IC is analogous compared to the basic model.

[6] Symmetric population allocation is also the social optimum because total surplus in this economy equals production minus commuting costs, which are both optimized at the symmetric allocation.

[7] Note that the wage differential stops increasing because everybody in the nearby city has the same IC cost (*tD*). If this cost was heterogeneous, the wage advantage would have to keep increasing to attract additional workers.

[8] Ogura's (2005) model goes further and shows that, when IC happens in equilibrium, the optimal strictness of UGC decreases with distance (i.e., $d\bar{x}_0^* / dD > 0$). This happens as greater distance implies higher IC cost, which are incorporated into land rents in the controlled place because the equilibrium wage advantage is determined by the IC cost. Higher land rents everywhere in the city implies greater marginal rent losses from tighter UGC and, therefore, less incentive for stricter controls. Hence, $d(\hat{N}_0 - \bar{x}_0^*) / dD < 0$, i.e., the equilibrium IC flow decreases with distance when UGC are adopted.

[9] This version is called the "unconstrained" gravity model. In the regional science and urban transportation literatures on commuting flows the "doubly-constrained" specification is more commonly used instead (see, for instance, Batten and Boyce, 1986). The doubly-constrained model includes constraints that force the aggregate flow from each origin to equal the number of workers commuting from there and the aggregate flow to each destination to equal the number of workers commuting to that place. While this constrained specification should generally produce

better statistical fit and forecast ability, the statistical methodology required is more complex. Because the purpose of this work is to simply test the significance of the effects of growth controls on IC flows, the simpler unconstrained specification is used (this also facilitates the use of alternative econometric methods to address other problems). In the context of population migration estimation, the unconstrained specification is used, for instance, by LeSage and Pace (2005) and Ashby (2007). In the trade literature, the use of the unconstrained model is still standard.

[10] While the data might seem outdated, this is the only publicly available source that has a comprehensive coverage of UGC measures adopted by jurisdictions in a large area. Other surveys are restricted to smaller areas or to regulations adopted during a restricted period. For instance, the study by the Pioneer Institute for Public Policy Research and Rappaport Institute for Greater Boston (2005) is restricted to places in eastern Massachusetts and the 1998 survey conducted by the California Department of Housing and Community Development (2000) is restricted to regulations adopted between 1995 and July 1998 in California.

[11] Measures calculated in analogous ways were used by Brueckner (1998) to study strategic adoption of UGC by jurisdictions and by Levine (1999) to examine the displacement of housing production.

[12] The values for *jobs* and *D_jobcenter* are underestimated if places received workers from other states. This problem arises because *jobs* was computed based on intrastate place-to-place commuting flows reported in the 1990 CTPP for the state of California. The extent of the impact of this limitation on estimation results is likely to be small, however, because counties bordering other states had only 10.79% of the state population in 1990).

[13] For the variable *jobs*, there are few observations with zero values, which were replaced by 1 to avoid losing these observations in the log transformation process.

[14] Further discussion on the Heckman selection model and on the need for a selection restriction are found in any modern econometric textbook. For instance, see Wooldridge (2006, pp. 618-620).

[15] Spatial dependence in the first-step (selection model) of the Heckit estimation method are difficult to take into consideration because estimation of spatial Probit models are cumbersome with current statistical programs available.

[16] This effect is suggested by White (1988) in the study of excessive commuting.

[17] Hamilton (1982) suggests these effects in his study of excessive commuting by workers.

[18] An anonymous referee noticed that it might be redundant to include *D_county* in the estimations because distance (included through the variable *lndistanceij*) should better capture labor market integration. *D_county* is kept in the final estimations because it exhibits strong statistical significance and its exclusion does not change the qualitative results (as expected, the size of the coefficient of *lndistanceij* is slightly reduced when *D_county* is included; results for estimations without *D_county* are available upon request).