A commuting-based spatial metric for local jurisdictions

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Abstract

Using a revealed-preferences argument with regard to households and their choice of a place of residence, the paper suggests to construct proximity weights for local jurisdictions from commuting patterns. The new metric captures the degree of substitutability of local jurisdictions from the point of view of a representative household and can be used to account for cross-sectional dependence in Tiebout-like settings with many jurisdictions. An application to U.S. cities and townships shows that the commuting-based metric accounts for the physical distance between jurisdictions as well as other conditions like the distribution of population centers and economic activity. Using the spillover effect of local police spending as an example, it is shown that the new metric leads to significantly higher estimates of the spillover compared to contiguity-based weights.

Keywords: Commuting patterns; Spatial weights; Police expenditures

JEL Classification: C21, H72, H77

1 Introduction

Econometric studies dealing with cross-sectional dependence require assumptions about appropriate spatial structures or metrics (Anselin, 1988, 1999, 2002). Such metrics are usually derived from functions of economic or geographic distance. Since they have to be imposed a priori and may or may not correspond to the true cross-sectional dependence among units, such metrics are commonly seen as critical components in empirical work.

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In local public finance and urban economics, models involving cross-sectional dependence have been frequently used in recent years. In a typical framework like tax or expenditure competition involving \( N \) local jurisdictions, the researcher would hypothesize about a relation between the choice of the variable of interest in some jurisdiction \( i \) and the corresponding choices of other jurisdictions, \( j \neq i \). The problem is then to define a spatial metric, specifying which of the \( N - 1 \) ‘other’ jurisdictions should be treated as a ‘neighbors’ of \( i \). The common approach is to define a composite neighbor as a weighted average of all other jurisdictions. Unfortunately, no consensus has evolved so far on how to choose the weights to determine this average, resulting in countless different metrics being used.

Dealing with cross-sectional dependence among unobservables, Conley (1999) points to the fact that sometimes the nature of the application suggests at least a certain type of metric.\(^1\) However, when it comes to the estimation of models with cross-sectional dependence among choice variables, it seems that most researchers agree that constructing proximity weights based on the jurisdictions’ geographical location, like the physical distance between them or contiguity, is generally acceptable, while using other characteristics and selecting the most similar jurisdictions as ‘neighbors’ is considered problematic. For instance, Baicker (2005) criticizes Case et al. (1993), one of the earliest contributions on the spillover effects of state spending, for using a metric based on the difference in the percentage of the population that is black. She argues that a characteristic like the percent of the population that is black is likely to be correlated with omitted variables in a state spending equation. Because in the standard procedures to estimate models of cross-sectional policy interdependence the weights are being used to construct instruments for neighbors’ policies, correlation between the weights and unobservables leads to an endogeneity issue that cannot be resolved easily. In contrast, the great circle distance or indicators for contiguity are variables which are arguably exogenous in most applications.

However, using physical distance to define spatial metrics may also come at a cost. Most

\(^1\)Among the many examples of studies motivating the choice of a metric from the nature of the application, see Case (1991) and Rincke (2006).
importantly, it selects neighbors without taking into account the fact that economic and social characteristics may well play an important role in shaping the true set of reference jurisdictions. If the choice of a spatial metric is essentially an issue of choosing a specification for an estimable equation, ignoring economic determinants and defining purely geography-based weights might lead to problems of miss-specification.

This paper suggests a strategy to overcome the ad-hoc choice of a spatial metric for applications involving a Tiebout-like economy of local jurisdictions. Taking a more structural approach to the problem, the idea is to derive a metric that captures the degree of substitutability of jurisdictions as places of residence from the point of view of a representative household. The key innovation of the approach is that it is assumption-free with respect to the characteristics making jurisdictions ‘similar’ to one another. Instead, the new metric is based on a revealed-preferences argument and derives a measure for the substitutability of jurisdictions from a comparison of local commuting patterns. This is motivated by the simple fact that, taking the workplace as given, households reveal their most preferred jurisdiction by choosing a place of residence. Therefore, the pattern of commuting originating from two arbitrarily selected jurisdictions contains information on the degree of substitutability of these jurisdictions as places of residence from the point of view of the average commuter-household. To give an example, if two communities within the Boston metropolitan area have all their residents commuting to Boston downtown, we can think of these communities as places of residence being perfectly specialized to serve households working in Boston downtown. This pattern of specialization suggests that for the average commuter-household living in either of the communities, the other community can be considered a close substitute. In contrast, if the commuting patterns of two communities are very different, the average commuter-household living in either of them will not consider the other community as an alternative place of residence. Hence, comparing commuting patterns and assigning large weights to communities with similar patterns effectively means to select neighbors of local jurisdictions which can be thought of being engaged in competition for the same set of residents.

Since commuting is essentially a local phenomenon, the approach accounts for the physical distance between jurisdictions without being burdened by assumptions on how exactly
distance should be used to define sets of reference jurisdictions. Furthermore, though related to the practice of using bilateral flows of factors of production or goods to determine the degree of ‘neighborliness’ of a given pair of jurisdictions (e.g., see Baicker 2005), the suggested approach is based on the comparison of the patterns of commuting flows going to all other jurisdictions. When measuring the relatedness of two jurisdictions, the new metric is thus comprehensive in the sense that it takes into account the position of both jurisdictions relative to all other jurisdictions.

Formalizing the idea that, conditional on the location of the workplace, the commuting behavior reveals the most preferred jurisdiction for each household, I suggest a simple procedure to determine the degree of similarity of commuting patterns originating from an arbitrarily selected pair of jurisdictions. The procedure provides us with a commuting-based distance measure, which in turn can be used to derive commuting-based proximity weights. If appropriately standardized, these weights can be employed in many applications dealing with policy interdependence among local jurisdictions such as cities, municipalities, counties, and school districts.

To show how the suggested procedure works in practice, I demonstrate the computation of commuting-based proximity weights for the sample of 559 cities and townships in Connecticut, Massachusetts, and Rhode Island. A brief descriptive analysis reveals that the comparison of commuting patterns gives proximity weights accounting for geographical distance as well as the spatial distribution of population centers and economic activity in a natural and flexible way. In particular, the commuting-based metric tends to assign high weights to contiguous municipalities. I then proceed to an empirical application focused on comparing the predictive power of the commuting-based proximity weights to that of a purely contiguity-based metric in a model of local policy interdependence. Using local police expenditures as an example, I show that the expenditure competition effect is much stronger if commuting-based weights are employed. Moreover, in a model that allows for competition between municipalities both in terms of contiguous neighbors as well as communities with similar commuting patterns, the commuting-based effect accounts for more than 62% of the overall competition effect.
The remainder of the paper is organized as follows. The next section presents the concept of commuting-based proximity weights. In Section 3, the approach is applied to real data, and the performance of the new metric in an estimation of local police expenditures is discussed. Finally, Section 4 offers some concluding remarks and suggestions how to use the concept in empirical work using country instead of local data.

2 The concept: A commuting-based spatial metric for local jurisdictions

2.1 A metric based on actual commuting flows

Consider a setting with a large number of local jurisdictions and a population of households, each consuming one unit of housing. Treating the household’s workplace as fixed, we can think of households choosing a jurisdiction to buy or rent housing, taking into account the local pattern of house prices (or rent levels), taxes, amenities, and commuting costs.

The idea of the new approach is to derive a proximity measure that exploits the information conveyed in the choices of households on the housing market and captures the degree of substitutability of communities as places of residence. In practical terms, we want to measure, for all pairs of communities, the degree of similarity of the pattern of outbound commuting. This is motivated by the fact that all households reveal their most preferred community by choosing a place of residence. Effectively, we can think of the jurisdictions as specializing to serve households associated to a particular set of workplaces. If two communities specialize in a similar way, i.e. if they end up with sets of resident households with similar commuting behavior, these communities can be thought of as being close substitutes from the point of view of the ‘average’ household living in either of them. To give an example, many municipalities in Fairfield county located at the southwestern edge of Connecticut share the common characteristic that a significant share of resident households commutes to New York City. The commuting-based metric would account for this common pattern of specialization and assign weights reflecting a
high degree of substitutability of the respective municipalities from the point of view of the average household residing in either of them. Many municipalities located farther to the east of Fairfield county share a more diversified pattern of outbound commuting, with significant shares of resident households commuting to a number of local centers of economic activity like Bridgeport and New Haven. Again, our metric would measure the degree of substitutability based on the similarity of these patterns.

The mechanics of the new metric are straightforward. For an economy of jurisdictions indexed by \( i = 1, \ldots, N \), let us denote the pattern of commuting originating from \( i \) as an \( N \times 1 \) vector, \( C_i \), with the \( j \)th element, \( c_{ij} \), being the number of commuters living in \( i \) and working in \( j \). The distance \( \delta_{ij} \) between two jurisdictions \( i \) and \( j \) in terms of the similarity of their commuting patterns is derived as

\[
\delta_{ij} = \frac{1}{2} \sum_{k \neq i,j}^N \left| \frac{c_{ik}}{\sum_{m \neq i,j}^N c_{im}} - \frac{c_{jk}}{\sum_{m \neq i,j}^N c_{jm}} \right|,
\]

where \( c_{ik}/\sum_{m \neq i,j}^N c_{im} \) is the share of commuters residing in \( i \) and working in \( k \) among all commuters living in \( i \) and working in some place \( m \neq i, j \). By taking the difference with the respective share for community \( j \) and adding up the differences in absolute values across all \( N - 2 \) communities (potentially) receiving commuters from \( i \) and \( j \), we end up with a measure taking values (after multiplication with the scale factor \( 1/2 \)) between a minimum of zero, indicating identical shares of commuters going to all places \( k \neq i, j \), and a maximum of one, indicating that there is no place \( k \neq i, j \) receiving commuters from both \( i \) and \( j \).

To get an intuition for how the computation of commuting-based distance works, consider the four-jurisdiction example displayed in Figure 1.

[Figure 1 about here]

The stylized map shows the pattern of commuting between all four communities. For ease of exposition, let each arrow represent a flow of one commuter, and assume that flows within communities are equal to zero. Communities \( A \) and \( B \) both send one commuter
to C as well as D, making the pattern of commuting originating from these communities to all other communities perfectly identical. Consequently, we have $\delta_{AB} = \delta_{BA} = 0$. As an example for the other extreme, C sends one commuter to A but no commuter to B, while the pattern for D is exactly the opposite. Consequently, we obtain $\delta_{CD} = \delta_{DC} = 1$.

Once we have obtained a matrix of commuting-based distances, it is straightforward to transform them into proximity weights. In the application to be discussed in the following, we will use a weight scheme given by

$$w_{ij}(\delta_{i1}, \ldots, \delta_{iN}) = \begin{cases} e^{-\delta_{ij}(1-\delta_{ij})} & \text{if } i \neq j \\ \sum_{k \neq i} e^{-\delta_{ik}(1-\delta_{ik})} & \text{if } i = j \end{cases},$$

where $\sum_{k \neq i} e^{-\delta_{ik}(1-\delta_{ik})}$ is just a scale factor that standardizes the weights such that $\sum_j w_{ij} = 1 \forall i$. Note that $\partial w_{ij} / \partial \delta_{ij} < 0$, i.e. the more different the commuting patterns between communities, the lower the corresponding proximity weights.

### 2.2 A metric based on imputed commuting flows

In many applications, a concern regarding the use of commuting-based proximity weights could arise from the potential endogeneity of the households’ choice of a place of residence. In the example discussed below, the variable of interest is local police spending. If households make their choice on the housing market taking into account the behavior of local governments in terms of police spending, this would result in the variable of interest, i.e. police spending, being determined simultaneously with commuting-based spatial weights. This would burden the estimation of a police expenditure equation accounting for the spending of ‘neighbors’ defined by a commuting-based metric with a severe endogeneity problem.

To address this issue, I suggest a simple procedure that removes the potentially endogenous components from the observed commuting flows before deriving the spatial weights. The idea is to impute place-to-place commuting flows from arguably exogenous variables like community size and distance, and to use the imputed flows instead of actual flows to derive the weights. Hence, the procedure follows the logic of a two-stage estimation
procedure that uses fitted values from a first-stage regression instead of actual values of an endogenous explanatory variable.

The alternative proximity weights are derived as follows. In a first step, we impute place-to-place commuting flows from a simple gravity model. A straightforward way to do this is to use non-linear least squares to estimate the parameters of the gravity model

\[ c_{ij} = \frac{\mu \text{pop}_i \theta \text{jobs}_j}{d_{ij}^\phi}, \]  

(3)

where \( \text{pop}_i \) gives the total population in \( i \), \( \text{jobs}_j \) denotes the number of jobs in community \( j \) and \( d_{ij} \) gives the physical distance between \( i \) and \( j \). Using the estimated values for the parameters \( \mu, \theta, \phi, \) and \( \varphi \), we compute fitted values for the commuting flows. In the second step, we use these fitted values to derive commuting-based proximity weights along the same lines as for the metric using the actual flows.

3 An application to cities and townships in the U.S.

In the following, we apply the concept of commuting-based proximity weights to the population of cities and townships in three U.S. states, namely Connecticut, Massachusetts, and Rhode Island. In a first step, we derive commuting-based proximity weights for all pairs of municipalities. In a second step, we use the different weights in a standard application of local public finance requiring such weights, namely the estimation of expenditure reaction functions, with local expenditures for police being the variable of interest. We compare the outcome of the spatial estimation procedure with the outcome using proximity weights based on the contiguity or common-border criterion.

3.1 Deriving commuting-based proximity

To derive the commuting based proximity weights for the 559 cities and townships in Connecticut, Massachusetts, and Rhode Island we take the information on place-to-place commuting flows at the level of Minor Civil Divisions from the 2000 Census. Since we have selected only three states for our application, we consider not just the flows between
the 559 communities covered, but also commuting originating from cities and townships in these states to municipalities in the remaining states. The reason is that our approach is based on the comparison of flows to all potential workplaces. Since, for instance, a considerable number of households living in Connecticut commutes to New York City, it is important to account for these flows when computing the proximity weights for all pairs of municipalities in our sample.

To facilitate the computation of the proximity weights, we set $\delta_{ij} = 1$ if the great-circle distance between communities $i$ and $j$ is greater than 30 kilometers.\(^2\) Since the bulk of commuting takes place locally, this truncation essentially helps to avoid very small proximity weights in cases where $\delta_{ij}$ is very close to one, and instead assigns the value zero as the truncated weight.\(^3\)

Table 1 provides some descriptive statistics on the new metric. The first four rows display the average share of the largest, three largest, five and ten largest weights in the overall weight sum of one. The remaining rows show the average great circle distance to the community with the largest, third largest, fifth and 10th largest weight.

[Table 1 about here]

The largest weight is 0.079 on average, whereas the 10 largest weights together add up to 0.530. Hence, on average the 10 communities with the largest weights account for 53% of the total sum of weights. More importantly, we note that the approach has the somewhat remarkable feature to account for the physical distance between municipalities without requiring information about this distance in any way. As the numbers show, the largest weight is assigned to a municipality with an average great-circle distance of only

\(^2\)Note that this does not mean that we ignore commuting between places which are more than 30 kilometers apart.

\(^3\)Without the truncation, $\delta_{ij}$ tends to take values slightly smaller than one even for municipalities which are hundreds of kilometers apart and, therefore, have very different patterns of outbound commuting. The reason is that the Census workflow data report some metropolitan areas like Boston or New York City attracting commuters from almost all municipalities in the region. For instance, municipalities like Greenwich, Stamford and Norwalk, located in Fairfield county at the southwestern edge of Connecticut about 250 kilometers from Boston, all have small numbers of individuals reporting a workplace in Boston. Without the truncation, our approach would have the unpleasant feature of yielding distances strictly smaller than one between such municipalities and all other communities with outbound-commuting to Boston.
8.4 kilometers. The distance to the community carrying the third largest weight is 11.3 kilometers, and the 10th largest weight is assigned to a municipality in a distance of 17.0 kilometers on average. Hence, the commuting-based proximity weights effectively define geographically close communities as reference jurisdictions. However, compared to the standard procedure to assign weights based on a contiguity or common-border criterion, the structural approach to compare actual commuting patterns across jurisdictions is much more flexible and takes into account a broad range of geographical conditions as well as the spacial distribution of population centers and economic activity.

To see how the assignment of proximity weights works in practice, we have selected two municipalities in Connecticut. Figure 2 shows two maps indicating the range of neighboring jurisdictions’ commuting-based proximity weights for Stratford (left) and Oxford (right). First of all, both maps confirm that our approach to evaluate place-to-place commuting flows assigns the highest weights to geographically close communities. However, we also note remarkable differences between the resulting patterns. The pattern of weights for Stratford comes close to one generated by some inverse function of distance alone. In particular, all four contiguous districts carry weights larger than 0.08. In contrast, the pattern for Oxford is skewed to the south, with five out of eight contiguous municipalities carrying relatively small weights in the range [0.02, 0.04] and only two contiguous communities with weights larger than 0.06. Apparently, the skewed pattern of weights for Oxford is due to the fact that the local economic activity is concentrated in places at the shore like Bridgeport and New Haven. The closer municipalities are located to the Bridgeport and New Haven labor markets, the more dominant is commuting to these municipalities. Effectively, this makes the commuting pattern of Oxford more similar to those of its immediate southern neighbors than to the patterns of municipalities to the north.

[Figure 2 about here]

Taken together, the descriptive analysis shows that the commuting-based metric takes into account the physical distance between jurisdictions in a flexible way. However, the metric also reflects other factors like the spacial distribution of population centers and
general economic activity.

3.2 Commuting-based proximity vs. contiguity in estimating expenditure reaction functions

3.2.1 Model and data

Let us think of a population of local jurisdictions having some autonomy to collect local tax revenue (such as from taxing property) and to provide local public goods (such as policing). The objective of local governments is to ascertain the wants of their residents for public goods and to tax them accordingly. In equilibrium, every community will have achieved its optimal size in terms of the number of households or residents for which local public services can be produced at the lowest average cost. As noted by Tiebout (1956), if the number of jurisdictions is large, in such an equilibrium households in most communities will find that there is a set of jurisdictions offering a pattern that makes the respective places close substitutes to the household’s actual place of residence.

Of course, exogenous shocks like changes in input prices or technology will affect the optimal amount of public goods provided by local governments as well as the optimal community size. To motivate the following empirical example, suppose that municipality $A$ manages to increase its overall efficiency, enabling it to provide more public services while keeping taxes constant. This will make $A$ more attractive relative to other places offering patterns which are close substitutes, eventually leaving these places with a sub-optimal community size. To prevent households from moving to $A$, these close-substitute municipalities can be hypothesized to try to make up for the improved efficiency of public goods provision in $A$. On the other hand, the efficiency improvement in $A$ will have little effect on jurisdictions offering a pattern that is no close substitute for $A$’s own pattern.

In the following, we will consider police spending of the cities and townships in the sample discussed above. For related work on spillover effects of local police spending, see Kelejian and Robinson (1993).
provided by the local governments under consideration here. The expenditure equation that we are going to estimate takes account of the notion that police spending in reference municipalities might affect a municipality’s own spending and reads

\[ y_i = \alpha + \beta y_{-i} + x_i \gamma + u_i, \]  

(4)

where \( y_i \) is municipality \( i \)'s level of police spending per capita, \( y_{-i} = \sum_j w_{ij} y_j \) is the same for \( i \)'s reference communities, \( x_i \) is a vector of community characteristics describing residents’ wants for public safety as well as the ability of the local government to pay for this kind of service, and \( u_i \) is a residual.

The parameters of Equation (4) are estimated using the spatial two-stage least square (2SLS) procedure suggested by Kelejian and Prucha (1998). It takes into account the endogeneity of \( y_{-i} \) by instrumental variables constructed as spatial lags of the exogenous characteristics \( x_i \) as well as spatial error correlation of the form

\[ u_i = \rho \sum_j w_{ij} u_j + e_i, \]  

(5)

where \( e_i \) is an i.i.d. residual. The estimation has three steps. After an initial 2SLS estimation ignoring spatial error correlation, a GMM procedure is used to estimate \( \rho \) from the residuals of the initial estimation. The estimated \( \rho \) is then used to perform a Cochrane-Orcutt type transformation of the estimation equation, removing spatial correlation from the residuals. Finally, the transformed equation is estimated by 2SLS.

Table 2 displays descriptive statistics on our data. Local police spending amounts to $121 per capita on average (in prices of 2000) and shows considerable variation across municipalities. Among the control variables, we use the percentage of young and elderly residents, income per capita, and the property crime rate to capture variation in the local demand for policing, with positive coefficients expected for all three variables. To account for differences in the ability to spend on local public goods, we also include total tax revenues per capita.

[Table 2 about here]
3.2.2 Results

In all estimations reported below, we use the spatial lags of population, the percentage of young, and the percentage of elderly residents as instruments for neighbors’ police spending. Since the crime rate is directly affected by policing, we have to define a set of suitable instruments for this explanatory variable, too. In the estimations reported below, we use the percentage of the population above age 15 separated or divorced as well as the percentage of the population below the poverty level as instrumental variables for the property crime rate, hypothesizing that both variables capture socially disruptive forces which can serve as exogenous predictors of the crime rate. Using these instruments, we impose the identifying assumption that local police spending depends on the crime rate but is unrelated to the socially disruptive forces captured by the instruments.

Table 3 reports the results of estimations using three different schemes of proximity weights. Column (1) displays an estimation where police spending of reference jurisdictions has been determined by using commuting-based proximity weights. The results point to a strong fiscal competition effect, with an increase of police spending among reference jurisdictions by one dollar triggering an increase of own spending by 65 cents. Furthermore, we find larger communities and municipalities with a higher share of elderly residents spending more on police per capita. Finally, as expected the estimation also indicates that a higher crime rate drives up police spending. The performance of the instruments seems to be satisfactory: the set of instruments passes the Hansen test of overidentifying restrictions, and the values of Shea’s partial $R^2$ point to a substantial predictive power of the excluded instruments in the first-stage regressions.\(^5\)

[Table 3 about here]

As mentioned above, using commuting-based proximity weights in an application of fiscal competition among local jurisdictions could give rise to an endogeneity problem with respect to the spatial weights. As suggested above, we solve this problem by computing fitted values for the place-to-place commuting flows and using the fitted values instead

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\(^{5}\)Both the Hansen test and the Shea’s partial $R^2$ are taken from the third step of the estimation procedure.
of the actual flows to derive the commuting-based metric. In a first step, using the total of 311,922 observations for place-to-place flows with $i \neq j$, we thus estimate the gravity model displayed as Equation (3) by non-linear least squares.\(^6\) Using the estimated values for the parameters $\hat{\beta}_i$, we can compute fitted values for commuting flows according to
\[
\hat{c}_{ij} = 0.006 \frac{\text{pop}_i^{0.58} + \text{jobs}_j^{0.75}}{d_{ij}^{0.07}}.
\] (6)

The estimates of all four parameters of the gravity models are significant at the 1% level, and with an $R^2$ of 0.73 the estimation has a reasonable overall fit. We then make use of the imputed flows to derive commuting-based weights as described before.

Column (2) reports the outcomes of our estimation procedure for local police spending using the adjusted metric. With only minor changes in the estimated coefficients, the results confirm the findings obtained before. We conclude that in the present application, a potential endogeneity of our original proximity weights is of no practical importance for the estimation of the determinants of local police spending.

Provided that the most often used criterion to derive proximity weights for local jurisdictions is contiguity, we also want to compare the estimation outcomes using commuting-based weights to the outcomes obtained with a contiguity-based metric. In Column (3), we have assembled results for our police expenditure estimation using contiguity-based weights assigning uniform weights to all contiguous neighboring jurisdictions and zero weight to all non-contiguous communities, again using the restriction $\sum_j w_{ij} = 1 \ \forall \ i$. Interestingly, the coefficient of reference municipalities’ police spending is now estimated to be 0.412, about 37% lower compared to the estimate in Column (1) and more than 41% lower compared to Column (2).

Of course, the fact that the estimate for the fiscal policy competition effect is stronger once we use commuting-based proximity weights does not indicate that this metric is more appropriate compared to a ‘traditional’ metric based on contiguity. Rather, the choice of a spatial metric in an application as the one presented here should be viewed as an assumption on the specification of the estimation equation. Our main finding

\(^6\)Note that we computed the number of jobs from the Census workflow data as the sum of all inbound flows of commuters plus the number of resident workers.
therefore comes down to the following: assuming that the degree of substitutability of communities as places of residence is a reasonable way of defining reference jurisdictions for the provision of local public goods, and assuming that our commuting-based proximity weights properly capture this degree of substitutability for the average household, we find much stronger expenditure spillover effects compared to a specification assuming contiguous communities forming the set of reference jurisdictions of local decision makers.

To further explore the relative power of the different weight schemes, we follow Baicker (2005) and estimate a model that includes two variables capturing the per-capita spending of neighbors, where the first one uses commuting-based \((y^\text{Com}_i)\) and the second employs contiguity based weights \((y^\text{Con}_i)\),

\[
y_i = \alpha + \beta^\text{Com} y^\text{Com}_i - \beta^\text{Con} y^\text{Con}_i + x_i \gamma + u_i. \tag{7}
\]

To account for the presence of the additional endogenous regressor, the estimation employs as instruments not only the spatial lag of the three demographic explanatory variables derived from the commuting-based metric, but also the spatial lags obtained from multiplying the matrix of contiguity-based weights with the matrix of the demographic variables. In total, we thus have eight instrumental variables for three endogenous regressors.

The results in Table 4 confirm the previous findings regarding the relative size of the estimates for the expenditure competition effect. As shown in Column (1), if the spending of contiguous neighbors is included together with spending of reference municipalities according to actual commuting flows, the former is barely significant at the 10% level. If we divide by the sum of the coefficients, we can interpret the coefficients as weights on the weighting matrices, giving the commuting-based metric a weight of 0.62 and the contiguity-based metric a weight of 0.38. Moreover, if we compute the spending of reference jurisdictions from imputed commuting flows, the spending of contiguous neighbors is no longer significant at conventional levels.

[Table 4 about here]
4 Conclusion

The choice of a spatial metric is critical in many applications involving cross-sectional dependence. Unfortunately, the literature offers little guidance on how to choose an appropriate metric. For applications in a Tiebout-like setting of local jurisdictions with households selecting a jurisdiction as a place of residence, the paper suggests a metric based on a comparison of commuting patterns. Essentially, it assigns weights according to the degree of substitutability of communities as places of residence. The new metric accounts for geographical distance as well as the spatial distribution of population centers and economic activity in a natural and flexible way. In addition, it is less burdened with specific assumptions on how physical distance has to be incorporated and what community characteristics should to be considered to determine the degree of similarity of jurisdictions.

While the idea to compare commuting patterns to derive proximity weights is limited to local jurisdictions such as cities, municipalities, counties, and school districts, the underlying principle can be applied quite generally. In studies of growth or international trade, for instance, one could use the patterns of international trade flows to derive spatial metrics. Such metrics could either be used to investigate issues like convergence, or one could use them to account for cross-sectional dependence in unobservables along the lines discussed by Conley (1999). Similarly, empirical work related to a wide range of issues from international tax and expenditure competition to cross-country correlation in the choice of regulatory regimes could benefit from an evaluation of trade patterns or foreign direct investment to determine countries which are likely to be points of reference for policy makers and other agents on the national stage.

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References


Each arrow in the stylized map represents a flow of one commuter. Flows within communities are assumed to be zero. The elements of the distance matrix $\delta$ have been computed from Equation (1).

Map on the left hand side shows pattern of commuting-based proximity weights for Stratford, whereas the map on right hand side displays the corresponding pattern for Oxford.
### Table 1: Descriptives for commuting-based spatial metric

<table>
<thead>
<tr>
<th>Characteristic of commuting-based spatial metric</th>
<th>Mean</th>
<th>St. Dev.</th>
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</thead>
<tbody>
<tr>
<td>Largest weight</td>
<td>0.079</td>
<td>0.049</td>
</tr>
<tr>
<td>Sum of three largest weights</td>
<td>0.211</td>
<td>0.110</td>
</tr>
<tr>
<td>Sum of five largest weights</td>
<td>0.322</td>
<td>0.149</td>
</tr>
<tr>
<td>Sum of 10 largest weights</td>
<td>0.530</td>
<td>0.180</td>
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<tr>
<td>Distance to community with largest weight</td>
<td>8.38</td>
<td>3.62</td>
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<tr>
<td>Distance to community with third largest weight</td>
<td>11.3</td>
<td>4.76</td>
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<tr>
<td>Distance to community with fifth largest weight</td>
<td>13.1</td>
<td>5.15</td>
</tr>
<tr>
<td>Distance to community with 10th largest weight</td>
<td>17.0</td>
<td>5.97</td>
</tr>
</tbody>
</table>

Sample consists of cities and townships in Connecticut, Massachusetts, and Rhode Island (N=559). Sources: Data on place-to-place commuting are from the U.S. Census Bureau (MCD/County-To-MCD/County Worker Flow Files). Distance has been computed using longitude and latitude of jurisdictions’ centroids.

### Table 2: Descriptive statistics for dependent and explanatory variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>St. Dev.</th>
<th>Min</th>
<th>Max</th>
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</thead>
<tbody>
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<td>Police spending</td>
<td>121</td>
<td>73.1</td>
<td>0.642</td>
<td>644</td>
</tr>
<tr>
<td>Spending of reference municipalities</td>
<td>122</td>
<td>47.1</td>
<td>37.9</td>
<td>382</td>
</tr>
<tr>
<td>Population (× 1,000)</td>
<td>19.3</td>
<td>33.5</td>
<td>0.055</td>
<td>589</td>
</tr>
<tr>
<td>% population &lt; 18 years</td>
<td>24.6</td>
<td>3.59</td>
<td>8.10</td>
<td>33.7</td>
</tr>
<tr>
<td>% population &gt; 65 years</td>
<td>13.4</td>
<td>4.11</td>
<td>3.44</td>
<td>36.0</td>
</tr>
<tr>
<td>Income per capita</td>
<td>29066</td>
<td>9942</td>
<td>11188</td>
<td>84806</td>
</tr>
<tr>
<td>Tax revenue per capita</td>
<td>1545</td>
<td>657</td>
<td>330</td>
<td>5912</td>
</tr>
<tr>
<td>Property crime rate (crimes reported per 1,000 residents)</td>
<td>20.4</td>
<td>18.5</td>
<td>1.54</td>
<td>222</td>
</tr>
<tr>
<td>% population &gt; 15 years separated or divorced</td>
<td>10.0</td>
<td>2.69</td>
<td>3.83</td>
<td>20.6</td>
</tr>
<tr>
<td>% population below poverty level</td>
<td>5.76</td>
<td>4.37</td>
<td>0.666</td>
<td>30.6</td>
</tr>
</tbody>
</table>

Table 3: Impact of reference municipalities’ police spending on own spending

<table>
<thead>
<tr>
<th>Weights based on</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>actual commuting flows</td>
<td>imputed commuting flows</td>
<td>contiguity</td>
</tr>
<tr>
<td>Spending of reference municipalities, $y_{-i}$</td>
<td>0.653*** (0.161)</td>
<td>0.701*** (0.129)</td>
<td>0.412*** (0.100)</td>
</tr>
<tr>
<td>Population</td>
<td>0.433*** (0.083)</td>
<td>0.444*** (0.081)</td>
<td>0.501*** (0.078)</td>
</tr>
<tr>
<td>% population &lt; 18 years</td>
<td>1.07 (0.897)</td>
<td>1.02 (0.868)</td>
<td>1.59* (0.874)</td>
</tr>
<tr>
<td>% population &gt; 65 years</td>
<td>2.43*** (0.777)</td>
<td>1.89** (0.750)</td>
<td>2.36*** (0.731)</td>
</tr>
<tr>
<td>Income per capita</td>
<td>0.0002 (0.0004)</td>
<td>0.00009 (0.0004)</td>
<td>-0.00007 (0.0004)</td>
</tr>
<tr>
<td>Tax revenue per capita</td>
<td>0.007 (0.006)</td>
<td>0.011* (0.006)</td>
<td>0.017*** (0.006)</td>
</tr>
<tr>
<td>Property crime rate</td>
<td>1.74*** (0.361)</td>
<td>1.48*** (0.358)</td>
<td>1.31*** (0.356)</td>
</tr>
<tr>
<td>Hansen test ($p$-value)</td>
<td>0.201</td>
<td>0.306</td>
<td>0.194</td>
</tr>
<tr>
<td>Shea partial $R^2$ for $y_{-i}$</td>
<td>0.29</td>
<td>0.35</td>
<td>0.24</td>
</tr>
<tr>
<td>Shea partial $R^2$ for crime rate</td>
<td>0.17</td>
<td>0.16</td>
<td>0.15</td>
</tr>
</tbody>
</table>

Sample consists of cities and townships in Connecticut, Massachusetts, and Rhode Island ($N=559$). Estimations account for spatial error correlation. Endogenous explanatory variables: spending of reference municipalities and property crime rate. Excluded instruments: reference municipalities’ population, reference municipalities’ % population < 18 years, reference municipalities’ % population > 65 years, % population > 15 years separated or divorced, % population below poverty level. Standard errors in parentheses. Significance levels: * 10%; ** 5%; *** 1%.

Table 4: Impact of neighbors’ police spending: commuting-based vs. contiguity based weights

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spending of neighbors, weights based on actual commuting flows</td>
<td>0.436** (0.195)</td>
</tr>
<tr>
<td>Spending of neighbors, weights based on imputed commuting flows</td>
<td>-</td>
</tr>
<tr>
<td>Spending of neighbors, weights based on contiguity</td>
<td>0.268* (0.161)</td>
</tr>
<tr>
<td>Hansen test ($p$-value)</td>
<td>0.142</td>
</tr>
<tr>
<td>Shea partial $R^2$ for $y_{Com}$</td>
<td>0.27</td>
</tr>
<tr>
<td>Shea partial $R^2$ for $y_{Con}$</td>
<td>0.25</td>
</tr>
<tr>
<td>Shea partial $R^2$ for crime rate</td>
<td>0.17</td>
</tr>
</tbody>
</table>

Sample consists of cities and townships in Connecticut, Massachusetts, and Rhode Island ($N=559$). Additional regressors (results omitted): See Table 3. Endogenous explanatory variables: spending of neighbors and property crime rate. Excluded instruments: Neighbors’ population, neighbors’ % population < 18 years, neighbors’ % population > 65 years, % population > 15 years separated or divorced, % population below poverty level. Standard errors in parentheses. Significance levels: * 10%; ** 5%; *** 1%.