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ISEE, Lindenwood University

7 March 2011

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March 2011
Revised, June 2012

Abstract

This paper examines the spatial interaction of neighboring cities over their employment cycles. Neighboring cities, which are large and closely integrated cities within the same metro area, tend to have relatively similar employment cycles. However, this is largely because they tend to be in the same state, not because they are neighbors. Depending on differences in size, density, and human capital, neighborness usually means that cities have relatively dissimilar employment cycles. I attribute this result to the tendency for cities within the same metro area to specialize according to function and human capital.

JEL Codes: R10, E32
Keywords: Neighboring cities, employment cycles

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I. Introduction

Just as the national business cycle is often characterized as a sequence of expansion and recession phases, local-level employment growth can be described as a sequence of switches between periods of expansion and contraction—an employment cycle.[1] As shown in Owyang, Piger, and Wall (2010), cities' employment cycles can differ substantially from the national cycle and from each other: During 1990-2008, the employment cycles of a typical pair of large U.S. cities were in the same phase 71 percent of the time, and cities in the same state or region, or with similar levels of human capital, tended to have more-similar cycles.

This paper focuses on the employment cycles of a special type of city—neighboring cities—which are large, economically integrated cities within the same metro area (e.g., Dallas and Fort Worth, Los Angeles and Santa Ana-Anaheim, or Oakland and San Francisco). Figure 1 illustrates the idea of a metro area comprising two overlapping neighbors (cities 1 and 2), as opposed to a metro area with a single agglomeration that attenuates continuously from the center (city 3). It's natural to expect that, because their economies are closely integrated, neighboring cities would have similar employment cycles. Countervailing this notion, however, are models of urban systems, which allow the possibility that the ebbs and flows of the business cycle can be experienced by neighboring cites in very different ways precisely because their economies are closely intertwined.

In the evolutionary hierarchy models of Fujita and Mori (1997) and Fujita, Krugman, and Mori (1999), neighboring cities arise out of a single evolutionary process through which one

[1] Note that, because state and city GDP data are too infrequent for too short a period of time, employment data are used to represent the effects of the business cycle.

agglomeration center becomes two, each serving a different set of functions within the metro-area economy. These cities develop beyond the usual notion of a central city and its suburb into partner cities serving different functions within the metro area. Lucas and Rossi-Hansberg (2002) and Berliant and Wang (2008) also have models in which neighboring cities arise and, unlike earlier models, the neighbors can differ in size.[2]

Just as any two cities' business-cycle experiences might differ because of differences in a variety of factors, so can neighboring cities. But, unlike a typical pair of distant monocentric cities, neighboring cities overlap in space, so their relative business cycle experiences will be more closely related to their spatial interactions. In Duranton and Puga (2005) and Rossi-Hansberg, Sarte, and Owens (2009), the production side this interaction results in the division of the functions of production (management and non-management) between central and non-central regions of a metro area. Thinking more broadly, functions within a metro area can be divided according to process: headquarters and subsidiaries, intermediate- and final-goods production, factory and distribution, etc. Likewise, different types of human capital are used in the various production and distribution processes, and these are endogenously distributed throughout the metro area.

Even with a division of functions, one might expect that neighbors' responses to the business cycle would be very similar given that productive factors, especially labor, are highly mobile between neighbors. On the other hand, the benefits of agglomeration attenuate fairly rapidly with distance (Rosenthal and Strange, 2008), so the spillovers that generate

[2] See Dobkins and Ioannides (2001) for a detailed look at the development of neighboring cities in the United States.

agglomeration might not extend across neighbors. Likewise, the rapid attenuation of the effects of agglomeration can, to some extent, insulate one neighbor from the effects of macroeconomic events in the other. Therefore, with a tendency for specialization within a metro area, the timing and intensity of economic downturns can differ a great between the central city and its neighbor, even if the cities share the same industries and firms. For example, if layoffs tend to hit intermediate producers and distribution centers first, and these functions tend to be located outside the central city, then the effects of a downturn will differ between the two neighbors. Similarly, the central city and its neighbor will be affected differently if the downturn hits low-human-capital labor earlier or harder and this type of labor is more prevalent one of the two cities. What makes a pair of neighboring cities different from a monocentric city is that the latter contains all of the functions and human capital that are split between the two neighbors. Because of this, the employment cycles of the neighboring cities could differ a great deal from each other while being relatively similar to the employment cycle of some other, monocentric city.

One can think of metro divisions within a metropolitan statistical area (MSA) as statistical delineations of neighboring cities. Metro divisions, which are determined statistically according to their levels of employment interchange, are distinct cities, each large enough to have its own agglomerative center.[3] Taking this definition at face value, my data set consists of quarterly payroll employment for 60 cities, 25 of which are metro divisions within 10 MSAs,

[3] According to the General Accounting Office (GAO-04-758), the combination of two or more adjacent metro division occurs when the employment interchange measure is at least 25. This measure is the sum of the percentages of residents the metro divisions who work in the other metro division. For employment interchange between 15 and 25, local opinion can be used to determine that two metro divisions are in the same MSA. Dobkins and Ioannides (2001), for example, found the growth rates of neighboring cities to be interdependent.

with the remainder being MSAs without metro divisions.[4] Figure 2 illustrates some of the variety of neighbors in my data set. Each of the metro areas has one city that is larger than its neighbor(s), but the differences in size and density across metro areas can be significant. In addition, state borders can either separate metro areas from each other, or divide metro divisions within a metro area. In principle, it would be desirable to disaggregate metro areas even further using more-granular data to yield even more metro-area subcenters, as in McMillen and Smith (2003). Unfortunately, the methodology that I use to determine the expansion and contraction phases—Markov-Switching—is difficult to implement for smaller areas (Owyang, Piger, Wall, Wheeler, 2008).

This paper is a contribution to the urban systems literature in that its purpose is to determine the links, if any, between the employment cycles of neighboring cities. Because of its methodology and attention to relatively high-frequency data, the paper follows directly from the literature applying the tools of empirical macroeconomics to geographically disaggregated data.[5] To a large extent, this literature exists as separate from the rest of urban/regional economics in that it has tended to look at the myriad high-frequency time-series differences across geographic entities within the U.S. rather than addressing traditional urban questions: The word "agglomeration" appears only rarely.[6] The present paper departs from these roots by focusing on

[4] I did not consider the four metro divisions of the Boston-Cambridge-Quincy MSA separately because the smallness of three of them make it difficult to apply the Markov-switching model that I used to determine employment cycles.

[5] Notable papers in this literature include, but are not limited to, Carlino and Mills (1993); Carlino and DeFina (1995, 1998, 1999, 2004); Clark (1998); Carlino and Sill (2001); Del Negro (2002); Partridge and Rickman (2002, 2005); Owyang, Piger, and Wall (2008); Owyang, Rapach, and Wall (2009); and Hamilton and Owyang (forthcoming).

[6] This literature does, however, share the general outlook of the urban system literature which sees the overall economy as a grouping of interrelated subnational economies (Abdel-Rahman and Anas, 2005).

the spatial and agglomerative links between cities, offering a new perspective on the organization of cities and the links between them.

II. City Employment Cycles

To determine each city's pattern of expansion and contraction, I apply the Markov-switching model of Hamilton (1989) to city-level payroll-employment data. The estimation procedure is a straightforward application of Kim and Nelson (1999), the details of which are outlined in Owyang, Piger, and Wall (2005). In this model, an employment cycle is assumed to have two phases—expansion and contraction—which the city economy switches between infrequently. Each phase has its own structure and, therefore, its own growth rate.[7] Deviations from the two growth rates are treated as noise. Put simply, the model compares a city's actual employment growth rate to its two phase growth rates and determines the probability that the city's employment is in contraction. Persistence matters in that the probability of being in contraction depends on the previous period's growth rate. By convention, a period is determined to be contractionary if the estimated probability of contraction exceeds 0.5.

The metro divisions' employment cycles are summarized by Table 1, which lists the cities in order of their MSA and metro division identification numbers. Note that, because the estimation uses growth rates, 1990:1 is excluded. Quarters for which the cities are in contraction are denoted with a "■" and expansionary quarters are blank. Periods of national employment contraction are indicated by a shaded background. As should be clear from the table, there is a

[7] Owyang, Piger, Wall, and Wheeler (2008) find that expansion growth rates are related to some of the usual variables used in growth regressions, but that these variables are not related to contraction growth rates.

strong tendency for any city to be in contraction around the same time as the country as a whole, indicating the occurrence of common macroeconomic events. Nonetheless, a city's cycle can differ a great deal from that of other cities and the country as a whole: (i) Some cities did not experience employment contraction at all during periods of national contractions; (ii) City-level contractions need not be in synch with each other; and (iii) Cities can experience idiosyncratic contractions when nearly all other cities are in expansion.

As shown elsewhere for a larger set of cities, there is a broad geographic pattern to the occurrence of city employment contractions (Owyang, Piger, and Wall, 2010). My present focus, however, is on the narrow patterns between neighboring cities. Specifically, an examination of Table 1 reveals that there can be substantial differences in the employment cycles of neighboring cities, although some neighbors are closely related. For example, Dallas-Plano-Irving and Fort Worth-Arlington are very much in synch; whereas Washington-Arlington-Alexandria and Bethesda-Frederick-Gaithersburg have relatively little in common; and one would not guess that Chicago-Naperville-Joliet, Gary, and Lake County-Kenosha are all in the same metro area.

To measure the extent to which two city employment cycles are in synch, I use their concordance, that is, the percentage of time the two cycles are in the same phase (Harding and Pagan, 2002). The concordance between the employment cycles of cities *i* and *j* is

$$C_{ij} = \frac{100}{T}\sum_{t=1}^{T}\left[S_{it}S_{jt} + \left(1-S_{it}\right)\left(1-S_{jt}\right)\right], \tag{1}$$

where S_{it} and S_{jt} equal 1 when city *i* or *j* is in contraction, and zero otherwise. *T* is the number of time periods. Applying this to the occurrence of employment contractions summarized by Table

1 yields measures of concordance for each of the 1770 city pairs. The remainder of the paper examines these concordances, with particular focus on the concordances between cities within the same metro area. Tables 2-4 summarize important differences in the concordances between neighbors and non-neighbors according to their geographic designations, industrial structures, size and density, and human capital.

As reported in Table 2, the mean concordance across all 1770 city pairs is 73.6, meaning that, on average, two cities were in the same phase of the employment cycle 73.6 percent of the time. Pairs of contiguous cities in the same metro area tended to be in synch more often than this, 81.1 percent of the time, so, arithmetically, the employment cycles of neighboring cities were more closely related than average. By comparing the two columns of Table 3, one can see a strong tendency for cities to be more in synch with their neighbors than with the entire set of cities, although four cities—Chicago-Naperville-Joliet, Miami-Miami-Beach-Kendall, Washington-Arlington-Alexandria, and Bethesda-Frederick-Gaithersburg—were more in synch with their non-neighbors than with their neighbors. Note also the large difference in the cities' mean concordances with other cities: Five had mean concordances lower than 70 and five had mean concordances of 80 or higher. The range of concordances between neighbors was also wide: Dallas and Fort Worth were in the synch 94.4 percent of the time, whereas Washington and Bethesda were in synch only 61.1 percent of the time and were much more in synch with other cities than with each other.

III. Geographic Designations

The first step is to distinguish between the effect of simple adjacency and the effect of neighborness, which is a special type of adjacency. Clearly we need to differentiate neighbors, which lie in the same metro area, from pairs of cities in different metro areas that merely abut where there is little activity (e.g., Santa Ana-Anaheim and San Diego, Austin and San Antonio, or Buffalo and Rochester). It is also necessary to account for the fact that neighboring cities tend to be in the same state and region.

As reported in Table 2, the mean concordance of city pairs whose principal cities lie in the same state is nearly as high as for neighboring cities: 81.1 versus 80.7. Further, some city pairs have a secondary state link in that one city's outer counties are in the same state as the principal city and/or outlying counties of the other. Because the mean concordance for these city pairs is also above average (77.4), there is some evidence that this secondary link might matter. It's beyond the present scope, but an obvious possibility for state effects to matter is that differences in state-level policies affect the timing and the length of employment cycles, thereby accounting for at least some of the above-average intra-metro concordance. Such policies might include corporate and personal income tax rates, unemployment insurance benefits, sales taxes, banking regulation, minimum wage, etc.

To control for the geographic designations discussed above, I estimate three versions of the following:

$$\ln C_{ij} = \alpha + \sum_{k=1}^{60} \alpha_k + \sigma A_{ij} + \beta N_{ij} + \boldsymbol{\gamma}' \mathbf{X_{ij}} + \varepsilon_{ij}, \tag{2}$$

where the α_ks are city dummies that are equal to 1 for $k = i$ or j, A_{ij} is a dummy variable that equals 1 if i and j are adjacent (whether or not they are in the same metro area), and N_{ij} equals 1 if i and j are adjacent and in the same metro area. The coefficient on N_{ij} is the direct effect of neighborness as separate from simple adjacency. Equation (2) also includes $\mathbf{X_{ij}}$, which is a vector of dummies indicating whether i and j have their principal cities in the same state, have outlying counties in the same state as the principal city or outlying counties of the other, have principal cities in the same Census division, or whether they are both the principal metro division in their metro areas.[8]

Results for the estimations of (2) are provided in Table 5. The first set of results, Model A, is determined under the assumption that neighborness is no different from adjacency and that there are no state and regional effects. This estimation yields a statistically significant effect for adjacency. Specifically, simple adjacency tends to add 13.8 points to a city-pair's concordance $[100 \times (e^{\hat{\sigma}} - 1)]$. Because the economies of neighboring cities are strongly intertwined, one might expect that they would tend to be more in synch with each other than would two cities that are simply adjacent. This is not the case, however, when neighborness is treated separately from adjacency, as in Model B: the effect of adjacency becomes even larger and the effect of neighborness is statistically no different from zero.

This result does not account for the possibility of state and regional effects, which were found by Owyang, Piger and Wall (2010) to be important. Nor does it account for the possible relationship across the principal cities of metro areas, harkening back to Christaller' s (1933)

[8] The principal metro division is the one that is first in the MSA's list of major cities.

central place theory. To differing degrees, every metro area has one main city atop the local hierarchy that serves as something like a central place. As discussed in the introduction, the fact that neighbors tend to develop into such a hierarchy suggests a separation of roles and functions within a metro area. The larger city, for example, might include headquarters and offices while the smaller city contains space-intensive activities such as production and transport. Under such a separation of roles and functions within a metro area, there would be a tendency for neighbors to have disparate employment cycles. Further, across metro areas, cities in the same tier of the urban hierarchy would tend to have similar employment cycles. There is certainly evidence of this as the average concordance between the principal cities in each metro area is 78.5, which is five points higher than the average concordance between non-principal cities. Further, neighbors are more distinct in size and density from each other than are non-neighbors: the average difference in the number of establishments between neighbors was 95.2 thousand, whereas the average difference between non-neighbors was 45.3 thousand; and the average difference in the number of establishments per square mile was 41 for neighbors and 24 for non-neighbors.

To control for the urban hierarchy, I remove the restriction on $\boldsymbol{\gamma}$ to obtain Model C, for which the effect of adjacency is statistically insignificant. Instead, the influence of adjacency on concordance is now picked up by the effect of cities being in the same state and by the position of cities in their local hierarchy. Being in the same state tends to account for 13.5 concordance point, while the concordance of two cities atop their urban hierarchy tends to be 3.4 points higher than for other pairs of cities.

IV. Agglomeration

The estimation in the previous section used the principal-cities dummy to account for the urban hierarchy and found that neighboring cities will differ because one of them serves as the central place within the metro area. Because there is a lot of heterogeneity across pairs of neighbors in terms of their relative sizes and densities, however, the principal-city dummy is probably too blunt to capture the full importance of functional specialization. While there is a tendency for neighboring cities to look like those in theoretical models—the principal city being larger and denser than its partner—this doesn't capture the variety across metro divisions. This point is illustrated by Figure 3, which plots the proportional differences in density and size for the neighbors in my data set. The neighbors that best fit the Christaller notion of urban hierarchy are New York/Newark, New York/Edison, Chicago/Gary, and Philadelphia/Wilmington. At the other extreme are San Francisco/Oakland, which are relatively twin-like, and Detroit/Warren and Los Angeles/Santa Ana-Anaheim, where the larger city is the less-dense city.

To capture the diversity of agglomeration between neighbors, I replace the principal-city dummy with measures of size and density to estimate

$$\ln C_{ij} = \alpha + \sum_{k=1}^{60} \alpha_k + \sigma A_{ij} + \beta N_{ij} + \boldsymbol{\gamma}'\mathbf{X_{ij}} + \boldsymbol{\omega}'\mathbf{S_{ij}} + \boldsymbol{\delta}'\left(N_{ij}\mathbf{S_{ij}}\right) + \varepsilon_{ij}, \tag{3}$$

where $\mathbf{S_{ij}}$ is a vector of variables measuring the extent to which i and j are similarly agglomerated. To differentiate the importance of agglomeration for neighbors from that of non-neighbors, the agglomeration vector is also interacted with the N_{ij} dummy. Similarity in agglomeration is measured by $\log(1 - |s_i - s_j|/(s_i+s_j))$, where s_i are the s_j are the sizes (number of establishments) or densities (establishments per square mile) of i and j.[9] As reported below, there is little difference in my results if size and density are calculated using employment rather than the number of establishments.[10] Table 6 provides the estimation results for four versions of (3): Model D assumes that there is no separate agglomeration relationship for neighbors and Model E does not impose this restriction. Both of these models measure size and density using the number of establishments. Models F and G use employment instead.

According to the results for Model D, any two cities, whether they are neighbors or not, will have a higher concordance if they are more similar in either size or density. The positive sign on size similarity might be because size is an indicator of the diversity of functions within a city: similarly diverse cities will have similar employment cycles. Also, if density is an indicator of the types of functions that a city performs, then cities of similar density might be expected to have similar employment cycles.

Model E is more intriguing in that it shows that the relationship between concordance and agglomeration for neighbors is very different than for non-neighbors: the coefficients on size and density are much larger and, for density, has the opposite sign. Consider a metro area with a large, dense principal city and a small, spread out secondary city. The difference in their densities indicates the extent to which they serve different functions within the metro area, such as headquarters and production. The less similar their densities, the greater the segregation according to function, and the more the cities are intertwined. At the extreme, the very dense

[9] The number of establishments is the average over 2000-2005 and is from the Census Bureau's *State and Metropolitan Area Data Book* as of February 4, 2009. Area is from the same source and is in square miles.
[10] Unfortunately, because it is not available for metro divisions, I was unable to use the area data from Saiz (2010).

city has the headquarters of all of the metro area's firms while the spread out city has all of their production. So, to a much greater extent than non-neighbors, the employment cycles for neighboring cities are more similar to one another the less-similar they are in density.

Size works in the opposite direction, perhaps because of firms for which density and, therefore, functional separation, are not particularly important. Some of these firms, which might include banks or insurance companies, don't have separate production facilities and might be found in both cities, with all of their functions in the same city. Similar-sized cities have similar numbers of these types of firms and will, therefore, have similar employment cycles.

The effects of neighbors' agglomeration on concordance are quantified for all neighbor pairs in the penultimate section. Note that the results do not depend on which measure of size and density is used. I have chosen to use the number of establishments, but as shown by Models F and G, I obtain very similar result using employment instead.

V. Industrial Structure and Human Capital

There is a large literature examining and explaining differences across sectors in the severity of business-cycle fluctuations (Stock and Watson, 1999), so one might expect that cities with similar industries would have similar employment cycles. Coulson (1993) and Clark (1998), for example, demonstrate how employment fluctuations can be decomposed into national, subnational, and industry shocks. Coupling this with the observation that neighboring cities tend to be more sectorally similar than are other pairs of cities (see Table 4), we might expect that this industry effect be more important for neighboring cities. This was not found by

Owyang, Piger, and Wall (2010), but they did not focus on the role that industrial similarity might play between neighboring cities.

To estimate the importance of industry differences, I include a new variable that measures the similarity in industry mix between two cities. Specifically, I use the industry similarity index $I_{ij} = \log(1 - \sum_k | x_{ik} - x_{jk} |)$, where x_{ik} and x_{jk} are the shares of total employment in industry k:[11]

$$\ln C_{ij} = \alpha + \sum_{k=1}^{60} \alpha_k + \sigma A_{ij} + \beta N_{ij} + \boldsymbol{\gamma}'\mathbf{X_{ij}} + \boldsymbol{\omega}'\mathbf{S_{ij}} + \boldsymbol{\delta}'\left(N_{ij}\mathbf{S_{ij}}\right) + \lambda I_{ij} + \theta N_{ij} I_{ij} + \varepsilon_{ij}, \qquad (4)$$

The estimation results for equation (4) are summarized by Table 6. Model H assumes that the relationship between industrial similarity and concordance is the same for neighbors and non-neighbors. Model G allows for a different relationship for neighbors. As expected, the results indicate that similarity in industrial mix is positively related to similarity in employment cycles between any two cities in the sample, including neighbors. It is perhaps surprising, however, that the relationship between neighbors is no different than that between any two cities. One might have expected that two neighbors with more-similar industrial mixes would be more tightly integrated and, therefore, have more-similar employment cycles. It is possible, however, that industrial mix is not sufficient to capture this integration between neighbors, and might even obscure it. This is because a firm might outsource many of its functions (accounting, legal services, maintenance, temporary workers, etc.), so the employees performing these functions are not counted as being employed in the firm's industry.

[11] These shares are averaged over the sample period.

The final category of potential determinants of concordance between neighboring cities is human capital. As reported in Table 4, between-neighbor differences in industrial mix and human capital differ from those between non-neighbors. Neighbors are relatively similar racially but relatively less-similar in educational attainment: The sum of absolute difference in race shares is 21.7 for neighbors and 25 for non-neighbors, and the difference in shares of the population aged 25 and older with at least a high school diploma was 4 percentage points for neighbors and 3.7 percentage points for non-neighbors. When comparing two non-neighboring cities, differences in their racial composition and educational attainment serve as measures of their differences in human capital. These human capital differences might lead to fairly straightforward differences in employment cycles. Between neighboring cities, however, one needs to take account of the ability of workers to commute between the two cities.

Differences in racial composition between neighbors can reflect spatial/racial mismatch. For whatever reason, there is a tendency for metro areas to be divided internally by race and, on a larger scale, for the largest city in a metro area to have a higher concentration of minority groups.[12] Potential employers, however, are spread more evenly across two cities.[13] The greater the spatial/racial mismatch between cities, the more likely it is that members of every racial group will commute between their city of residence and their city of employment. According to spatial/racial mismatch, therefore, the more-similar two neighbors are in their racial composition, the less commuting there will be between the cities, and the less integrated their labor markets

[12] Martin (2004) and Hellerstein, Neumark, and McInerney (2008) provide recent estimates of the extent of spatial/racial mismatch.

[13] This is, admittedly, a very partial-equilibrium explanation and takes the location of employers and residents as given. Because the present concern is with relatively high-frequency events, however, mobility is most likely a secondary concern. See Arnott (1998) for a general equilibrium treatment of spatial mismatch.

will be. In other words, spatial/racial mismatch can mean that neighboring cities that are more similar in their racial compositions will have lower concordance, all else equal.

Just like any two cities, we might expect educational similarity to be related to concordance between neighboring cities because downturns hit the less-educated more sharply.[14] There is a second effect for neighbors, however, because of the relative ease with which people can move residence and/or jobs within a metro area. People will choose which city to live in and might choose to work in the other city. If we think of educational similarity as a measure of the employment substitutability of residents of one city for residents of the other, then neighboring cities that have similar levels of educational attainment will have more-integrated labor markets. Therefore, neighbors' employment cycles will be more similar to one another the more similar the cities' educational attainment.

To control for human capital similarities, I use a racial similarity index that makes use of population racial shares, and an educational similarity index that uses the share of the population aged 25 and older with at least a high school diploma.[15] Each of these variables is included on its own and in interaction with the neighbor dummy. Adding these variables to (4), I estimate

$$\begin{aligned}\ln C_{ij} = \alpha + \sum_{k=1}^{60}\alpha_k + \sigma A_{ij} + \beta N_{ij} + \boldsymbol{\gamma}'\mathbf{X_{ij}} + \boldsymbol{\omega}'\mathbf{S_{ij}} + \boldsymbol{\delta}'\left(N_{ij}\mathbf{S_{ij}}\right) \\ + \lambda I_{\mathbf{ij}} + \theta N_{ij} I_{ij} + \boldsymbol{\kappa}'\mathbf{H_{ij}} + \boldsymbol{\delta}'\left(N_{ij}\mathbf{H_{ij}}\right) + \varepsilon_{ij},\end{aligned} \tag{5}$$

where $\mathbf{H_{ij}}$ is a vector of the two human capital similarity indices. The estimation results for three versions of (5) are presented in Table 8: Model J assumes that the effect of human capital

[14] Hoynes (2000) and Engemann and Wall (2010) show how the effects of recessions are deeper those with less than a high school degree.

[15] Race and education data are for 2006 from the *State and Metropolitan Area Data Book*. For robustness, I included higher levels of educational attainment also, but this did not add anything to the results, possibly because of the levels of educational attainment are highly correlated.

similarities are the same for neighbors and non-neighbors and Model K removes this restriction. Model L is included to demonstrate the role of city effects in the estimation and imposes the restriction on the most-general specification (Model K) that city effects are zero.

As one can see from the results for Model J and K, I find no general relationship across cities between concordance and human capital similarity, although there is a significant relationship for neighboring cities. Specifically, consistent with spatial/racial mismatch, neighboring cities with similar racial mixes have less-similar employment cycles; and, consistent with the notion that educational similarity indicates greater substitutability of labor between neighbors, neighboring cities with similar educational attainment have more-similar employment cycles.

The final estimation, Model L, is a test of the importance of allowing for city-specific effects, which control for the differing tendencies of cities to be in concord with the rest. They capture the links between a city and the rest of the country that might make its relationships over the business cycle differ from the average. New York, for example, might have financial links with other cities that are not captured by the included variables: It is not just the size of its financial sector that matters, but the fact that it is the center of the nation's financial system. Similarly, the experiences of cities like Orlando and Las Vegas might be closely linked to those of every other city if its recreation and entertainment industries are very sensitive to fluctuations everywhere else. As is apparent from the results for Model L, the results depend a great deal on whether or not city effects are included: the coefficients on several variables reverse sign or become statistically insignificant. Finally, a likelihood-ratio test easily rejects the null hypothesis that city-specific effects do not matter for the estimation.

VI. Neighborness Quantified

According to the results of the previous sections, there is no direct effect of neighborness on concordance, although there are effects via agglomeration and human capital. This section quantifies these effects for each of the neighbor pairs, finding that neighborness tends to decrease the concordance of neighbors' employment cycles. Note that the regression results show the effects of similarities between neighbors, but, for expositional purposes, this section quantifies those results in terms of differences between neighbors.

For reference, the proportional differences between neighbors in size and density (the differences divided by the sums) are presented in Table 9A. These are the same data presented earlier in Figure 3. Table 9A also provides the differences in the sums of racial shares and in the percentage with a high school diploma. The effects of these differences on the neighbors' concordances are presented in Table 9B, which also includes each pair's concordance and the total effects of neighborness. Because they are part of the same process, the effects of size and density are combined together to obtain the total effect of agglomeration on concordance.

Recall from Figure 3 that, although there is a tendency for size and density differences between neighbors to go hand in hand, there are significant deviations from this tendency. Also recall from the discussion in section IV that this means that size and density differences, which have opposite effects on concordance, tend to be in tension. All of this is evident from Table 9B in that the effect of agglomeration on neighbors' concordance varies a great deal: Chicago and

Lake County, which are relatively similar in density but very different in size, have a concordance of 66.7, which would be 21.6 points higher if they had the same size and density. At the other end, New York and Newark, which differ a great deal in both size and density, have a concordance of 80.6, which would be 7.7 points lower than if they had the same size and density. More often than not, agglomeration has a negative effect on neighbors' concordance, and the average effect is to reduce it by 3 points.

Racial and educational differences can have very large effects for some neighbors. The biggest differences in neighbors' racial composition are for Detroit/Warren and New York/Nassau-Suffolk. According to the estimates, the concordances for these city pairs are 15.7 and 11.8 points higher, respectively, because of their large differences in race shares. Differences in educational attainment affect the concordance of four city pairs by 10 points or more: For Miami and Fort Lauderdale, the almost 11 point difference in educational attainment is responsible for an almost 18 point lower concordance.

The total effect of neighborness on concordance tends to be negative. That is, being neighbors means that concordance is 4.3 points lower, on average. There are five pairs of neighbors for which neighborness has double-digit negative effects on concordance. The largest of these effects, driven primarily by agglomeration, is 21.2 points for Chicago and Lake County. Although for most pairs of neighbors the effect of neighborness is negative, there are notable exceptions. For example, neighborness means that, largely due to their very different racial compositions, concordance is 11.7 point higher for Detroit and Warren.

VII. Concluding Remarks

On average, the employment cycles of neighboring cities are more similar to one another than are the cycles of non-neighboring cities. Much of this is due to the tendency for neighboring cities to be in the same state. Once this and other effects are controlled for, neighborness makes the employment cycles of the average pair of neighboring cities less similar to one another. There is a good deal of heterogeneity in the effect of neighborness on the concordance of employment cycles, and it depends on differences in agglomeration and human capital. In particular, the more similar neighbors are in density and racial composition, the less similar their employment cycles will be; and the more similar they are in size and educational attainment, the more similar their employment cycles will be. I attribute these results to the tendency for cities within the same metro area to specialize according to function and human capital.

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Figure 1. Neighboring Cities

The height indicates the level of employment, population, etc. at that location

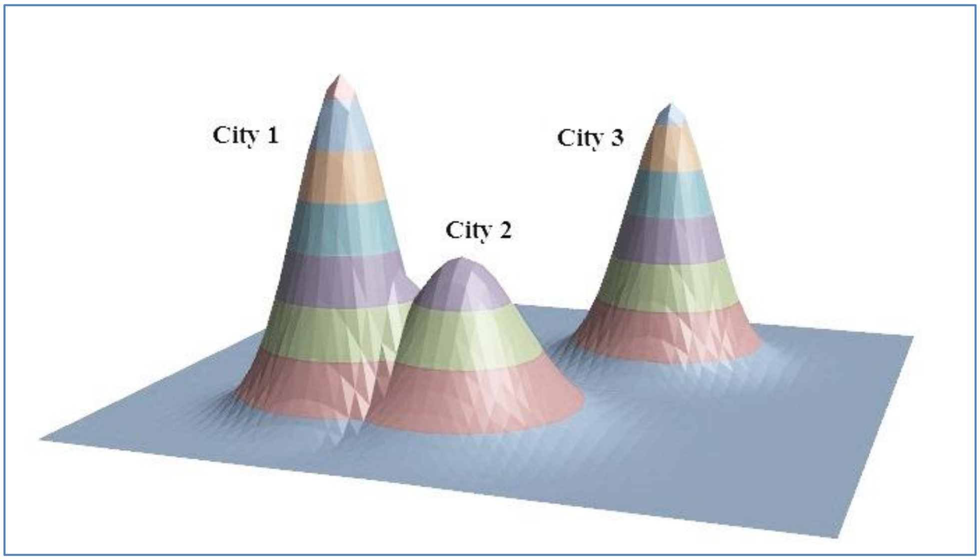


Figure 2. The Variety of Neighboring Cities

The height indicates the level of employment, population, etc. at that location.

The black lines are state borders.

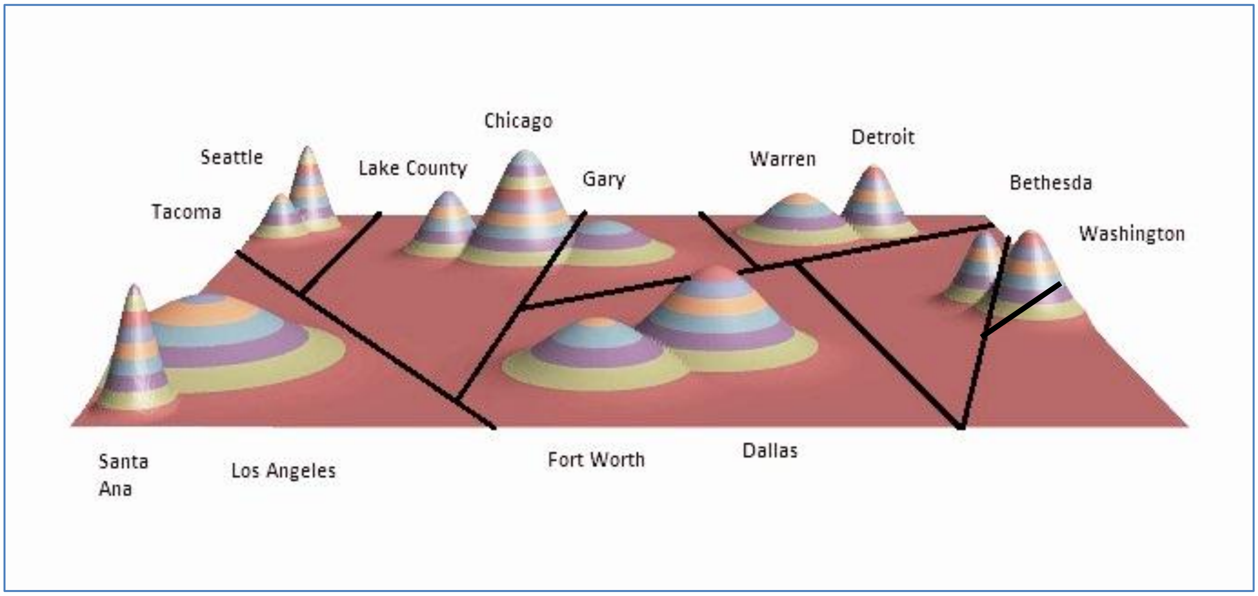


Figure 3. The Variety of Agglomeration Between Neighboring Cities

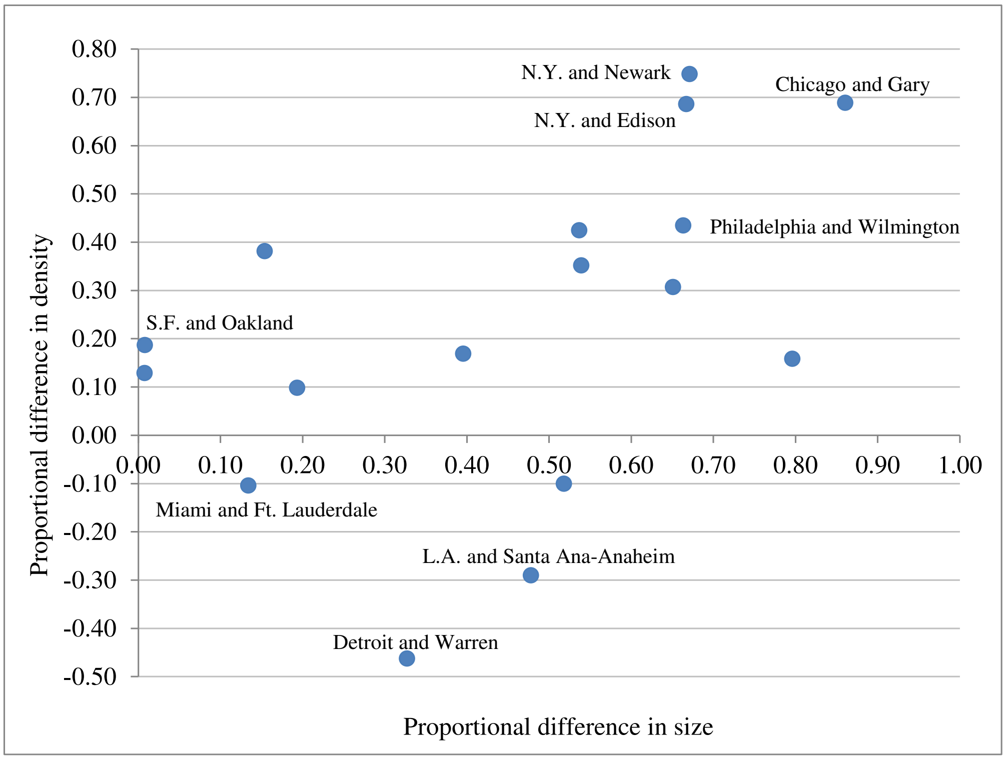
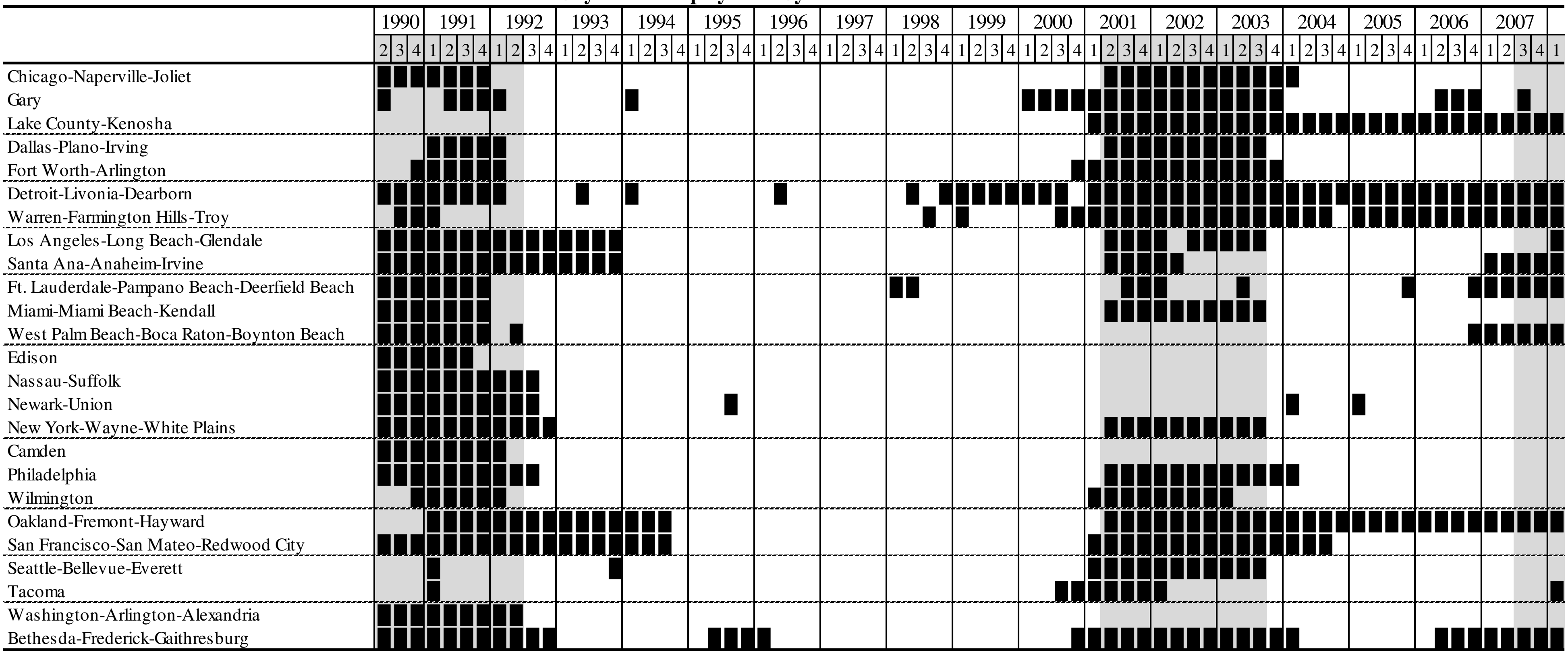


Table 1. City-Level Employment Cycles for the 25 Metro Divisions



A ■ indicates a quarter in which the city was in an employment contraction. The shaded areas are periods during which national employment was in contraction (Owyang, Piger, and Wall; 2012). Metro divisions within the same MSA are grouped together and separated by a dashed line.

Table 2. Mean Concordance and Geography

All City Pairs	73.6
Neighbors	81.1
Same Principal State	80.7
Same Secondary State	77.4
Same Census Division	74.0

Table 3. Mean Concordances for Metro Divisions

MSA	Metro Division (City)	With Neighbor(s)	With All Cities
Chicago-Naperville-Joliet, Il-IN-WI	Chicago-Naperville-Joliet, IL	72.9	80.8
	Gary, IN	79.2	72.6
	Lake County-Kenosha, Il-WI	66.7	66.1
Dallas-Fort Worth-Arlington, TX	Dallas-Plano-Irving, TX	94.4	80.1
	Fort Worth-Arlington, TX		80.6
Detroit-Warren-Livonia, MI	Detroit-Livonia-Dearborn, MI	75.0	56.6
	Warren-Farmington Hills-Troy, MI		65.3
Los Angeles-Long Beach-Santa Ana, CA	Los Angeles-Long Beach-Glendale, CA	86.1	74.4
	Santa Ana-Anaheim-Irvine, CA		70.2
Miami-Ft. Lauderdale-Pompano Beach, FL	Ft. Lauderdale-Pompano Beach-Deerfield Beach, FL	84.0	71.0
	Miami-Miami Beach-Kendall, FL	79.2	81.3
	West Palm Beach-Boca Raton-Boynton Beach, FL	88.9	70.3
New York-Northern New Jersey-Long Island, NY-NJ-PA	Edison, NJ	86.8	72.1
	Nassau-Suffolk, NY	84.7	71.9
	Newark-Union, NJ-PA	85.4	69.5
	New York-Wayne-White Plains, NY-NJ	81.5	79.7
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	Camden, NJ	82.6	72.7
	Philadelphia, PA	84.0	80.0
	Wilmington, DE-MD-NJ	86.1	79.9
San Francisco-Oakland-Fremont, CA	Oakland-Fremont-Hayward, CA	75.0	59.6
	San Francisco-San Mateo-Redwood City, CA		70.0
Seattle-Tacoma-Bellevue, WA	Seattle-Bellevue-Everett, WA	86.1	77.0
	Tacoma, WA		72.2
Washington-Arlington-Alex'a, DC-VA-MD-WV	Washington-Arlington-Alexandria, DC-VA-MD-WV	61.1	72.5
	Bethesda-Frederick-Gaithersburg, MD		70.3

Table 4. Differences in Agglomeration, Industry, and Human Capital

	Neighbors	Non-Neighbors
Difference in number of establishments (thousands)	95.2	45.3
Difference in establishments per square mile	41.0	24.0
Sum of differences in industry shares	19.8	24.5
Sum of differences in race shares[a]	21.7	25.0
Difference in share with high school diploma	4.0	3.7

[a] White, Black, Asian, and American Indian or Alaska Native

Table 5. Concordance and Geographic Designations

	Model A		Model B		Model C	
	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.
Constant	4.448*	0.015	4.448*	0.015	4.457*	0.015
Adjacent	0.129*	0.027	0.158*	0.036	0.060	0.037
Neighbor			-0.044	0.051	-0.020	0.045
Principal State					0.127*	0.022
Secondary State					0.027	0.022
Census Division					-0.012	0.009
Principal Cities					0.033†	0.017
Log likelihood	1300.709		1301.082		1330.713	
R^2	0.5609		0.5611		0.5755	
Adjusted R^2	0.5457		0.5452		0.5601	

A * or † indicates statistical significance at the 5 percent and 10 percent levels, respectively. City dummies are suppressed for space considerations. Standard errors are heteroskedasticity-corrected.

Table 6. Concordance and Agglomeration

	Model D		Model E		Model F		Model G	
	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.
Constant	4.474*	0.017	4.472*	0.017	4.473*	0.017	4.470*	0.017
Adjacent	0.059	0.038	0.062	0.038	0.060	0.038	0.064†	0.038
Neighbor	-0.026	0.046	0.021	0.052	-0.026	0.045	0.030	0.050
Principal State	0.125*	0.022	0.124*	0.022	0.125*	0.022	0.123*	0.022
Secondary State	0.026	0.022	0.020	0.022	0.027	0.022	0.023	0.022
Census Division	-0.012	0.009	-0.013	0.009	-0.012	0.009	-0.013	0.009
Size	0.019*	0.009	0.017†	0.009	0.018*	0.009	0.014	0.009
Neighbor×Size			0.203*	0.043			0.204*	0.032
Density	0.013†	0.007	0.013†	0.007	0.015*	0.007	0.015*	0.007
Neighbor×Density			-0.208*	0.064			-0.194*	0.049
Log Likelihood	1333.905		1339.040		1333.285		1339.976	
R^2	0.5771		0.5795		0.5768		0.5799	
Adjusted R^2	0.5610		0.5629		0.5607		0.5634	

A * or † indicates statistical significance at the 5 percent and 10 percent levels, respectively. City dummies are suppressed for space considerations. Models D and E use the number of establishments to calculate size and density, whereas Models F and G use total employment. Standard errors are heteroskedasticity-corrected.

Table 7. Concordance and Industrial Mix

	Model H		Model I	
	Coeff.	s.e.	Coeff.	s.e.
Constant	4.485*	0.018	4.485*	0.018
Adjacent	0.058	0.039	0.058	0.039
Neighbor	0.023	0.052	0.015	0.088
Principal State	0.121*	0.023	0.121*	0.023
Secondary State	0.016	0.022	0.016	0.022
Census Division	-0.012	0.009	-0.012	0.009
Size	0.016†	0.009	0.016†	0.009
Neighbor×Size	0.203*	0.043	0.204*	0.042
Density	0.013†	0.007	0.013†	0.007
Neighbor×Density	-0.209*	0.065	-0.207*	0.070
Industrial Mix	0.061†	0.034	0.061†	0.034
Neighbor×Industrial Mix			-0.044	0.307
Log Likelihood	1340.577		1340.580	
R^2	0.5802		0.5802	
Adjusted R^2	0.5634		0.5632	

A * or † indicates statistical significance at the 5 percent and 10 percent levels, respectively. City dummies are suppressed for space considerations. Standard errors are heteroskedasticity-corrected.

Table 8. Concordance and Human Capital

	Model J		Model K		Model L	
	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.
Constant	4.494*	0.023	4.496*	0.023	4.278*	0.011
Adjacent	0.055	0.039	0.055	0.040	0.007	0.046
Neighbor	0.023	0.089	0.062	0.067	0.107	0.099
Principal State	0.120*	0.023	0.120*	0.023	0.087*	0.019
Secondary State	0.014	0.022	0.015	0.022	0.029	0.032
Census Division	-0.013	0.009	-0.013	0.009	0.002	0.011
Size	0.016†	0.009	0.017†	0.009	-0.037*	0.011
Neighbor×Size	0.204*	0.041	0.196*	0.032	0.135*	0.051
Density	0.012†	0.007	0.013†	0.007	0.001	0.007
Neighbor×Density	-0.210*	0.071	-0.224*	0.061	-0.162*	0.080
Industrial Mix	0.060†	0.034	0.060†	0.034	-0.038†	0.020
Neighbor×Industrial Mix	-0.012	0.309	0.139	0.236	0.029	0.468
Racial Mix	0.015	0.024	0.016	0.024	0.136*	0.017
Neighbor×Racial Mix			-0.210*	0.094	0.077	0.068
Share with a HS Diploma	0.031	0.118	0.032	0.118	-0.475*	0.113
Neighbor×Share with a HS Diploma			1.804*	0.537	0.728	0.501
Log likelihood	1341.019		1343.138		639.807	
R^2	0.5804		0.5814		0.0734	
Adjusted R^2	0.5629		0.5634		0.0335	

A * or † indicates statistical significance at the 5 percent and 10 percent levels, respectively. City dummies are suppressed for space considerations, except for Model L, which does not allow for them. Standard errors are heteroskedasticity-corrected.

Table 9A. Differences Between Neighbors

	Agglomeration		Human Capital	
Neighbor Pair	Size[a]	Density[b]	Race[c]	Education[d]
Chicago/Gary	86.1	68.9	10.0	2.4
Chicago/Lake County	79.6	15.8	27.0	3.6
Dallas/Fort Worth	39.6	16.9	9.0	2.2
Detroit/Warren	32.7	46.3	67.0	7.4
Los Angeles/Santa Ana	47.8	29.0	15.0	7.7
Miami/Fort Lauderdale	13.4	10.4	14.0	10.8
Fort Lauderdale/W. Palm Beach	15.4	38.1	20.0	1.1
New York/Edison	66.7	68.6	36.0	8.0
New York/Nassau-Suffolk	53.7	42.4	42.0	8.8
New York/Newark	67.1	74.8	17.0	4.8
Newark/Edison	0.8	12.9	29.0	3.2
Philadelphia/Camden	53.9	35.2	13.0	0.6
Philadelphia/Wilmington	66.3	43.5	9.0	1.1
Camden/Wilmington	19.3	9.8	5.0	0.5
San Francisco/Oakland	0.8	18.7	15.0	1.0
Seattle/Tacoma	65.1	30.7	10.0	2.1
Washington/Bethesda	51.8	10.1	30.0	2.6
Average	44.7	33.6	21.6	4.0

[a] Proportional difference in the number of establishments. [b] Proportional difference in establishments per square mile. [c] Difference in the sum of race shares differences.
[d] Difference in percentage of people 25 years and older with a high school diploma.

Table 9B. The Effects of Neighborness on Concordance

Neighbor Pair	Concordance	Agglomer-ation[a]	Race	Education	Total Effect[b]
Chicago/Gary	79.2	-10.1	1.9	-3.7	-11.9
Chicago/Lake County	66.7	-21.6	6.2	-5.8	-21.2
Dallas/Fort Worth	94.4	-6.0	2.1	-4.2	-8.1
Detroit/Warren	75.0	3.8	15.7	-7.7	11.7
Los Angeles/Santa Ana	86.1	-4.4	3.1	-12.0	-13.4
Miami/Fort Lauderdale	79.2	-0.3	3.1	-17.9	-15.2
Fort Lauderdale/W. Palm	88.9	6.3	3.9	-1.6	8.7
New York/Edison	79.2	3.7	8.4	-11.9	0.2
New York/Nassau-Suffolk	84.7	-2.7	11.8	-14.9	-5.7
New York/Newark	80.6	7.7	3.3	-6.9	4.0
Newark/Edison	90.3	2.4	6.1	-4.7	3.9
Philadelphia/Camden	80.6	-4.5	2.5	-0.9	-2.9
Philadelphia/Wilmington	87.5	-7.7	1.9	-1.8	-7.7
Camden/Wilmington	84.7	-1.6	0.9	-0.8	-1.5
San Francisco/Oakland	75.0	3.2	2.4	-1.2	4.3
Seattle/Tacoma	86.1	-10.8	2.1	-3.5	-12.2
Washington/Bethesda	61.1	-8.6	5.9	-3.5	-6.2
Average	81.1	-3.0	4.8	-6.1	-4.3

[a] The combined effect of size (proportional difference in establishments per square mile) and density (difference in the sum of differences in race shares). [b] The sum across the three effects, which is the total effect that being neighbors has on the concordance of the two cities.