Empirical Polycentricity: The Complex Relationship Between Employment Centers

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Abstract

This paper empirically finds that employment subcenters have the expected connections with the central business district, but additionally have important relationships with each other. Using data from Houston, Texas, USA, we use a new proximity measure to estimate a polycentric density function, and show that the estimated gradient using the total derivative, allowing for the relationship between all subcenters, is much different than the gradient using only the own center coefficients. Further, we model asymmetry in the density function by limiting the employment center influence using commuting data, and testing the influence of over-lapping areas for both population and employment. We find significant asymmetry both within, and even outside of the commuting areas. We conclude that subcenters have important linkages to each other in addition to the CBD, and that therefore the polycentric city is more complex than additional centers mimicking the CBD.

February, 2014

Acknowledgements: We would like to thank Ronald Elul and Dan McMillen for helpful comments. We also benefitted from comments from seminar and meeting participants at Tulane, the Regional Science Association International meetings and the American Real Estate and Urban Economics Association meetings.

I. Introduction

The goal of the research reported here is to expand our understanding of the role of multiple employment centers in large cities. Specifically, we show that subcenters do not interact solely with the Central Business District (CBD), instead they also have economically important relationships with each other. We empirically demonstrate that these interactions are quantitatively important through a careful examination of both population and employment density. We first identify employment subcenters following what is becoming standard in the literature by using the McMillen (2001, 2002, 2004) methodology for finding employment density concentrations. We then estimate a series of density functions, using both polycentric specifications as well as individual subcenter analyses, to show that subcenters have significant interactions with each other, not solely with the CBD.[1] Further, we find that the existence of the demonstrated interactions depends on how the extent of influence of each employment center is specified. That is, the use the extent of commuting distances to find our original employment center boundaries, but when we extend them further we find additional significant interactions.

The primary insight that arises when we consider how employment subcenters interact with each other, rather than solely with the CBD, is that the density function around any given subcenter will be asymmetric. The standard monocentric model implies that density equidistant from the centroid of the CBD should be equal everywhere. This thinking has affected the modelling of polycentric cities, where conditional on distance to the CBD the assumption has been that density equidistant from the center centroid should be equal everywhere. Clearly, however, if there are significant economic or other factors which generate demand for access to

[1] We use the term "employment center" to refer to all employment centers, including the Central Business District (CBD). We distinguish the CBD from the other employment centers by referring to the other employment centers as "subcenters."

more than one employment center, then the density around a center will not be symmetric. Rather, we would expect even conditional on distance to the CBD that density would be higher towards a second subcenter compared to away. Thus our statistical search for relationships between subcenters is a statistical search for asymmetry in the density function around each employment center.

The importance of potential asymmetry in the density function arises in at least two dimensions. One, if it exists, asymmetry signifies that residents and firms have demand for multiple centers of employment concentration, which suggests that substitution for the CBD is not the only motivation for subcenter formation. Two, asymmetry suggests that the definition of a subcenter itself may be problematic, because if there are multiple dimensions to demand for subcenters, then different contexts may impact how firms and residents form their demand and thus how they identify a location as being central.[2]

Our specification of the polycentric density function uses thirteen subcenters, plus the CBD. Our data are Census tracts, so our definition of an employment center consists of a single tract or group of contiguous tracts. One key in our work is that we limit the geographic range of influence of all employment centers including the CBD (Craig and Ng, 2001; McMillen 2001, McMillen and Smith, 2003; Redfearn, 2006; Kohlhase and Ju, 2007).[3] We limit the boundary of

[2] One debate has been whether the employment center definition should include only employment concentration, or in addition should require influence on surrounding areas (Craig and Ng, 2001; McMillen, 2004). We believe our work here makes this argument moot, because influence can depend on the dimension being examined (for example not just employment, but entertainment or shopping, or various elements of between-firm interactions). Our work here shows both possible definitions result in asymmetric densities.

[3] It is conceptually difficult to distinguish the size of an employment center (for example whether partial or multiple census tracts) from its area of influence. Our approach here essentially allows the data to dictate the answer, as we are not able to determine the within tract distribution of employment. Redfearn (2007) does not really discuss the area of influence, but

employment center influence here by using commuting data, which is an objective method of specifying the geographic extent of influence.

Estimation of the polycentric density function implies that the density gradient using only the estimated coefficients for the own center and the CBD is quite different from the density gradient when we use all of the subcenters which have overlapping areas of influence.[4] The method to demonstrate this result is to calculate the total derivative from the estimated parameters for centers that share influence, rather than the partial derivative. That is, because distance to one subcenter cannot be changed without changing the distance to other centers, the only appropriate way to determine the estimated gradient is to use the total derivative. The total derivative, however, will only be different if, in fact, the relationship to the other subcenters is also important for determining population or employment densities. We calculate the gradient using the total derivative for each subcenter at a particular point, and find that in fact the gradient is quite different from the gradient calculated from the partial derivative, powerful evidence that suggests further exploration of the linkages between subcenters.

To follow the implication of this evidence, we estimate density functions around each individual subcenter. We find that these estimates support the suggested asymmetry, because density towards other subcenters is greater than elsewhere, even after controlling for distance to the CBD or the own centroid. Further, while we show that commuting patterns are an important element by which density asymmetry can be found, relationships go further because even directional density is distinct in many cases. Estimation of density around individual subcenters

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his method might be an alternative estimation procedure, although distinguishing the definition of the subcenter from its area of influence may be immaterial (or un-identified).

[4] We estimate the polycentric density function utilizing a specification due to Perdue (2012). The Perdue specification defines proximity as distance from the employment center boundary, rather than distance from the employment center centroid.

is found to show significant variation in how neighboring subcenters affect the own center. A final aspect of subcenter influence is that the asymmetric density relationships we uncover hold not only for employment density, they hold for population density as well.

Theory suggests subcenters arise when the usual "diminishing" assumptions that cause the formation of traditional downtowns reverse- that the marginal congestion costs outweigh the marginal agglomeration benefits (Mills, 1967; Fujita and Ogawa, 1982; Berliant and Wang, 2008; Agarwal, Guiliano and Redfearn, 2012). In this view, subcenters linked solely to the CBD might be characterized as the "mimic" view, where each subcenter serves as a substitute for the CBD but does not necessarily have a relationship with other subcenters.[5] On the other hand, given that multiple employment subcenters develop in each city, it might be surprising if they do not have a relationship with each other, as well as to the CBD.[6] We characterize this view as the "polycentric" view, which implies that the separate character of each subcenter may be important to either firms or individuals, in which case relationships between the subcenters may be as important as the relationship between each subcenter and the CBD.[7] Our empirical work here clearly illustrates that the polycentric view is predominant.

We proceed by first specifying the polycentric density function in section 2, and our tests for whether subcenters are related to each other as well as to the CBD. The estimation is conducted using 2000 Census data for the Houston MSA, as described in section 3. Section 4 describes how we use the data to select the employment centers which are analyzed in section 5.

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[5] For example, theory generally specifies that not one, but two subcenters would arise simultaneously, on directly opposite sides of the CDB.

[6] This supplants, in our view, the discussion about whether subcenters are complements or substitutes with the CBD (Sivitanidou, 1996; Anas, Arnott, and Small, 1998), because the relationship between subcenters also needs to be taken into account.

[7] While we are not aware of the theory which prescribes this, a result may be that the two subcenters would be closer together than on the opposite sides of the CDB.

There we find that all subcenters have economically important and distinguishable relationships with some of the other areas outside of the CBD, although not with all of them. We find distinctions in which subcenters are linked by population compared to those linked by employment. We conclude that subcenters have value to individuals as well as to firms, which means their multi-dimensionality suggests a more complex origin than simply a market response to congestion.

II. Polycentric Density Function Specification

This section develops the specification for estimating the polycentric density function. There are three keys to the specification. The first is the selection of subcenters, the second is the specification of the density function itself. Finally, we incorporate asymmetry in the density function by specifying an area of influence using data on commuting to work. The density function specification uses proximity, as measured by distance from the edge of the commuting area, to allow each subcenter to potentially add to the expected density compared to the standard monocentric specification. The key innovation in our work, however, is in how we interpret the coefficients from the polycentric estimation. Specifically, it is impossible to change distance to one location without simultaneously changing the distance to other locations. Thus the coefficients themselves cannot be individually interpreted, a total derivative needs to be calculated which allows the overlap between areas of influence to be taken into account.

A. Identification of Employment Centers

We identify candidate employment areas of concentration using McMillen's (2001, 2003) locally weighted regression (LWR) procedure.[8] We further refine the list of areas for our analysis based on distinguishing among the employment concentrations that are found to influence population (Craig and Ng, 2001, McMillen, 2003).[9] The idea behind this is to identify areas which affect the shape of the city in a statistically identifiable manner.

Figure 1 shows a map of the Houston metropolitan area, with the 21 identified employment concentrations. While most of the concentrations are within the central county of the Houston metropolitan area (Harris); there are eight identified concentrations in five of the outlying counties.[10] Table 1 illustrates the widely varying differences between the areas with employment concentrations. The CBD, for example, has over 150,000 employees, while Cleveland has fewer than 1,000. Similarly, the densities vary from slightly over 100 workers per square mile to well over 80,000 in the CBD. We discuss below the population density functions that will restrict the areas we examine most intensely to thirteen.

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[8] One difference in our procedure is that we specify the bandwidth based on miles, rather than the number of tracts, so as to uphold symmetry in the treatment of employment concentrations centrally located from those concentrations the fringe (since the size of census tracts varies with density). In robustness checks, we find the identified areas are not very sensitive to reasonable variation in bandwidth, which suggests the results from the LWR procedure are not vastly different from the cross-validation procedure advocated by Redfearn (2007).

[9] It is not clear we should worry whether employment concentrations as identified by the LWR should be required to have influence on surrounding areas, nor is it necessarily clear whether we should test for influence on population or employment. In the end, using our definition of areas with population influence allows us to limit the number of areas we examine without changing our qualitative conclusions at all.

[10] As of the 2000 Census region definition.

B. Specification of the Polycentric Density Function with Limited Areas of Influence

Our specification of the polycentric density function is first proposed by Perdue (2012). This specification has two distinct advantages. First, it uses commuting patterns of households to empirically limit the area of the city which an individual employment center can influence, no area in Houston (including the CBD) is found to affect densities in the entire metropolitan region. Second, our density function specification uses proximity as its running variable, which is defined as the distance from the employment center edge (thus proximity rises closer to the center). We use both population and employment density functions to measure potential attractiveness. The test of asymmetry in the density functions arises when the commuting areas of employment centers overlap. We find asymmetry is important, that it is not a result of collinearity with distance to the CBD, that it is not a result due solely to using commuting areas to measure the extent of economic influence, and that it is not necessarily reciprocal between employment centers,

The proximity measure in our density function calculates distance from the edge of the commuting area on a ray toward the centroid for each employment center (Perdue, 2012). That is, if r_j is the commuting area radius for employment center j, and if d_{ij} is the distance between the centroid of tract i and the centroid of employment center j, then we define proximity m_{ij} as the distance from tract i to the border of the area of influence, defined as the distance between tract i and the commuting radius of employment center j so that:

$$m_{ij} = r_j - d_{ij} \qquad (1)$$

Our specification of the polycentric density function then follows the usual specification of including the identified employment centers in a multiplicative way. The difference in this specification is that we use m_i as defined in (1) rather than using distance from the employment center centroid.

The border of the area of influence used above is defined by commuting patterns, where the influence of an employment center is assumed to go to zero after 90% of the commuters are represented. Many papers have imposed a similar limitation, the advantage of our specification is that we use data to justify the assumption.[11] The resulting specification of the polycentric population density function is therefore:

$$D_i = A\prod_{j=1}^{J}\exp(\beta_j m_{ij} I_{ij})\exp(u) \tag{2}$$

where j =1, 2, …, 14, indexes the thirteen influential employment subcenters plus the CBD, i indexes the census tracts that are our units of observation, D_i is the population density in tract i, as above $m_{i\,j}$ is the proximity variable as defined in (1), $I_{i\,j}$ is an indicator variable that equals one if tract i is within the commuting area of employment center j and zero otherwise, and u is the error term..

One advantage of using the proximity variable defined in Equation (1) is that it properly defines the distance from the edge of the commuting area as a “good,” rather than as a “bad” which typifies the usual specification. The result of this change is that now the coefficients are expected to have positive signs, as the difference in density conditional on distance from the CBD is expected to increase as proximity rises, indicating a location closer to the center of the employment subcenter. In part, this reflects that using the standard negative exponential starts

[11] Most research restricts the area of influence to avoid the situation where a small outlying concentration is estimated to influence the development of a location on the extreme opposite side of the city.

from the monocentric trend line, and subcenter density estimates reflect reductions below, rather than additions above, the expected density. Thus measuring the impact of a subcenter using distance *from* the boundary allows employment centers to be modeled as increasing in local density as is illustrated in Figure 2, where the solid line is from the specification in equation (2), while the dashed line is from a standard negative exponential density function.[12]

C. Calculating the Polycentric Gradient from the Total Derivative

We estimate the polycentric specification using (2), which includes setting the influence of employment centers to zero after the commuting area boundary is reached. We use the estimated coefficients from the polycentric density function in (2) to calculate the total gradient of how density changes between two locations. That is, in any polycentric specification such as equation (2), the gradient is not apparent from the estimated coefficients because moving a location closer to the CBD changes the location relative to the other subcenters as well. Thus comparing expected densities between Census tract 1 and tract 2 involves not only the distance to the CBD, but the distance to other subcenters which influence the two tracts.

As a consequence, the generalized density gradient associated with a given center depends on the weighted sum of all the coefficients from within the commuting area. Of course, the weight on subcenters outside the commuting area will be zero, but we need to account for areas where the commuting areas overlap. The weights depend on how distance to other employment centers change when the distance to center j changes by DST_j (in what follows we suppress the other subscript for simplicity). That is:

[12] Another way of saying this is that the proximity specification allows the equivalent of a dummy variable for the center of the subcenter.

$$\frac{\frac{dDen}{dDST_j}}{Den} = \beta_1 I_{1j}\frac{dDST_1}{dDST_j} + \beta_2 I_{2j}\frac{dDST_2}{dDST_j} + \beta_j + \ldots + \beta_{14} I_{14j}\frac{dDST_{14}}{dDST_j} \quad (3)$$

where for the own-center $j, \frac{dDST_j}{dDST_j} = 1$.[13] The I indicator variable indicates which of the fourteen subcenters has a commuting area which overlaps the own center j.

III. Using Single Employment Center Density Functions to Estimate Asymmmetry

Asymmetry in the estimated density function means that density is not equal everywhere around a given employment center, even when equidistant from the commuting area boundary. We specify the source of asymmetry in our specification through the overlapping commuting areas. We find below that estimating population or employment density for each employment center allows us to identify with which other employment center a given area interacts through overlap. We demonstrate asymmetry in three dimensions. First, we show that the asymmetry in population densities does not necessarily arise due to the same alternative employment centers as we find when estimating employment density functions.[14] Second, we not only test whether the asymmetry results in greater overall density, we frequently find using slope dummy variables on distance that one of the employment centers has a stronger pull than others. Finally, again using slope dummy variables, we find that the sphere of influence for some subcenters extends beyond the commuting area, suggesting a potentially more complex overall relationship between employment centers.

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[13] We have also suppressed the I indicator variable from (3) which would limit the relevant subcenters to be those within the commuting area of subcenter j.

[14] Of course it is well known that density gradients are not equal for population and employment even in a monocentric context. Our work here opens broader questions involving why households or firms might have demands for multiple employment centers.

Figure 3 graphically demonstrates our specification of asymmetry through the overlap in commuting areas. The Figure shows two subcenters, EC1 and EC2, where the solid circles around each centroid indicate the commuting areas of influence. The area marked by the vertical lines represents where the two areas of influence overlap, indicated below by the dummy variable OL. When we estimate the density function using as data solely tracts within the commuting area for EC 1, we allow for the possibility that density in the shaded overlap area is greater than elsewhere. Similarly, we test whether the same overlap area has a higher density using only the data around EC 2.

If residents and/or firms are attracted to multiple employment centers, we would expect density to be higher in the OL area. Further, the slope dummy in the Overlap area should show that as distance to EC2 is shortened, density should rise. The result of the total gradient is less clear, in that the relationship between the subcenters will determine the total effect of trading location for one employment center relative to the other.

Equation (4) shows the specification with slope dummy variables for the two-node example of Figure 3 with overlapping commuting areas:

$$\ln D_i^s = \beta_0 + \beta_1(m_{is}) + \beta_2 OL_i^{s,t} \cdot (m_{it}) \tag{4}$$

where D_i^s is the density in tract *i* in the commuting area of employment center *s* (the error term is omitted for simplicity). $OL_i^{s,t}$ is the dummy variable which indicates census tracts with overlapping commuting areas for the own employment center *s* with another employment center *t*, using our proximity specification *m* which is the distance from the employment center boundary shown in equation (1). Note that we allow the slope dummy to rise as the distance gets closer to the other employment center, since *m* is indexed by t for the OL dummy.[15]

To further explore the polycentric explanation for why employment centers might have influence in other ways than solving the agglomeration vs. congestion trade-off, we test a final element. Specifically, after allowing for overlap in the commuting areas between employment centers, we additionally test for asymmetry in density for areas that are not in the overlap, but which are nonetheless "close" to neighboring employment centers. Clearly, if commuting defines the entire reason for demand to be close to a subcenter, the influence of Near on density should be zero. If shopping, entertainment, other business relationships, or any other attribute affects location, areas in Near may be important.

Figure 4 demonstrates graphically this second test of asymmetric influence using the overlapping areas. The dotted circle going through the centroid of employment center (EC) 1 demarks areas of EC1 which are closer to EC2 than other areas in EC1, indicated by Near, but which are not within the commuting area of EC2. The area in Near will have a distinct density if nearness to EC2 is valued in area 1, even if the Near areas are outside of the commuting area of EC2. [16]

Equation (5) below shows the Near asymmetric density specification for an employment center which has overlapping commuting areas with only one other area:

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[15] It would be equally valid to have indexed the slope dummy with distance toward s.

[16] The area $NEAR_i^{s,t}$ may be significant because of deficiencies in how we measure commuting areas, or because the root cause of relationships between employment centers resides in individuals, rather than firms, or because of dimensions of demand not captured by commuting. We are agnostic on the cause, and simply endeavor to demonstrate relationships between employment centers on a variety of dimensions.

$$\ln D_i^s = \beta_0 + \beta_1(m_{is}) + \beta_2 OL_i^{s,t} \cdot (m_{it}) + \beta_3 NEAR_i^{s,t} \cdot (m_{is}) \qquad (5)$$

where D_i^s is the density in tract i in the commuting area of employment center s (the error term is suppressed). The proximity variable m is defined as in (1), it is the distance from the commuting area boundary to tract i. $OL_i^{s,t}$ is the overlap dummy variable defined in (4), and $NEAR_i^{s,t}$ is a dummy variable showing the area towards a neighboring employment center whether or not it is within the commuting area, shown in the horizontal stripes of Figure 4.[17]

The distance from the boundary in the OL and NEAR areas can be measured to either of the subcenters, which we show by the s and t subscripts. One attribute of polycentricity which has received some attention is the extent to which subcenters are complements or substitutes with the CBD, or indeed with each other (Heikkila, Dale-Johnson, Gordon, Kim, Peiser, and Richardson, 1989; Sivitanidou, 1996; Anas, Arnott, and Small, 1998). Examining the relationship between employment centers using the specification in (5), or indeed from (2) or (4) as well, allows a range of relationships between each pair of centers. And in fact, we find a variety of empirical relationships between subcenters.

IV. Data

The study uses employment and population data at the census-tract level for the Houston Metropolitan Statistical Area as defined in the year 2000. Houston was selected as the area of study based on the existence of previous work identifying employment centers (Craig and Ng, 2001; McMillen, 2001), and the City of Houston’s status as a relatively free market city. While

[17] In the empirical work below we define NEAR to include the overlap area as well. Estimates which completely separate NEAR and OL show the same qualitative conclusion, which is that there is significant demand for areas in NEAR even if they are not in OL.

the City of Houston does have significant government involvement in land use decisions, it retains a unique status as the only large American city without centralized zoning, or a "plan". Its remaining regulations are on the whole no more restrictive or prescriptive than those in any other major American city (Lewyn, 2005).

Data on employment was obtained from the Census Transportation Planning Package 2000 Part 2 Place of Work Data and Part 3 Journey to Work Data. The Place of Work data estimates the place of work for all workers using data from a sample of residents compiled from the census long form; we use this data to calculate employment by census tract. We use the Journey to Work data to estimate commuting areas for each employment center. The commuting radii are determined by where 90% of commuters to an employment center are captured. Data from the 2000 Decennial Census (100% count) gives the total population for each tract.

V. Empirical Results Showing Employment Center Relationships

The empirical results robustly show that subcenters are economically related to each other, and not just to the CBD. We show this in three steps. First, separate estimates for the polycentric density function for population and employment are used to demonstrate the total gradient is unequal to the partial gradient using only the own and CBD coefficients. These estimation results, as in all of our estimates, also show that population has a different relationship and relative value for proximity to the employment centers than do firms. We then estimate single employment center density functions and identify the employment centers with which each has an overlap in their commuting areas. In addition to showing the variety of interactions, these estimates show the relationship between employment centers is not necessarily symmetric. That is, while we find significant estimates on OL (overlap) variables for many subcenters, we do not necessarily find that the relationship holds in reverse. Our third empirical step demonstrates further variety in the relationship as overlapping commuting areas are not found to fully define the asymmetries in density. That is, we find significant coefficients on many of the NEAR slope dummy variables- that is, on areas outside of the commuting overlap.

A. Influence Limitation and Selection of Employment Centers

To statistically determine the limit to the area of influence for each employment center, we define the commuting area by a quadratic regression extended until 90 percent of the workers to a specific employment center are captured.[18] Table 2 shows the resulting distances of the commuting area radii. Figure 5 shows how the estimated commuting areas overlap in the set of employment centers for Houston.

Table 3a presents the log population density function results using the polycentric specification from equation (2), while Table 3b presents the employment density estimates. This specification uses the proximity definition from (1), plus the limited areas of influence. The tables use all of the 21 employment concentrations based on the LWR regressions. The coefficient estimates are all found to be positive except for one area.[19] Six of the employment concentrations are not found to have significant impacts on population density, and seven for employment density. As we discuss above, positive coefficients are to be expected because we

[18] This process gives very similar answers when we specify that commuters to an employment center are not over-represented in the distribution.

[19] We are puzzled by the Galleria results, because it is the second largest employment concentration behind only the CBD. We speculate that one problem is the collinearity with the other close-to-CBD employment concentrations. Anas, Arnott, and Small (1998) encounter a similar problem along Wilshire Boulevard. An alternative is to define the subcenter as a line (in our case down US 59 to the CBD), in the case of Anas, Arnott, and Small (1998) it would be the entire boulevard. We originally discussed alternative subcenter shapes in an unpublished working paper (Craig, Kohlhase, and Pitts, 1996).

measure distance from the edge of the employment center to a specific tract using proximity (*m*). In the rest of our work we restrict our analysis to the significant positive thirteen employment subcenters in addition to the CBD as found in the population results. The selection of subcenters would have been similar, though not identical, had we used the employment results in Table 3b to select the areas, although our qualitative discussion would be essentially identical.[20] Similarly, had we not restricted our analysis and used all 21 areas of employment concentration, our qualitative results about asymmetry in employment center interactions would be identical.

B. Total Gradients vs. Partial Gradients

The first method we use to demonstrate that subcenters interact with each other, rather than solely with the CBD, is to investigate the total gradient from estimation of the polycentric density specification in equation (2). We accomplish this by showing that the total gradient found utilizing all subcenters with overlapping commuting areas is quite different than the partial gradient using only the own coefficients.

The results of this examination are shown in Table 4a for population, and in Table 4b for employment. Because of nonlinearity in the location of subcenters relative to the CBD, the total gradient varies based on location, thus this table shows the gradient for the last mile to the subcenter centroid on a line from the CBD. The first column shows the calculation of the partial density gradient, using only the own coefficient and, if within the commuting area, that of the CBD.[21] The second column, in contrast, shows the total gradient allowing for simultaneous

[20] That is, Freeport would have been added while West Chase and Lake Jackson dropped. Freeport is close to Lake Jackson. In both regressions, the Galleria is the only location with a negative point estimate.

[21] The choice of location is important only for calculating the change in distance between the other employment centers and the own center.

changes in distance to other subcenters with overlapping commuting areas, these other areas affect both the estimated gradient as well as its standard error (see equation 3).

Table 4a shows a dramatic change for some, but not all of the calculated gradients. As shown in the third column, three areas have very strong differences at the 1% level between the total and partial gradients, Webster, Woodlands, and Baytown.[22] Four other areas, however, are statistically different at least at the 10% level. Further, even the sign of the gradient changes between the partial and total gradients for the Woodlands, and insignificantly so for two other areas. The results are similar, although not identical, for employment as seen in Table 4b. All three of the areas with statistically significant differences between the total and partial gradients for population are also found to have strong differences for employment as well. Of the three additional areas with weaker differences for population, however, we find that one area (Greenspoint) has a much stronger difference between the partial and total gradients, while for the other two there is no statistically significant difference.

C. Estimation Results Using Single Employment Center Areas with Overlap

We expand our investigation into the nature of employment center linkages by estimating regressions using only the data from the commuting area of each employment center individually, and by therefore testing for linkages to neighboring employment centers specifically. The results from these regressions show the wide variety of how subcenters interact with the CBD, and with each other. The first empirical test uses simply a dummy variable indicating any overlap between the commuting areas of two or more employment centers. In the

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[22] Note that areas with exactly zero differences are those that do not intersect with the commuting area of any other subcenter (so the total derivative used for the total gradient is equal to the partial).

second, we add a slope dummy variable allowing the estimated density to vary with distance to other employment centers. The dummy variable test shows compellingly that both residents and firms value access to multiple employment centers, including but definitely not limited to the CBD. The slope dummy regressions show a richer variety of results. First, the commuting areas we develop are clearly useful, in that the OVERLAP times distance dummy illustrates the bulk of the positive interaction, but this is by no means complete as illustrated by results using the NEAR dummy variable defined in equation (4). Additionally, we show the rich heterogeneity in the relationship between employment centers. We find that extra employment in OVERLAP areas does not necessarily occur in the same areas as extra residential population. We also show that if firms or residents of one employment center value access to a neighbor, the reciprocal relationship does not necessarily hold. That is, the firms or residents of the neighboring area do not always value the own employment center as a neighbor.

Table 5 presents test results for whether overlapping commuting areas have higher density than portions of the city under the influence of a single employment center commuting area. The results decisively show that in virtually every instance where a statistical test is possible, for both population and employment, densities are statistically significantly greater in areas under the influence of multiple employment centers.[23] The exception is Galvestion, an area bordering the Gulf Coast beach. This is strong evidence that both residents and firms value access to multiple employment centers in general. It does not, however, suggest anything about the nature of the interaction.

Given the strong dual attraction results presented in Table 5, Tables 6 through 9 explore variation in the nature of the attraction. Table 6 reports the results for how density in the own

[23] Three subcenters plus the CBD are entirely covered by multiple subcenters, leaving no area with which to identify the differential impact of Overlap.

employment center is impacted by the proximity (distance) to neighboring employment centers where the commuting areas of the two employment centers overlap. Table 7 does the same thing for employment. Table 8 tests whether the commuting areas are sufficient to capture the limit to the attraction of multiple employment centers by showing whether density responds to proximity in areas NEAR to others even outside the commuting area overlap. Table 9 repeats this test for employment. In these regressions we separately identify the source subcenter of the overlapping commuting areas. Each column of the tables represents a single regression, using only the data in a given center's commuting area. The rows indicate with which areas the overlap occurs in the specification from equation (4). The coefficients indicate how density responds in the overlap areas when distance to the 'other' subcenter decreases (proximity rises). For example, using the first column of Table 6 we see that ten of the thirteen subcenters overlap to some degree the commuting area surrounding the CBD. Of those ten areas, we find that within six of them that as proximity to the 'other' subcenters rises, the differentiation between density that otherwise would occur (based on the own coefficient) also rises.[24]

Going across the rows of Table 6 shows that every employment center is found to have a significant statistical interaction with at least one other area. Thus we see that the centers have significant interactions with each other, and not just with the CBD. In addition to the significant interaction, for 41 out of the 45 statistically significant interactions the coefficient is positive, indicating greater density is found when, holding constant the proximity to the own subcenter, the proximity to the neighboring subcenter improves. While there are a relatively large number of statistically significant interactions, they are in fact less than half of the total possible number.

[24] Here and below we find evidence of interactions between subcenters that is inconsistent with our expectations. We believe a full research effort is required to develop understanding of the full range in the relationship between subcenters, our goal here is to elucidate that such effort will expand our understanding of the economics of a multi-centric city.

It remains for the future to determine whether this is because of the dynamic growth and decline of subcenters, or because of another phenomenon.

Table 7 reports the results on whether overlapping commuting areas fully capture how multiple employment centers are attractive to population. Each column reports on a regression using the own employment center commuting area data, and shows estimates on a slope dummy variable which indicates how proximity to neighboring centers affects density (the estimated β_3 coefficients on the slope dummy variables NEAR*proximity from equation 3) even outside the neighboring area's commuting reach. If commuting patterns define the totality of employment center interactions, the coefficients on NEAR should all be zero. On the other hand, if there are other factors which influence population demand for multiple employment centers, it may be that these additional factors will be manifested in the coefficients on NEAR.

The results reported in Table 7 show a variety of patterns which suggest that commuting patterns do not fully describe the causes of demand for multiple subcenters by households.[25] The results show that ten out of the thirteen tested subcenters show statistically significant increases in density for areas outside of the overlapping commuting area, but which are nonetheless in the direction of the neighboring subcenter.[26] Additionally, we find only five out of thirteen subcenters that do not have a positive impact on estimated density in another subcenter.[27] The variety in these results clearly suggest that commuting patterns do not describe the entirety of

[25] For example we find sixteen negative coefficients on NEAR, and thirteen positive coefficients. The negative coefficients represent a different type of interaction, but only after accounting for potentially positive interaction in the commuting areas.

[26] NEAR is never significant for Conroe and Lake Jackson, while for Baytown we find only a single negative coefficient.

[27] Of these, four are found to have negative interactions, and only one (Baytown) is found to have no interactions at all.

why households have demand for multiple subcenters. Another way of stating this is that the CBD clearly does not eliminate the demand for other subcenter attributes even outside of the working relationship.

Tables 8 and 9 repeat the Table 6 and 7 analysis using employment density instead of population. The results in Table 8 show considerably more interactions between the subcenters for employment than we found for the population density results in Table 6. This might not be surprising since the market areas are defined by commuting patterns, but we also find that firms have considerable demand for multiple employment centers. The asymmetric directional impact in Table 9 shows attractions even extending beyond the commuting area comparable to those in Table 7. That workers do not comprise the entirety of agglomeration effects has been well known, although our results certainly suggest the relationship extends farther in distance than typical commutes.[28]

The results in Tables 6 through 9 as they pertain to the complexity of relationships between subcenters are summarized in Tables 10 and 11. If employment possibilities are the only important element driving the interaction between employment centers, we should see that the impact of proximity on employment is mirrored between firms and residents. Similarly, if there is a direct commercial relationship between firms from one area to another, we should see that the relationship is reciprocal. In fact we find that while these two statements are often true, they are not the general rule.

Table 10 presents the similarity in results between the population connections found in Tables 6 and 7, and the employment connections found in Tables 8 and 9. The first two columns of Table 10 show the connections using the commuting areas (Tables 6 and 8). It might not be

[28] This might not be surprising given the different sources of potential agglomeration economies (Rosenthal and Strange, 2004; and Ellison, Glaeser, and Kerr, 2010).

surprising that there are considerably more connections with employment than population, since employment is the supposed motivation for subcenter formation. When we look at connections beyond commuting areas (Tables 7 and 9), however, columns 4 and 5 show that virtually the same number of subcenters impact employment as population. Thus, the NEAR results are not just an artifact of residential demands. The other interesting result highlighted in the table is that, looking at column 3 with the commuting areas, nine of the subcenters have connections between identical areas for both population and employment.[29] For the NEAR areas outside of the commuting areas, only three areas have identical connections for population and employment. Thus there are at least some areas where the dual attraction of the own and a neighboring subcenter for population does not seem correlated with the attraction for firms. This disparity is much greater for the areas outside of the commuting areas (NEAR) than for the commuting areas (OVERLAP).

Table 11 presents a different dimension of potential heterogeneity between subcenters. It shows whether the connections we find are reciprocal between subcenters. That is, if density in subcenter B is affected when the commuting areas overlap with its neighbor subcenter A, the table shows whether density in subcenter A is reciprocally affected by the overlap in commuting area with subcenter B. The first column shows the number of times that we find connections when using OVERLAP in the commuting areas for population. Of the 45 total connections, we find in about 2/3 of the cases that the reciprocal relationship holds. We find for employment that the relationship within the commuting areas is a little stronger, about 73% of the cases are reciprocal. Even so, however, this means that in at least a quarter of the cases that an overlapping area is important for residents or firms in one subcenter, but not in the other. When

[29] This can be seen when the number in column 3 is equal to the minimum in columns 1 and 2 for the same row.

we examine the NEAR areas that are outside of the commuting area the reciprocity is much less. Even for employment only about a quarter of the relationships hold for both neighbors, and for population the share is even less.

We believe the lack of reciprocity we document in Table 11 powerfully suggests that the elements that make certain areas attractive are considerably more complex than suggested by our current theoretical models. Other possibilities for population include shopping and entertainment variety. To explain such results for firms seems to require a more complex relationship between firms and workers beyond what has been developed to date.

VI. Summary and Conclusion

This paper provides an empirical exploration of the importance of employment subcenters to both individuals and firms. We perform our analysis by first estimating a polycentric density function for population and employment, and second by estimating individual density functions for each subcenter. Our methodology is novel in four dimensions. We are the first paper to employ the proximity specification (distance from the boundary) of Perdue (2012) in estimating population and employment density functions. Second, we estimate a polycentric density function where we restrict the geographic area of influence of each identified employment center using an objective statistical measure, the reach of commuters to work. Third, we properly interpret the polycentric density function results using the total derivative to generate the estimated gradient. Finally, we separately examine how overlapping commuting areas cause densities around each subcenter to be asymmetric, since densities rise going toward a neighboring subcenter. The results from our empirical examination imply that the urban economic impacts of employment concentrations are far more important than simply the trade-off between congestion and agglomeration, suggesting the need for a richer theoretical framework.

Our empirical evidence for the multiplicity of subcenter interactions comes from three separate statistical steps. First, our estimation of the polycentric density function shows significant distinctions between the own gradient using only the own coefficients and that of the CBD, compared to the total gradient using the simultaneous change in relative distance to the other subcenters that share overlapping commuting areas. The significant differences in the total gradients compared to the own gradients suggest that the influence of other subcenters on the own areas are empirically important.

Second, we estimate asymmetric density functions by separately accounting for overlapping market areas based on commuting. We find abundant evidence for asymmetry in the density function, as the overlap in commuting areas is often found to be significant when interacted with direction to other subcenters. Irrespective of the direction of the relationship, however, we find that all areas with sufficient data have higher population and employment density in the overlapping areas. On the one hand density function asymmetry seems commonsensical because the subcenters arise in the same metropolitan area. On the other hand our work indicates that understanding the causes of the asymmetry is challenging.

As an additional test, we examine a second layer of asymmetry outside of the commuting areas. We test for asymmetry based on the direction to neighboring subcenters, and find non-universal but nonetheless additional evidence that for some subcenters there are further attractions which indicate that subcenters are linked to each other. A final pair of findings are that the relationships between subcenters are not necessarily straightforward. We find that important interactions for employment are not necessarily important for population, and we find that the attractions are not necessarily reciprocal, so that a relationship going toward subcenter A is not necessarily returned when going toward statistically important subcenter B.

The multi-dimensional characteristics of the linkages between subcenters should provide an important impetus to the theoretical literature for understanding polycentric urban economies. Specifically, recent literature has established that cities are attractive to residents because of their variety (Albouy, 2008). In some sense, urban economists have considered employment subcenters as an efficiency consequence of congestion, but not as a positive attribute to urban lifestyles in their own right. To the extent that alternative clusters of employment contribute not only to the productive efficiency of cities, but to efficiency in other dimensions such as consumption or employment, then a focus on production will be too limited. In this polycentric view, no subcenter will exactly mimic the CBD, each will have a distinct physical form and sense of place, and will be attractive to firms and individuals for a variety of reasons. Finally, we believe our work speaks to the search for the appropriate definition of subcenters themselves. Craig and Ng (2001) and others (McMillen, 2001; 03; Redfearn 2007) advocate for a consistent statistical definition, but the polycentric view of subcenters suggests that the definition of subcenters may be sensitive to context.[30] We therefore await the theoretical development that will guide the specification explaining the different functions of the non-CBD employment clusters.

[30] See Agarwal, Giuliano, and Redfearn (2012) for a recent review of the progress of the literature in this direction, it is still incomplete.

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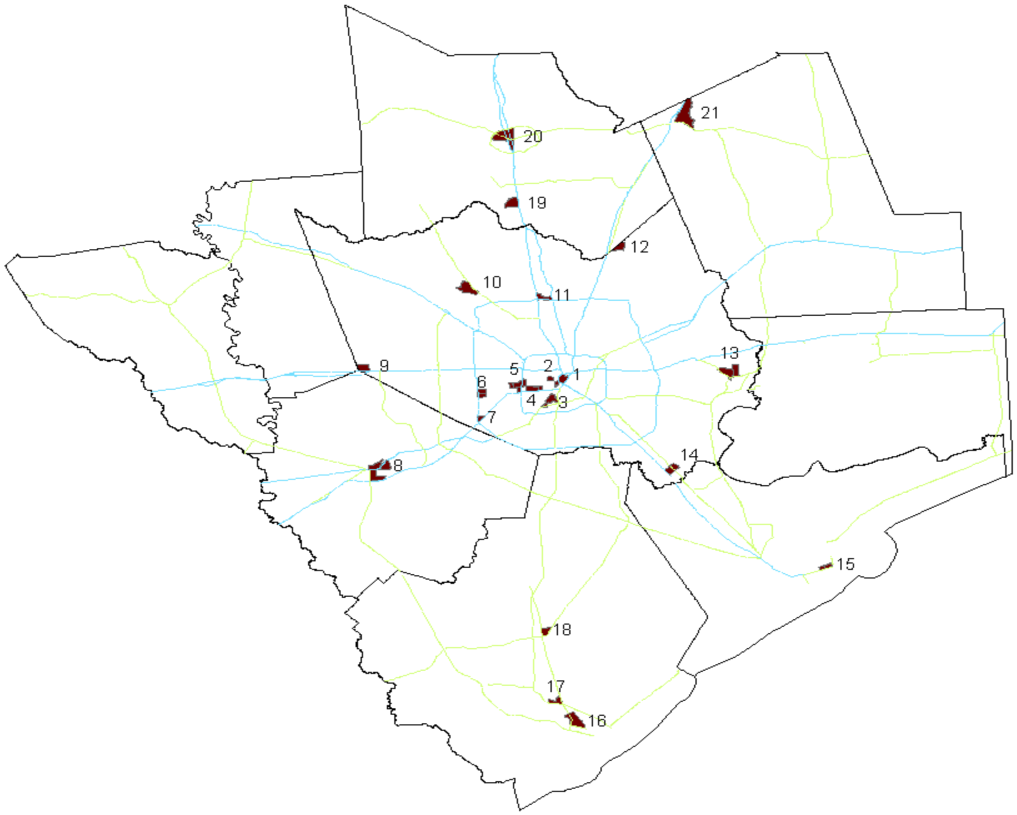
Figure 1- Employment Concentrations in the Houston Metropolitan Area[1, 2]

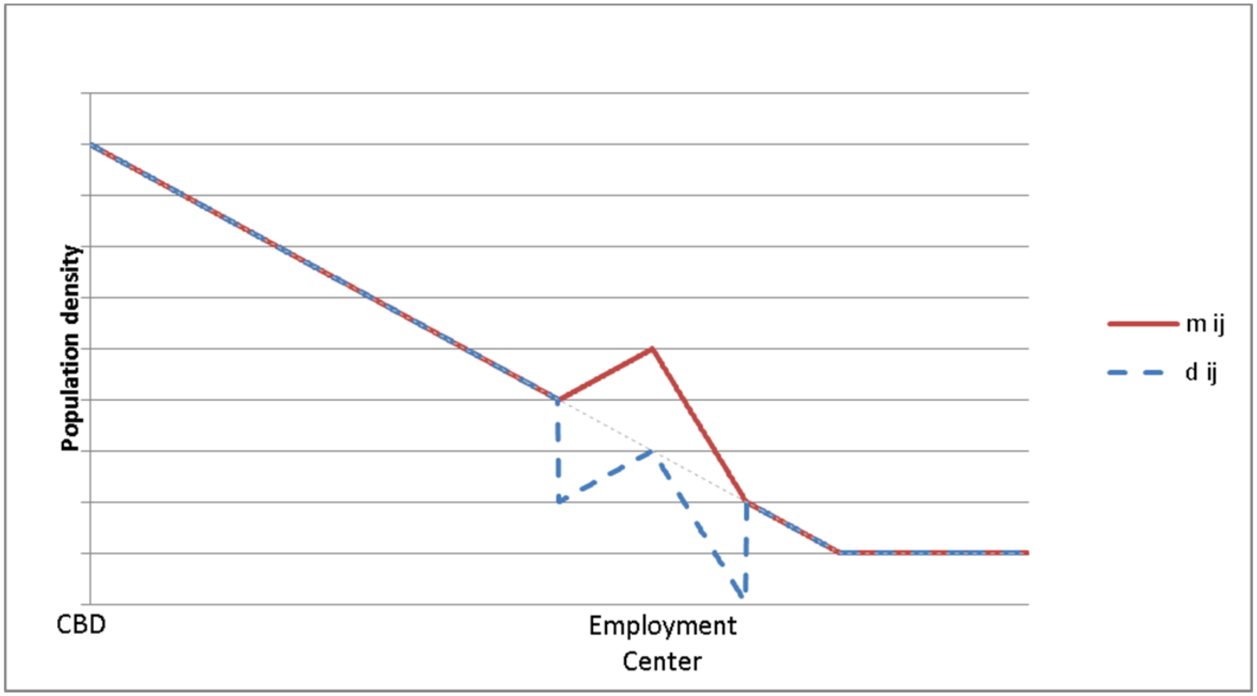


Employment Concentrations[3]

1	CBD
2	Allen Parkway
3	Medical Center
4	Greenway Plaza
5	Galleria
6	Westpark
7	US 59 & BW 8
8	Richmond
9	Katy
10	SH 249 & FM 1960
11	Greenspoint
12	Kingwood
13	Baytown
14	Webster
15	Galveston
16	Freeport
17	Lake Jackson
18	Angleton
19	Woodlands
20	Conroe
21	Cleveland

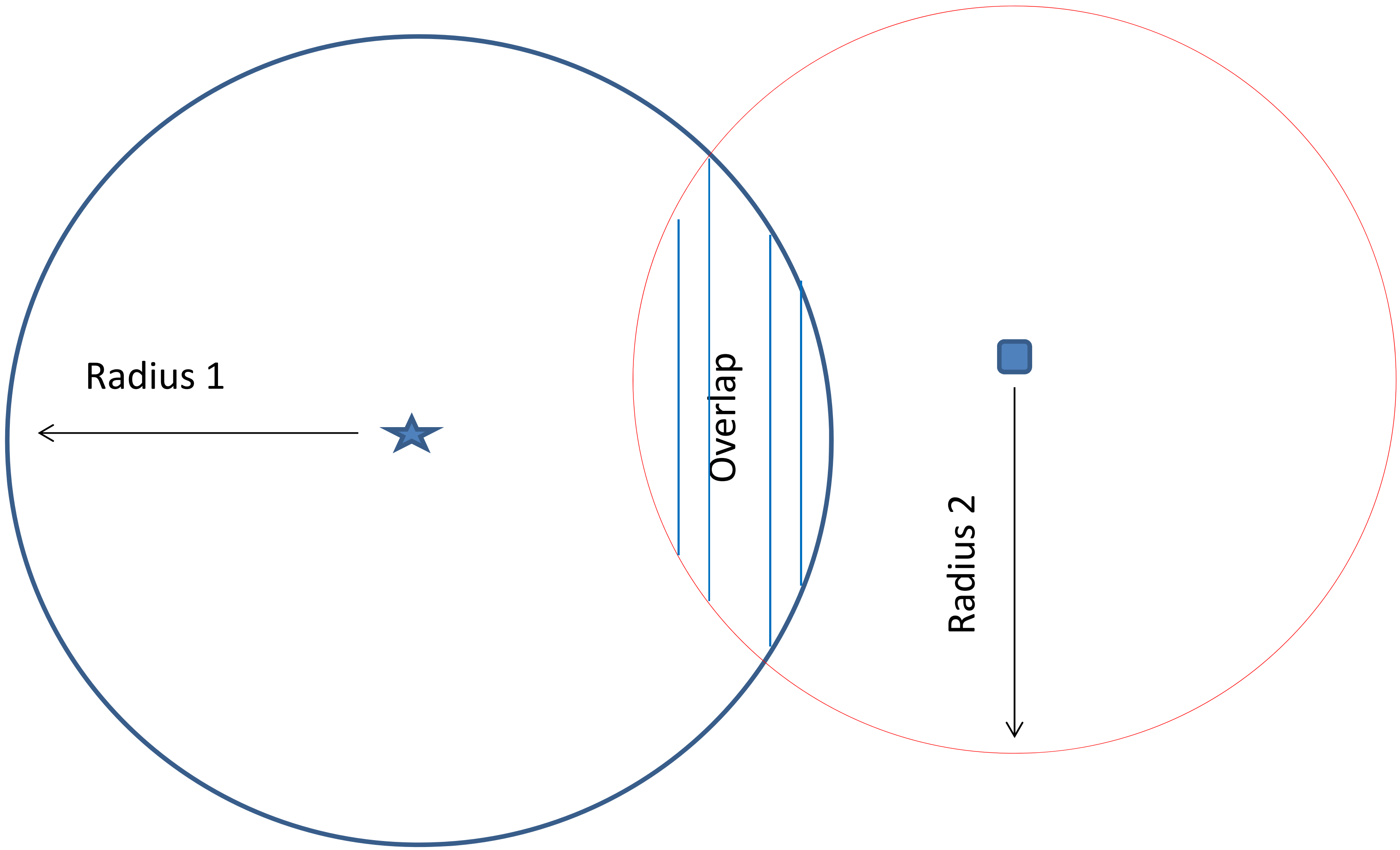
Notes:
1. Metropolitan Statistical Area (MSA) as defined by the Office of Management and Budget, 1999.
2. Employment Concentrations defined as locally statistically significant concentrations of employment following first stage of McMillen (2001).
3. Employment concentrations identified using local names, major highway intersection, or political jurisdiction.

Figure 2: Two-Node Specification with Proximity Compared to Centroid



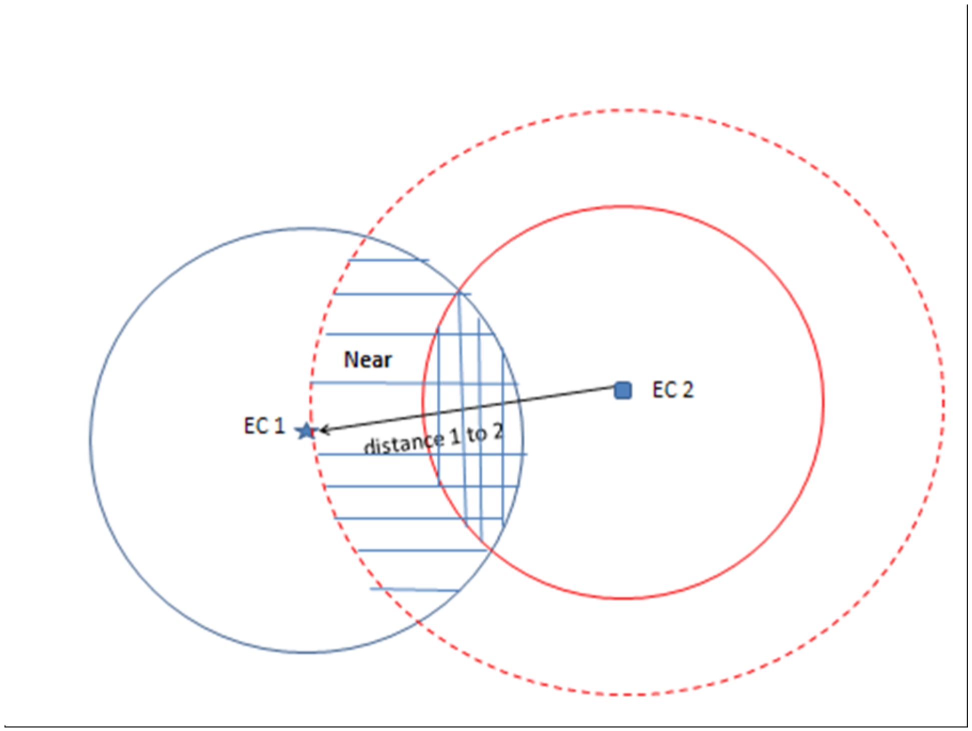
Notes: If the employment center centroid is the peak in the figure, then the proximity specification (m) allows the estimates to capture increased density from the otherwise monocentric specification, while estimating density from the centroid of the employment center (d) sets up a reduction in density because the subcenter centroid is on the monocentric line, while everything else within the commuting area is offset.

Figure 3: Overlapping Commuting Areas



Notes: The solid circles represent the extent of the area of influence based on commuting data for each subcenter. We desire to test whether the density in the area marked "overlap" is equal, conditional on distance from the commuting area edge, to other areas within the same subcenter not marked "overlap." We perform this test both in subcenter 1, and in subcenter 2.

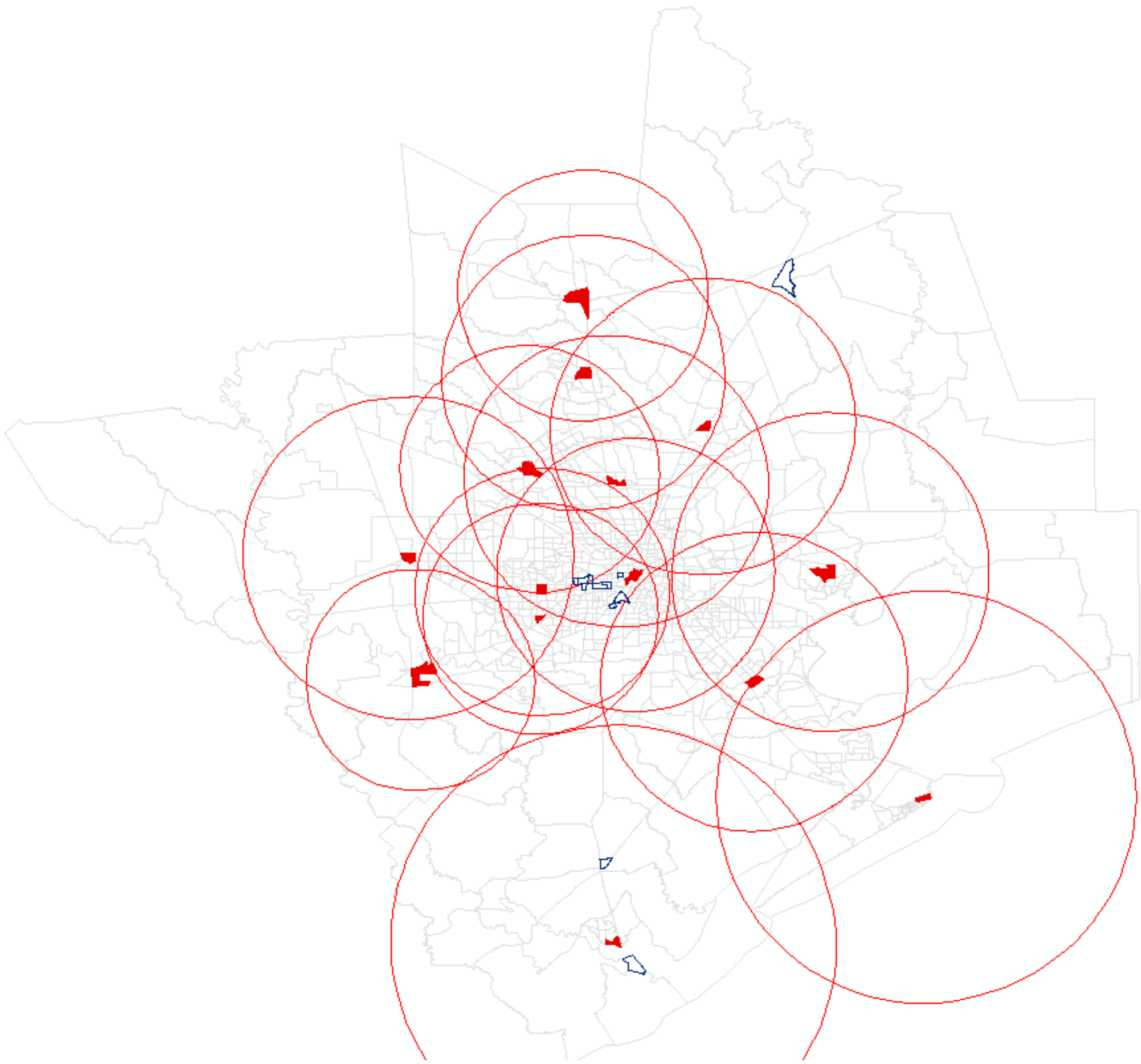
Figure 4: Overlap (defined as double cross hatch) and Near (horizontal lines)



Notes: See Figure 3. The dotted circle through the centroid of EC 1 delineates the area in EC 1 that is closer to EC 2 than otherwise. The cross-hatched area is OL (see Fig 3), the area marked NEAR with the horizontal lines represents proximity to EC 2 but that is outside of the commuting area of influence.

Figure

Figure 5- Estimated Commuting Patterns for Employment Centers



Table

Table 1- Characteristics of Employment Concentrations

Employment Concentration[1, 2]	Number of Census Tracts	Total Workers[3]	Workers/ sq mile	Proportion of Metropolitan Area Workers[4]	Proportion of Total Employ. Center Workers[5]
CBD	2	155,105	84,033	7.70%	32.00%
Galleria	4	68,067	27,708	3.40%	14.00%
Medical Center	2	58,067	30,073	2.90%	12.00%
Greenway Plaza	2	53,057	28,543	2.60%	11.00%
Galveston	2	16,509	15,997	0.82%	3.40%
Greenspoint	1	16,502	11,836	0.82%	3.40%
Willowbrook	1	16,361	5,234	0.81%	3.40%
Westchase	1	15,538	11,197	0.77%	3.20%
Conroe	3	13,048	2,358	0.64%	2.70%
Webster	1	10,520	5,890	0.52%	2.20%
Woodlands	1	10,306	4,820	0.51%	2.10%
Freeport	1	10,015	3,177	0.49%	2.10%
Allen	1	9,578	19,341	0.47%	2.00%
Baytown	2	8,475	2,304	0.42%	1.70%
Richmond	3	6,752	1,258	0.33%	1.40%
Alief	1	5,277	9,529	0.26%	1.10%
Lake Jackson	1	4,453	3,583	0.22%	0.92%
Katy	1	2,310	1,246	0.11%	0.48%
Angleton	1	2,101	1,577	0.10%	0.43%
Kingwood	1	1,836	1,371	0.09%	0.38%
Cleveland	1	739	118	0.04%	0.15%
Total		484,629		24.02%	100%

Notes:

1. Employment concentrations defined as locally statistically significant concentrations of employment following first stage of McMillen (2001). Employment data from 2000 Census Transportation Planning Package Part 3 Journey to work.

2. Employment concentrations identified using local names, major highway intersection, or political iurisdiction

3. Workers located within each employment concentration that reside within the Houston Metropolitan area.

4. Proportion of total metropolitan employment contained within the employment concentration.

5. Share in each employment concentration of the total employment in all concentrations.

Table

Table 2 - Estimated Radii of Influence for Employment Concentrations

Employment Concentratic	Radius of Influence (miles)[3]
CBD	18.25
Galleria	15.61
Medical Center	16.28
Greenway Plaza	17.49
Galveston	26.18
Greenspoint	19.68
SH249 & FM1960	16.14
Westchase	16.87
Conroe	16.46
Webster	20.03
Woodlands	18.4
Freeport	51.34
Allen	15.58
Baytown	21.26
Richmond	14.47
US59 & BW8	15.59
Lake Jackson	29.56
Katy	21.81
Angleton	17.62
Kingwood	19.98
Cleveland	24.01

Notes:

1. Employment concentrations defined as local statistically significant concentrations of employment following first stage of McMillen (2001). Employment data from Census Transportation Planning Package Part 3, Journey to Work.

2. Employment concentrations identified using local names, major highway intersections, or political jurisdiction.

3. The distance is estimated using a quadratic specification where observations are restricted to lay within a certain distance from the concentration, that is, the distance within which 90 percent of the concentration's workers reside.

Table

Table 3a - Polycentric Estimates Using ln(Population Density) [1]

CBD	0.151***
	(0.06)
Galleria	-0.289***
	(0.08)
Medical Center	0.11
	(0.07)
Greenway	0.13
	(0.09)
Galveston	0.167***
	(0.01)
Greenspoint	0.081***
	(0.03)
Willowbrook	0.155***
	(0.02)
Westchase	0.127**
	(0.05)
Conroe	0.135***
	(0.02)
Webster	0.165***
	(0.01)
Woodlands	0.082***
	(0.02)
Freeport	-0.008
	(0.02)
Allen Parkway	-0.013
	(0.07)
Baytown	0.119***
	(0.02)
Richmond	0.138***
	(0.03)
Alief	0.177***
	(0.03)
Lake Jackson	0.092**
	(0.04)
Katy	0.103***
	(0.02)
Angleton	0.03
	(0.06)
Kingwood	0.107***
	(0.02)
Cleveland	0.01
	(0.03)
Constant	4.214***
	(0.21)
Observations	878

Notes: robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

1. Using census tracts from the entire MSA, specification based on proximity (eqns 1 and2). Significant positive marginal gradients are used to define “employment centers”, as distinct from “employment concentrations”.

Table

Table 3b - Polycentric Estimates Using ln(Employment Density) [1]

CBD	0.197***
	(0.06)
Galleria	-0.106
	(0.09)
Medical Center	0.10
	(0.08)
Greenway	0.06
	(0.11)
Galveston	0.223***
	(0.01)
Greenspoint	0.106***
	(0.03)
Willowbrook	0.234***
	(0.03)
Westchase	0.09
	(0.06)
Conroe	0.285***
	(0.04)
Webster	0.230***
	(0.01)
Woodlands	0.134***
	(0.02)
Freeport	0.055**
	(0.02)
Allen Parkway	0.06
	(0.08)
Baytown	0.243***
	(0.02)
Richmond	0.251***
	(0.04)
Alief	0.219***
	(0.04)
Lake Jackson	0.07
	(0.05)
Katy	0.201***
	(0.03)
Angleton	0.05
	(0.08)
Kingwood	0.193***
	(0.03)
Cleveland	0.03
	(0.05)
Constant	0.880***
	(0.33)
Observations	877

Notes: robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

1. Using census tracts from entire MSA, specification based on proximity (eqns 1 and2)..

Table

Table 4a – Estimated Population Gradient Moving toward the Subcenter from the CBD[1]

Employment Center[2]	Estimated Own Gradient[3]	Estimated Total Gradient[4]	Difference (own minus total)
Galveston	0.167***	0.167***	0
	(0.012)	(0.012)	(0.017)
Greenspoint	-0.071	0.117*	-0.188*
	(0.075)	(0.061)	(0.097)
Willowbrook	0.155***	0.036	0.119*
	(0.023)	(0.067)	(0.071)
Westchase	-0.024	0.081	-0.105
	(0.089)	(0.069)	(0.103)
Conroe	0.135***	0.054	0.082*
	(0.024)	(0.035)	(0.042)
Webster	0.165***	0.296***	-0.131***
	(0.013)	(0.021)	(0.024)
Woodlands	0.082***	-0.051**	0.133***
	(0.019)	(0.025)	(0.031)
Baytown	0.119***	0.041**	0.078***
	(0.017)	(0.018)	(0.025)
Richmond	0.138***	0.106***	0.032
	(0.030)	(0.031)	(0.043)
Alief	0.026	0.028	-0.003
	(0.060)	(0.069)	(0.091)
Lake Jackson	0.092**	0.092**	0.000
	(0.037)	(0.037)	(0.052)
Katy	0.103***	-0.022	0.125*
	(0.021)	(0.065)	(0.069)
Kingwood	0.107***	0.048	0.059
	(0.021)	(0.040)	(0.045)

Notes:

1. Movement the last mile from the CBD towards the own subcenter centroid.
2. Employment Centers identified as local statistically significant concentrations of employment with effects on population (see text).
3. Estimated own gradient calculated using the partial gradient of the employment center and CBD, if the employment center falls within the CBD estimated commuting area. Otherwise, partial Gradient is the reported coefficient from the Polycentric Density Regression reported in Table 3.
4. The total gradient takes into account that moving from each employment center towards the CBD changes the distance to other employment centers within the overlapping commuting area (Perdue, 2012). Standard errors of the coefficients calculated using the delta method.

Table

Table 4b – Estimated Employment Gradient moving toward the Subenter from the CBD[1]

Employment Center[2]	Estimated Own Gradient[3]	Estimated Total Gradient[4]	Difference (total minus own)
Galveston	0.223***	0.223***	0
	(0.013)	(0.013)	(0.020)
Greenspoint	-0.091	0.215***	-0.307***
	(0.076)	(0.060)	(0.097)
Willowbrook	0.234***	0.161**	0.073
	(0.028)	(0.081)	(0.085)
Westchase	-0.111	0.081	-0.192
	(0.100)	(0.074)	(0.124)
Conroe	0.285***	0.151***	0.133**
	(0.040)	(0.052)	(0.066)
Webster	0.230***	0.381***	-0.151***
	(0.014)	(0.023)	(0.027)
Woodlands	0.134***	0.011	0.123***
	(0.025)	(0.032)	(0.041)
Baytown	0.243***	0.134***	0.109***
	(0.021)	(0.021)	(0.029)
Richmond	0.251***	0.188***	0.063
	(0.037)	(0.036)	(0.052)
Alief	0.022	0.097	-0.076
	(0.061)	(0.073)	(0.095)
Lake Jackson	0.065	0.065	0.000
	(0.046)	(0.046)	(0.065)
Katy	0.201***	0.117	0.084
	(0.027)	(0.079)	(0.084)
Kingwood	0.193***	0.119**	0.074
	(0.027)	(0.047)	(0.054)

Notes:

1. Movement the last mile from the CBD towards the own subcenter centroid.
2. Employment Centers identified as local statistically significant concentrations of employment with effects on population (see text)
3. Estimated own gradient calculated using the partial gradient of the employment center and CBD, if the employment center falls within the CBD estimated commuting area. Otherwise, partial Gradient is the reported coefficient from the Polycentric Density Regression reported in Table 3.
4. The total gradient takes into account that moving from each employment center towards the CBD changes the distance to other employment centers within the overlapping commuting area (Perdue, 2012). Standard errors of the coefficients calculated using the delta method.

Table

Table 5: The Impact on Density of Overlapping Commuting Areas

Single Employment Center Density Function Estimation

	Observations	ln(Pop) Overlap = 1	ln(emp) Overlap = 1
CBD	543	n/a[a]	n/a[a]
Galveston	66	-0.18	-0.31
		(0.77)	(0.89)
Greenspoint	471	n/a[a]	n/a[a]
Willowbrook	246	2.31***	4.61***
		(0.12)	(0.12)
Westpark	469	n/a[a]	n/a[a]
Conroe	38	1.40***	1.75***
		(0.46)	(0.42)
Webster	257	1.20***	1.32***
		(0.26)	(0.40)
Woodlands	122	1.73***	2.08***
		(0.15)	(0.36)
Baytown	220	3.21***	4.01***
		(0.78)	(0.53)
Richmond	71	3.95***	2.98***
		(0.18)	(0.19)
Alief	375	n/a[a]	n/a[a]
Lake Jackson	37	2.30**	1.95**
		(1.02)	(0.93)
Katy	267	3.48***	3.71***
		(0.49)	(0.55)
Kingwood	195	2.33***	3.58***
		(0.30)	(0.54)

Notes:

Each reported coefficient is on a dummy variable in a separate regression of density on proximity and a constant. The dummy designates tracts in two or more commuting areas. Each regression uses only the data in each row's commuting area.

[a] Indicates there are too few observations that are not in overlapping areas to estimate the coefficient.

Table

Table 6 - Influence of Overlap Proximity on Population Density[1]

Neighbors	Downtown	Galveston	Greenspoint	Willowbrook	Westchase	Conroe	Webster
Downtown CBD	0.115***		0.016	0.048	0.095***		0.143***
	(0.020)		(0.040)	(0.060)	(0.030)		(0.040)
Galveston		0.312***					0.047
		(0.040)					(0.030)
Greenspoint	0.103***		0.033*	0.111***	0.047	0.516**	-0.170**
	(0.03)		(0.02)	(0.04)	(0.04)	(0.24)	(0.09)
Willowbrook	0.04		-0.008	0.017	0.059	-0.188	
	(0.03)		(0.04)	(0.04)	(0.04)	(0.41)	
Westchase	-0.052		0.023	0.049	0.02		0.472**
	(0.04)		(0.03)	(0.05)	(0.04)		(0.22)
Conroe			-0.054	-0.001		0.140***	
			(0.090)	(0.150)		(0.040)	
Webster	0.123***	0.294***	0.064		0.117**		0.080***
	(0.020)	(0.050)	(0.090)		(0.060)		(0.020)
Woodlands	0		-0.038	0.038	0.006	0.072	
	(0.06)		(0.04)	(0.04)	(0.08)	(0.06)	
Baytown	0.052*	0.211***	-0.086*		0.064		0.065***
	(0.03)	(0.05)	(0.05)		(0.18)		(0.02)
Richmond	0.127*				-0.009		
	(0.07)				(0.04)		
Alief	0.195***		0.042	0.056	0.116**		-0.539**
	(0.04)		(0.04)	(0.06)	(0.06)		(0.23)
Lake Jackson		0.192*					-0.203*
		(0.10)					(0.11)
Katy	0.091***		-0.023	0.055	0.049		
	(0.03)		(0.05)	(0.04)	(0.03)		
Kingwood	-0.057		-0.057	-0.069	0.091	-0.349**	0.438*
	(0.04)		(0.04)	(0.07)	(0.08)	(0.15)	(0.24)
Constant	5.724***	0.99	7.716***	6.080***	6.101***	4.280***	5.871***
	(0.34)	(0.87)	(0.75)	(0.62)	(0.43)	(0.43)	(0.44)
Observations	543	66	471	246	469	38	257

Notes

[1] Coefficients from Eq. (4), dependent variable is ln(population density) . These are the estimates on the “overlap” slope dummies. Each column is a regression using only the observations in the own EC’s commuting area. Robust std. errors in parentheses, * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Blanks indicate no overlap.

Table

Table 6 cont. - Influence of Overlap Proximity on Population Density[1]

Neighbors	Woodlands	Baytown	Richmond	Alief	Lake Jackson	Katy	Kingwood
Downtown	0.042	0.251***	-0.093	0.111***		0.172***	0.216***
	(0.11)	(0.05)	(0.13)	(0.03)		(0.05)	(0.05)
Galveston		0.096*			0.16		
		(0.05)			(0.14)		
Greenspoint	0.05	0.04		0.08		0.02	0.02
	(0.05)	(0.04)		(0.05)		(0.05)	(0.03)
Willowbrook	0.197***			0.03		0.202***	0.200***
	(0.05)			(0.05)		(0.04)	(0.05)
Westchase	-0.011	0.447***	0.345**	-0.043		0.023	0.065
	(0.10)	(0.15)	(0.15)	(0.04)		(0.05)	(0.06)
Conroe	0.124***						0.07
	(0.03)						(0.06)
Webster		0.224***		0.05	0.566***		0.745***
		(0.04)		(0.06)	(0.07)		(0.12)
Woodlands	0.03					0.06	0.062*
	(0.05)					(0.07)	(0.04)
Baytown		0.168***		0.621***			0.02
		(0.04)		(0.17)			(0.04)
Richmond			0.147**	0.00		0.146***	.
			(0.06)	(0.04)		(0.04)	
Alief		-0.423**	-0.005	0.179***	.	0.216***	-0.203
		(0.20)	(0.16)	(0.06)		(0.05)	(0.22)
Lake Jackson					0.177***		
					(0.02)		
Katy	-0.063		0.019	0.095***		0.102***	-0.233
	(0.07)		(0.07)	(0.03)		(0.03)	(0.30)
Kingwood	0.101**	0.204***		0.27		0.33	0.114***
	(0.04)	(0.07)		(0.19)		(0.44)	(0.04)
Constant	4.741***	3.136***	4.584***	5.866***	2.182***	4.280***	4.683***
	(0.43)	(0.88)	(0.96)	(0.43)	(0.46)	(0.33)	(0.45)
Observations	122	220	71	375	37	267	195

Notes: [1] Estimates Eq. (4), dep. variable is ln(population density) . The reported coefficients are the estimates on the “overlap” slope dummies. Each column is a regression using only the observations in the own EC’s commuting area. Robust std. errors in parentheses, * p<0.10, ** p<0.05, *** p<0.01. Blanks indicate no overlap.

Table

Table 7 – Coefficients on “Near*Proximity” (not in Overlap Area) for Population Density

Neighbors

	Downtown	Galveston	Greenspoint	Willowbrook	Westchase	Conroe
Downtown			-	-0.055***	-	
				(0.02)		
Galveston						
Greenspoint	-			-	-	-
Willowbrook	-		-		-0.060***	-
					(0.02)	
Westchase	-		-	0.115**		
				(0.06)		
Conroe			0.063**	0.113**		
			(0.03)	(0.05)		
Webster	-0.047*	-0.034*	-		-	
	(0.03)	(0.02)				
Woodlands	-0.065***		-	0.059**	-	-
	(0.02)			(0.03)		
Baytown	-	-	-		-	
Richmond	-				0.073***	
					(0.03)	
Alief	-		-	-	-	
Lake Jackson		0.047*				
		(0.03)				
Katy	-		-0.025**	-	-0.031*	
			(0.01)		(0.02)	
Kingwood	-		-0.064***	-	-	-
			(0.02)			
Baseline Own Co	0.194***	0.307***	0.049	-0.13	0.225***	0.125**
	(0.04)	(0.04)	(0.04)	(0.10)	(0.07)	(0.05)
Constant	5.490***	0.84	7.785***	6.033***	6.579***	4.464***
	(0.34)	(0.96)	(0.83)	(0.64)	(0.44)	(0.52)
Observations	543	66	471	246	469	38

Notes: 1**.** Estimates Eq. (5), dependent variable is ln(population density).. The table shows estimated coefficients on the slope dummy, the coefficient on (Near*proximity). Near (=1) delineates those tracts which are closer to a neighboring employment center than the distance between the two employment center centroids. Each column is a regression using only the census tracts of the given employment center’s commuting area. : Robust standard errors in parentheses, * p<0.10, ** p<0.05, *** p<0.01. ” –“ insignificant results left out in the interest of clarity; blanks indicate no overlap. 2. Baseline own coeff reports the coefficient on own proximity, that is, the coefficient on distance from the tract to the commuting area boundalry.

Table 7 – Coefficients on “Near*Proximity” (not in Overlap Area) for Population Density (cont.)

		Webster	Woodlands	Baytown	Richmond	Alief	Lake Jackson	Katy	Kingwood
Neighbors	Downtown	-	-	-	-	-		-0.103**	-
								(0.05)	
	Galveston	-		-0.071**			-		
				(0.03)					
	Greenspoint	-	0.094**	-		-		-	0.187**
			(0.04)						(0.08)
	Willowbrook		-			0.037*		-	-0.061*
						(0.02)			(0.04)
	Westchase	-0.137***	-	-	0.385**	0.027*		-	-
		(0.04)			(0.18)	(0.02)			
	Conroe		-						-
	Webster			-		-	-		-
	Woodlands							-	-0.073*
									(0.04)
	Baytown	-				-			-
	Richmond					-		-	
	Alief	0.265***		-	-			0.140***	-0.149*
		(0.06)						(0.05)	(0.08)
	Lake Jackson	-							
	Katy		-		-0.110*	-			-0.181**
					(0.06)				(0.09)
	Kingwood	-	-	-		-		-	
	Baseline Own Co	0.051	-0.053	0.285***	0.228**	0.170*	0.168***	-0.039	0.166***
		(0.07)	(0.08)	(0.07)	(0.09)	(0.10)	(0.03)	(0.03)	(0.04)
	Constant	5.322***	4.592***	2.728**	4.401***	6.034***	2.186***	4.187***	4.408***
		(0.57)	(0.48)	(1.17)	(1.24)	(0.56)	(0.48)	(0.28)	(0.47)
	Observations	257	122	220	71	375	37	267	195

Notes: 1**.** Estimates Eq. (5), dependent variable is ln(population density).. The table shows estimated coefficients on the slope dummy, the coefficient on (Near*proximity). Near (=1) delineates those tracts which are closer to a neighboring employment center than the distance between the two employment center centroids. Each column is a regression using only the census tracts of the given employment center’s commuting area. : Robust standard errors in parentheses, * p<0.10, ** p<0.05, *** p<0.01. ” –“ insignificant results left out in the interest of clarity; blanks indicate no overlap. 2. Baseline own coeff reports the coefficient on own proximity, that is, the coefficient on distance from a tract to the commuting area boundary.

Table

Table 8 - Influence of Overlap Proximity on Employment Density[1]

Neighbors	Downtown	Galveston	Greenspoint	Willowbrook	Westchase	Conroe
Downtown	0.239***		0.322***	0.261***	0.236***	
	(0.02)		(0.05)	(0.06)	(0.03)	
Galveston		0.429***				
		(0.04)				
Greenspoint	0.079**		0.035*	0.08	0.05	1.031***
	(0.03)		(0.02)	(0.05)	(0.04)	(0.28)
Willowbrook	0.094***		0.239***	0.181***	0.120***	-0.744*
	(0.03)		(0.05)	(0.05)	(0.03)	(0.37)
Westchase	0.079		0.042	-0.018	0.06	
	(0.05)		(0.04)	(0.07)	(0.05)	
Conroe			0.17	0.283***		0.301***
			(0.11)	(0.10)		(0.06)
Webster	0.186***	0.445***	0.222***		0.01	
	(0.02)	(0.06)	(0.04)		(0.05)	
Woodlands	0.358***	.	0.160***	0.116***	0.301**	0.114**
	(0.06)		(0.04)	(0.04)	(0.12)	(0.05)
Baytown	0.148***	0.260***	0.142***		0.357***	
	(0.02)	(0.05)	(0.04)		(0.06)	
Richmond	0.169		.	-0.536	0.06	
	(0.13)			(0.64)	(0.04)	
Alief	0.139**		0.216***	0.281***	0.138**	
	(0.06)		(0.06)	(0.08)	(0.06)	
Lake Jackson		0.532***				
		(0.11)				
Katy	0.157***		0.182***	0.167***	0.127***	
	(0.04)		(0.05)	(0.05)	(0.03)	
Kingwood	0.042		0.194***	0.137*	-0.017	-0.518***
	(0.06)		(0.05)	(0.08)	(0.07)	(0.15)
Constant	2.570***	-2.900***	1.537*	2.114***	3.020***	1.136
	(0.38)	(0.96)	(0.78)	(0.54)	(0.42)	(0.70)
Observations	543	66	471	246	469	38

Notes: Estimates of Eq. (4), dependent variable is ln(employment density) . The reported estimates are on the "overlap" slope dummies. Each column is a regression using only the observations in the own EC's commuting area. Robust standard errors in parentheses, * p<0.10, ** p<0.05, *** p<0.01. Blanks indicate no overlap.

Table

Table 8 - Influence of Overlap Proximity on Employment Density[1] (cont.)

Neighbors	Webster	Woodlands	Baytown	Richmond	Alief	Lake Jackson	Katy	Kingwood
Downtown	0.194***	0.217*	0.347***	0.246	0.196***		0.211***	0.249***
	(0.03)	(0.12)	(0.04)	(0.16)	(0.03)		(0.05)	(0.06)
Galveston	0.111***		0.098**			0.10		
	(0.03)		(0.05)			(0.17)		
Greenspoint	0.110**	0.109**	-0.024		0.039		0.071	0.088**
	(0.05)	(0.05)	(0.03)		(0.04)		(0.05)	(0.03)
Willowbrook		0.183***			0.02		0.153***	0.183**
		(0.07)			(0.04)		(0.04)	(0.07)
Westchase	0.210*	-0.213*	0.194	-0.02	0.134**		0.096*	0.06
	(0.12)	(0.13)	(0.12)	(0.16)	(0.06)		(0.05)	(0.07)
Conroe		0.232***						0.12
		(0.05)						(0.10)
Webster	0.144***	.	0.263***		-0.1	0.559***		0.709***
	(0.03)		(0.04)		(0.06)	(0.09)		(0.14)
Woodlands		0.069*					0.138**	0.153***
		(0.04)					(0.07)	(0.04)
Baytown	0.144***		0.230***		0.791***			0.126**
	(0.02)		(0.04)		(0.19)			(0.06)
Richmond				0.121*	0.082*		0.166***	
				(0.07)	(0.04)		(0.04)	
Alief	-0.117		0.331	0.216	0.032		0.150***	0.355
	(0.13)		(0.27)	(0.15)	(0.08)		(0.05)	(0.46)
Lake Jackson	-0.116					0.181***		
	(0.17)					(0.03)		
Katy		0.162**		0.08	0.087**		0.109***	0.33
		(0.08)		(0.06)	(0.04)		(0.03)	(0.41)
Kingwood	-0.131	0.148***	0.206***		-0.277		-0.487	0.157***
	(0.12)	(0.05)	(0.07)		(0.28)		(0.33)	(0.06)
Constant	3.271***	2.208***	0.84	3.252***	3.719***	0.911*	2.597***	1.699**
	(0.52)	(0.66)	(0.81)	(0.84)	(0.45)	(0.49)	(0.37)	(0.76)
Observations	257	122	220	71	375	37	267	195

Notes: Estimates of Eq. (4), dependent variable is ln(employment density) . The reported estimates are on the "overlap" slope dummies. Each column is a regression using only the observations in the own EC's commuting area. Robust standard errors in parentheses, * p<0.10, ** p<0.05, *** p<0.01. Blanks indicate no overlap.

Table 9 - Coefficients on “Near*proximity” (not in Overlap Area) for Employment Density

Neighbors

“Near”[1]	Downtown	Galveston	Greenspoint	Willowbrook	Westchase
Downtown			-	-	-
Galveston					
Greenspoint	-			0.051**	-
				(0.02)	
Willowbrook	0.067***		-		-
	(0.02)				
Westchase	0.038**		-	-	
	(0.02)				
Conroe	.		-	-	
Webster	0.084***	-	-		-
	(0.02)				
Woodlands	-		-	-	-
Baytown	-	-	0.079***		-0.078***
			(0.02)		(0.02)
Richmond	-0.050**				0.062**
	(0.02)				(0.03)
Alief	-		-	-	-0.035**
					(0.02)
Lake Jackson		-			
Katy	0.071***		-	-	-0.073***
	(0.02)				(0.03)
Kingwood	-0.032*		-	-0.128**	-
	(0.02)			(0.04)	
Baseline	0.155***	0.435***	-0.007	0.002	0.127
Own Coeff[2]	(0.04)	(0.05)	(0.06)	(0.10)	(0.08)
Constant	2.938***	-3.142***	1.262	2.64***	3.083***
	(0.40)	(1.12)	(0.82)	(0.56)	(0.46)
Observations	543	66	471	246	469

Notes: [1] Estimates of Eq. (5), dependent variable is ln(employment density). The table shows coefficients on the “near” slope dummies excluding overlap area. Near (=1) delineates those tracts which are closer to a neighboring employment center than the distance between the two employment center centroids. Each column is a regression using only the census tracts of the own EC commuting area. Robust standard errors in parentheses, * p<0.10, ** p<0.05, *** p<0.01. ” –“ insignificant results left out in the interest of clarity. Blanks indicate no overlap.

[2] Baseline own coeff. reports the coefficient on own proximity, that is, the coefficient on distance from the tract to the commuting boundary.

Table

Table 9 - Coefficients on "Near*proximity" (not in Overlap Area) for Employment Density (cont.)

	"Near"[1]	Conroe	Webster	Woodlands	Baytown	Richmond	Alief	Lake Jackson	Katy	Kingwood
	Downtown		-	-	-	-	-		-0.107**	-
									(0.05)	
	Galveston		-		-			-		
	Greenspoint	-	-	-	-		-		-	-
	Willowbrook	-		-			-		0.102**	-
									(0.04)	
	Westchase		-0.291***	-	-	-	-		-	0.158**
			(0.06)							(0.08)
	Conroe			-						-
	Webster				-		-	-		0.091**
										(0.04)
Neighbors	Woodlands	-							-	-0.096**
										(0.05)
	Baytown		-				-0.08***			-0.109***
							(0.03)			(0.04)
	Richmond		.				-		-	
	Alief		0.367***		-	-			0.106**	-0.240***
			(0.06)						(0.05)	(0.09)
	Lake Jackson		-							
	Katy		.	0.170***		-0.219***	-0.071**			-0.154*
				(0.05)		(0.08)	(0.03)			(0.09)
	Kingwood	-	-	-0.067*	0.058**		-		-	
				(0.03)	(0.03)					
	Baseline	.30***	0.186**	-0.062	.236***	0.349***	-0.048	0.18***	-0.018	0.187***
	Own Coeff[2]	(0.07)	(0.08)	(0.12)	(0.07)	(0.09)	(0.10)	(0.04)	(0.04)	(0.05)
	Constant	1.04	2.099***	1.865**	0.46	1.708*	3.95***	0.881*	2.453***	1.778**
		(0.85)	(0.57)	(0.73)	(1.10)	(0.89)	(0.49)	(0.52)	(0.35)	(0.77)
	Observations	38	257	122	220	71	375	37	267	195

Notes: [1] Estimates of Eq. (5), dependent variable is ln(employment density). The table shows coefficients on the "near" slope dummies excluding overlap area. Near (=1) delineates those tracts which are closer to a neighboring employment center than the distance between the two employment center centroids. Each column is a regression using only the census tracts of the own EC commuting area. Robust standard errors in parentheses, * p<0.10, ** p<0.05, *** p<0.01. " –" insignificant results left out in the interest of clarity. Blanks indicate no overlap.

[2] Baseline own coeff. reports the coefficient on own proximity, that is, the coefficient on distance from the tract to the commuting boundary.

Table 10: Summary of the Effects of Subcenters on Each Other

	Effects on Overlapping Commuting Area (Coefficients from Tables 6 and 8)			Effects of "Near" Outside of Overlap (Coefficients from Tables 7 and 9)		
	# of Employ Centers where overlap is significant		*Same Emp. Centers Sig for Pop & Emp*	*# of Employ Centers where 'Near' is significant*		*Same Emp. Centers Sig for Pop & Emp*
	Pop	*Emp*		*Pop*	*Emp*	
CBD	6	7	5	2	6	1
Galveston	3	3	3	2	0	0
Greenspoint	1	8	1	3	1	0
Willowbrook	1	6	0	4	2	0
Westchase	3	6	2	3	4	2
Conroe	2	4	2	0	0	n/a
Webster	7	5	4	2	2	2
Woodlands	3	7	3	1	2	0
Baytown	6	4	4	1	1	0
Richmond	1	0	0	2	1	1
Alief	3	5	3	2	2	0
Lake Jackson	1	1	1	0	0	n/a
Katy	4	6	4	2	3	2
Kingwood	4	6	4	5	6	3
TOTAL	**45**	**68**	**36**	**29**	**30**	**11**

Notes: This table shows the extent to which employment centers are related to each other in all dimensions. Cols 1 and 4 summarize the population results (Tabs 6&8), columns 2 and 5 the employment results (Tabs 7&9). Cols 3 and 6 express whether the results are for identical centers. Cols 1-3 are for overlapping commuting areas. Cols 4-6 are for areas outside of the overlap, but which are in the identical direction (thus showing attraction outside of commuting).

Table 11: Summary of Reciprocal Effects

	Within the Commuting Area				Within the "Near" Area			
	Number of Significant Overlaps *Pop*	Number of Reciprocal Overlaps *Pop*	Number of Significant Overlaps *Emp*	Number of Reciprocal Overlaps *Emp*	Number of Significant Overlaps *Pop*	Number of Reciprocal Overlaps *Pop*	Number of Significant Overlaps *Emp*	Number of Reciprocal Overlaps *Emp*
CBD	6	4	7	7	2	0	6	1
Galveston	3	1	3	2	2	0	0	n/a
Greenspoint	1	1	8	4	3	1	1	0
Willowbrook	1	0	6	5	4	1	2	0
Westchase	3	1	6	3	3	1	4	0
Conroe	2	0	6	2	0	n/a	0	n/a
Webster	7	4	5	4	2	0	2	0
Woodlands	3	1	7	7	1	0	2	1
Baytown	6	4	4	4	1	0	1	1
Richmond	1	0	0	n/a	2	1	1	0
Alief	3	3	5	3	2	0	2	1
Lake Jack.	1	1	1	0	0	n/a	0	n/a
Katy	4	4	5	4	2	0	3	2
Kingwood	4	3	5	3	5	1	6	2
TOTAL	45	27	68	48	29	5	30	8
		67.50%		72.73%		17.24%		26.67%

Notes: The first two columns are from Table 6, the next two from Table 7, the third pair from Table 8 and the last pair from Table 9. In regressions using the commuting area of each employment center, this table reports the number of centers with overlapping commuting area which are significant. The first four columns test the effect of distance to the neighboring center where the commuting areas overlap. The second set of four columns tests the effect of being Near to the neighboring center even if outside the other center's commuting area.