

# The Floor Area Ratio Gradient: New York City, 1890-2007

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## Abstract

An important measure of the capital-land ratio in urban areas is the Floor Area Ratio (FAR), which gives a building's total floor area divided by the plot size. Variations in the FAR across cities remain an understudied measure of urban spatial structure. We examine how the FAR varies across the five boroughs of New York City. In particular, we focus on the FAR gradient over the 20<sup>th</sup> century. First we find that the gradient became steeper in the early part of the 20<sup>th</sup> century, but then flattened in the 1930s, and has remained relatively constant since the mid-1940s. Next we identify the slope of the gradient across space, using the Empire State Building as our core location. We find significant variation of the slope coefficients, using both ordinary least squares and geographically weighted regressions. We then identify subcenters, and show that while accounting for them can better capture New York's spatial structure, by and large the city remains monocentric with respect to its FAR. Lastly, we find a nonlinear and nonmonotonic relationship between plot sizes and the FAR across the city.

*Key Words:* New York City, floor area ratio, locally weighted regression

**JEL Classification:** C14, R14, R33

## 1. Introduction

There is a large literature in economics on measuring the nature of urban spatial structure. The focus of these works tends to concentrate on density or price measures relative to the urban core.<sup>1</sup> Collectively, this work has provided several key findings about the urban landscape. First, the price and density gradients drop off at an exponential rate moving away from the center. Second, over the 20<sup>th</sup> century there has been a steady and persistent flattening of the gradient, as central cities have, to some degree, “hollowed out,” while suburban districts have seen large population and employment increases. Third, especially since the mid-20<sup>th</sup> century, urban spatial structure has become poly-centric. With the rise of “edge cities” and smaller suburban agglomerations, population gradients -- while still dropping rapidly from the center -- tend to be “bumpy” across space.

The aim of this work is to explore an important, but understudied, form of urban density—the intensity of land use that comes from the buildings themselves; that is, the structural density of the city (Brueckner, 1987). In particular we focus on the density of commercial structures. The few studies on structural density have tended to focus on housing (McMillen, 2006), but much less work has explored the “shape” of commercial buildings across space and over time.

One important measure of structural density is the floor area ratio (FAR), which is the ratio of total usable floor space to the size of the plot. For example, a 10-story building constructed on the entire lot would have a FAR of 10, as would a 20-story building on half the lot. The FAR is also a useful indicator of the capital-land ratio (McMillen, 2006, Clapp, 1980). As land values rise closer to the city center where transport costs are lower, the monocentric city model implies firms would substitute more capital (structure) for land (O’Sullivan, 2010).

As McMillen (2006) stresses, the monocentric model is static in nature. It details how density should fall with distance from the center, at a given time, on the assumption that the parameter values are fixed. To address this issue we investigate the density gradient over both time and space. However, it might be the case that density and building age are related. If it is the case, for example, that older structures tend to exhibit a steeper FAR gradient with respect to the center, then not accounting for the age of the structure might bias the effects of distance from the center. Thus if age and distance are positively correlated, omission of the age variable will tend to bias the distance coefficients downward (or closer to zero). In this paper we control for possible vintage effects by including in the regression the years of completion for each building.

In particular we focus on New York City from 1890 to 2009, and look at the FAR gradient across the city. Using a data set over such a long period allows us to investigate the shape of the gradient over time. Second, we investigate the degree to which the city is monocentric or not. As

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<sup>1</sup> Anas, et al. (1998) summarize the findings on the population density gradient. Work on land prices include McMillen 1996 for Chicago and Atack and Margo (1998) for 19<sup>th</sup> century New York. McMillen and Singell (1992) provide evidence for wage gradients.

we discuss in more detail below, we use the location of the Empire State Building as the center of the city. New York City is comprised of 469 square miles of land, and contains a population of 8.2 million people. Because it is so large, it can be considered a metropolitan region worthy of investigation unto itself. Despite New York's importance, its land use patterns remain understudied.

In this paper we ask: (1) What does the structural density gradient look like relative to the center? (2) Has it changed appreciably over time? (3) Is there evidence of poly-centricity within the city itself? (4) Does controlling for the building age affect the estimates of the FAR gradient?

Since we have data on the plot size, we also examine how lot size affects structural density across the city, investigating if lot size has a uniform effect, then is its effect positive or negative? On one hand a large lot size can promote structural density, since it allows for a more efficient building layout and helps avoid the "elevator problem" with skyscrapers, which must allocate a large fraction of internal space for elevator shafts. But this may apply only where land values are high. In areas where land values are lower, a large plot may encourage less density because of a concave relationship between price per square foot and size (Colwell and Munneke, 1997). In other words, if the marginal cost of land is decreasing, so will the marginal provision of structure. It remains an empirical question how plot size and structure density are related.

To answer these questions, we employ the methods of locally weighted regression. By and large, the density gradient literature has assumed a constant gradient coefficient across space, and uses ordinary least squares (OLS) to estimate the size of this coefficient. This assumption, however, can lead to biased estimates or standard errors since gradients can change over both time and space (McMillen and Redfean, 2010). While OLS, for example, can include time dummy variables, they are not able to capture the subtle movements of the gradient.

The LWR procedure estimates a separate coefficient for each observation. In particular, we estimate geographically weighted regressions, which are based on the geographic distances of each building from the others.<sup>2</sup> We also incorporate a time dimension into the weight matrix that links all the buildings together. Since our data set includes buildings completed over the 20<sup>th</sup> century, buildings completed in a certain year can only be influenced by completions in the same or prior years.

LWR models are a more general approach that nests OLS. If the OLS assumption about constant gradient coefficients is correct, then LWR and OLS will yield the same results. However, for New York City, we find there is and has been a significant amount of variation in the FAR gradient coefficients over both time and space, which demonstrates that the OLS assumptions do not apply in this situation.

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<sup>2</sup>In particular we use one specific form of Locally Weighted Regressions, namely Geographic Weighted Regressions, which sets the weights as a function of the Euclidean distance between two buildings. For the remainder of the paper we use the term LWR when referring to the method used in this paper.

Based on our results, we find that the gradient for the city as a whole dropped over the first half of the 20<sup>th</sup> century, then remained relatively steady between the late-1940s and mid-1980s, and then dropped to a new plateau over the last quarter century. The evidence also suggests a further flattening of the gradient since 2005.

On first approximation the monocentric model appears to be a good representation of structural density in the city, but LWRs reveal several different “centers of gravity,” which vary across boroughs. For example, the Empire State Building is a useful “center” for structures completed within about 8 miles. After that, however, the further away one moves from the center, the less likely its influence is on the density gradient. In particular we find positive gradient coefficients at several points outside the center of the city. This provides evidence of several smaller “nodes” within the city or adjacent to it. In addition we find that the exclusion of the year of completion variable does not appreciably affect the distance coefficients, suggesting we need not be overly concerned with vintage effects.

As another test for spatial structure, we first run an OLS regression of the log of the FAR on several control variables, including the distance from the Empire State Building. Based on the OLS residuals we then identify five areas in the city with clusters of large positive residuals. We then include these “subcenters” in the regressions and find that while distance to subcenter and airports are statistically significant, they do not increase the  $R^2$  by very much; this suggests that New York remains largely monocentric. Finally we investigate the LWR coefficients of plot size on the FAR relative to the center. We find that closer to the core, the effect is positive, and that after about four miles away from the center the effect becomes negative, on average, and after 10 miles virtually all the coefficients are negative. Further, since the functional form is non-linear, it suggests that using OLS to estimate its affects may not be appropriate.

The rest of the paper is as follows. The next section provides a brief literature review. Then Section 3 discusses the data and the results from ordinary least squares. Section 4 discusses the results from the geographically weighted regressions. Section 5 discusses how we identify subcenters and the results of OLS regressions with the subcenters. Section 6 presents the estimated plot size coefficients on the FAR across the city. Finally, Section 7 provides some concluding remarks.

## **2. Literature Review**

There is a large literature on land rent and population gradients (Anas, et al., 1998), but little known work that directly addresses the FAR gradient. Some works have contributed to the FAR gradient literature indirectly, by examining the intra-urban location of tall buildings. One of these is Frankel (2007), who studies the determinants of locations of tall buildings in the Tel-Aviv municipal region. He finds, for example, a rising probability that 25+ floor buildings will be constructed in the core district; and the likelihood of these very tall buildings falls as one moves away from the center. Clapp (1980) looks at the determinants of office space in the Los Angeles

metropolitan region, by estimating hedonic office rent equations. He finds that while subcenter access and distance to employees are important factors, they are weak relative to the pull of the central business district, where the benefits of face-to-face contacts remain strong.

For New York City, Atack and Margo (1998) investigate land value gradients during the 19<sup>th</sup> century, and find a general flattening of the land price gradient after the Civil War. Haughwout et al. (2008) investigate the land value gradient from 1999 to 2006 in the New York City metropolitan area; their aim is to create a land value index over the period. However, their data show a substantial amount of land value variation in Manhattan, which suggests a standard gradient model is too simple

McMillen (2006) is the only known work that directly addresses the FAR gradient. This research includes estimation of the FAR gradient for individual homes in the city of Chicago, based on both OLS and Spline function approaches. McMillen (2006) notes that closer to the core, lower commuting costs should raise the value of land, which then should cause the FAR to be higher. This is a crucial reason for studying the FAR gradient – that is, to confirm this common underpinning of urban economics. If one confirms that the FAR gradient is downward sloping and monotonic in a city with only one core, this is consistent with the monocentric city model (O’Sullivan, 2010). One of our aims in this paper is to demonstrate that the FAR gradient for Manhattan implies a variation of the monocentric city model with perhaps two cores – the Empire State Building, and lower Manhattan—is applicable to the city. Furthermore, we demonstrate that several of the boroughs of New York City have cores of their own, implying a somewhat more intricate model than the simple monocentric city model might imply for a smaller city.

As McMillen and Redfearn (2010) discuss, the use of OLS to measure effects that vary across geographic space can lead to biased results. One can include both spatial and time related fixed effects in the FAR gradient equation but these coefficients cannot capture the complex nature of a spatial structure. Thus it is necessary to employ more spatially-oriented estimation procedures. In particular, locally weighted regressions (LWR), by generating separate coefficient estimates for each observation, allow for a much more nuanced measurement of an urban area’s spatial patterns. Specifically, McMillen and Redfearn (2010) demonstrate that LWR leads to a much smoother distribution of residuals than fixed effects estimation, as well as helps to mitigate against omitted variable bias.

McMillen (1996) uses LWR to analyze land values in Chicago. His results show how the spatial distribution of land values evolved from the 1830s to the 1990s. In the earliest period of Chicago’s history, land values were generally rising uniformly approaching the city center. However, LWR estimation shows that by the early twentieth century, land values took on a much more diverse picture, with multiple and smaller peaks throughout the city. By 1990 the land value gradients were quite varied throughout the city. A standard OLS approach would have difficulty in capturing this complex pattern.

Meese and Wallace (1991) estimate hedonic housing price models with LWR to compare to standard OLS estimates in several municipalities in California. By using LWR they can see how index values are determined, once freed from the functional form restrictions of OLS. They find that the LWR-generated indexes offer both considerable flexibility and precision. McMillen and Redfearn (2010) estimate hedonic price functions in Chicago using LWR. Their results show that the effect of distance to an elevated subway line in Chicago can have either a positive or negative effect on housing price in different neighborhoods.

### 3. Data

The data set comes from the 2012 “PLUTO” file provided by the New York Department of City Planning ([http://www.nyc.gov/html/dcp/html/bytes/dwn\\_pluto\\_mappluto.shtml](http://www.nyc.gov/html/dcp/html/bytes/dwn_pluto_mappluto.shtml), 2013). This file lists extensive information for every property in the City of New York, including a unique identification number (the “BBL”—borough, block and lot number), building address, latitude and longitude coordinates, year completed, number of floors, the floor area ratio, the lot size, the building type (and sub-type), and other information related to zoning, and land use.

For our analysis, we included observations from 1890 to 2009 which only had a single structure on the property. In addition, we removed some properties that had some extreme outlier characteristics, such as lots less than 100 square feet, and floor area ratios greater than 100. This created a base data set with 662,161 total properties of all types. Of this we only investigate commercial properties, i.e., those that housed a business of some kind.

The work on spatial structure aims to look at density changes relative to the central core. For this paper, we chose the location of the Empire State Building (ESB), at West 34<sup>th</sup> Street and 5<sup>th</sup> Avenue as the “center.” We choose this location because the ESB is generally considered the economic “center of gravity” of the city (Haughwout, et al., 2009). It is in between lower Manhattan and the high-rise office district between 42<sup>nd</sup> and 59<sup>th</sup> Streets. Manhattan, in particular, in terms of its structural density is poly-centric.<sup>3</sup> Because we are interested in the city as a whole (which extends some 20 miles outward from the ESB), we use it as an approximate center.

We also note that the Empire State Building was completed in 1931, and our data set includes buildings from 1890 to 2009, so a large fraction of structures were completed before the ESB. However, the ESB represents a kind of central base location, from which the gradient can be calculated. Moving the center a mile or two in one direction does not appreciably affect the conclusions. We also explore the issues of multiple centers in the paper as well.

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<sup>3</sup> See Barr and Tassier (2013) for the reason why midtown emerged as a separate business district.

### 3.1 Descriptive Statistics

Table 1 lists the different types of commercial properties in our sample. There are approximately 41,400 structures in our data set. Stores comprise the greatest proportion of commercial structures, with a total of approximately 16,000 or 40 percent. Garages/gas stations, and offices, are the next most common groups of commercial structures, with approximately 6,000 of each type. The remaining types of properties include warehouses (approximately 5,200), factories (approximately 3,600), and a relatively small number of lofts, hospitals, hotels, and theaters.

**{Table 1: Distribution of Building Types across NYC}**

Table 2 lists the distribution of structures across the five boroughs. Brooklyn (approximately 33 percent) and Queens (approximately 30 percent) have the greatest amount, with Staten Island (slightly under 7 percent) last. Manhattan (17 percent) and Bronx (13 percent) are in the middle.

**{Table 2: Distribution of Commercial Structures in the Five Boroughs of NYC}**

Table 3 provides descriptive statistics for the FAR. As expected due to its relatively high land values compared with the other boroughs, Manhattan has the greatest average FAR (and the greatest standard deviation). Also, as predicted by its relatively low land values, Staten Island has the lowest structural density in the city.

**{Table 3: Descriptive Statistics for FAR across the Five Boroughs of NYC }**

### 3.2 The FAR Gradient

Figure 1 shows the scatter plot of the log of FAR versus distance from the Empire State Building. On average the gradient is negative, as would be expected; though it does not appear to be linear, as there appears to be a general flattening of the gradient further from the core. Except for the “bump” for downtown Manhattan, there does not appear to be any obvious other sub-centers or deviations from the negative slope, but we will return to this issue in more detail in Section 5.

**{Figure 1: Scatter plot of lnFAR vs Distance to ESB}**

### 3.3 OLS Results

In this section we present evidence on the nature of the FAR gradient from OLS equations. Table 4 presents the results. We present four equations. Equation (1) is the distance gradient from a simple OLS regression. It shows that on, average, the FAR decreases about 13% per mile. Equation (2) is the gradient with quadratic and cubic terms. As the scatter plot shows, adding these terms provides a better fit, in terms of capturing the “shape” of the gradient.

**{Table 4: OLS Results}**

Equation (3) provides an additional set of controls. We add in the log of the plot size and log of plot size squared, the year and the year squared, borough dummies, and building type dummies. For this we included dummies for the sub-categories of building. For example, “warehouses” are further divided by the city into “fireproof,” “semi-fireproof,” “frame, metal,” etc. (See Pluto Data Dictionary for full list of types).

Equation (1) shows that the simple OLS regression is able to account for about 25% of the variation in the FAR gradient across the city. Adding the squared and cubed terms—Equation (2)—brings it up to 31%.

For the plot area, we see a negative relationship overall. For the Year variable there is a negative relationship, but the quadratic terms show a leveling off over time. Finally, we can see differences in average FAR levels across the city. As expected Manhattan has the greatest far (Staten Island is the omitted borough); Brooklyn, the Bronx and Queens, have roughly similar FAR values, on average, while Staten Island has the lowest structural density in the city.

Equation (4) is the same as equation (3) but with the addition of polynomial terms for the distance variable. They add a marginally better fit. In general, the addition of controls reduces the size of the gradient coefficient. The polynomial terms show monotonicity is preserved.

#### 4. Locally Weighted Regressions

Here, we use a version of weighted least squares, as suggested by McMillen and McDonald (2004). Implementation of the model gives an estimated parameter for each target observation (i.e., building):

$$\beta_i = (\sum w_{ij} X_j X_j')^{-1} (\sum w_{ij} X_j Y_j),$$

where  $X_j$  is a vector of control variables including the constant and the distance to the core for each observation except  $i$ ;  $Y_j$  the dependent variable (log of FAR) for all observations except  $i$ ;  $w_{ij}$  is the weight that building  $j$  is given for building  $i$ ; and the summations given by  $\sum$  are taken over all buildings,  $j$ , and  $w_{ii}=0$ .

We use a Gaussian (standard normal) weighting function (kernel) given by

$$w_{ij} = \mathbf{K}\left(\frac{d_{ij}}{b}\right) = \begin{cases} e^{-\frac{1}{2}\left(\frac{d_{ij}}{b}\right)^2} & \text{if } year_i \geq year_j \\ \mathbf{0} & \text{otherwise} \end{cases}$$

where  $d_{ij}$  is the Euclidian distance between building  $i$  and  $j$  (as measured in degrees latitude and longitude). McMillen (2010) notes that the choice of the kernel has little effect on the results since most kernel choices have rapid decay with distance.  $b > 0$  is the bandwidth parameter, discussed more below.

If the year of completion of the target observation, building  $i$ , was after the other buildings in the data set then the weight is a function of the geographic distance. If not, then the weight was set to zero.<sup>4</sup>

The bandwidth parameter determines the “variance” of the weights. A larger  $b$  means that, ceteris paribus, observations further away will have large weight values. For the LWRs, the bandwidth value was selected using the standard cross-validation (C-V) method. The C-V algorithm runs a LWR for each observation for a specific bandwidth value. Then a statistic is generated that is the mean squared residual of the LWR, where the residual is the difference between the target value (i.e.,  $\ln FAR_i$ ) and the predicted target value, after omitting the  $i$ th observation from the model. The bandwidth that minimizes this statistic is used. See McMillen and McDonald (1997) for more information.

For each estimated coefficient we also calculate a standard error, given by equation 2.21 in Fotheringham et al. (2002). This approach is similar to the F-statistics calculations procedure described in the appendix of McMillen and Redfean (2010).

#### 4.1 LWR Results

For the LWRs, we regressed the log of the floor area ratio ( $\ln FAR$ ) on the log of plot size ( $\ln Area$ ), the year the building was constructed ( $Year$ ) and the distance to the Empire State Building ( $DESB$ ). Note that the results are from using a bandwidth that minimize the C-V, which in this case gives  $b=0.02$ . We also compare the results from a regression of  $\ln FAR$  on  $DESB$  and  $\ln FAR$  on  $DESB$  and  $\ln Area$ , omitting the year.

Table 5 gives the descriptive statistics for the results. We separate the coefficient results into each borough for comparison. First, focusing on the distance coefficients we see that, on average, Manhattan has the largest (in absolute value) coefficients, and that the average and median are negative.

#### 4.2 FAR Gradient over Time

Figure 2 shows the averages of the coefficients for each year. Figure 2a shows the (unweighted) averages of all the coefficients with standard errors bands equal  $\pm 1.96$ \*(average of the standard errors). They show that starting in the 1920s, there was a general flattening of the gradient across the city. Then between around 1940 and 1985 the gradient remained relatively constant, hovering in the -0.11 range, when it started to flatten again. However, since the mid-2000, the average has started to decline a bit.

Anas et al. (1998) report estimates for the population density gradient at three points in time (in miles), 1900, 1940, and 1950. They find it to be 0.32, 0.21, and 0.18, respectively. McDonald and McMillen (2007) report population a density gradient of 0.12 for New York in 2000. While

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<sup>4</sup> Setting some weights equal to zero is analogous to specifying a “window” (see McMillen and Redfean, 2010).

our results show the same direction, the FAR gradient for the city of New York appears to have small coefficients (in absolute value). For the decade of 1900 to 1909 our coefficient averages about 0.11, for the 1940s, the average is 0.05, 1950s is 0.06, and for 2000s is 0.04. Note that some of the difference across studies might also be related to the size of regions. Here we focus on only New York City, but when other studies include metropolitan areas it is likely to increase the size of the gradient, if density falls off rapidly outside of the central city proper.

Figure 2b shows the averages of the coefficients over time for each borough separately. It shows that there are different patterns between Manhattan and the outer boroughs over time (Staten Island is omitted to increase clarity). By and large, the outer boroughs showed a general gradient flattening between 1900 and 1940, and have remained relatively constant since then.

**{Figure 2a and 2b: Avg. LWR coefficients over time.}**

Manhattan, on the other hand, has shown a different pattern. First, the average coefficients have consistently remained large (in absolute value) as would be expected given its importance in the national economy and its higher land values. Second we see that an opposite trend as compared to the other boroughs: the gradient in Manhattan appears to have steadily fallen until the early 1960s. From there, over time, the gradient has flattened out. The gradient coefficients also show much more variation from year to year in Manhattan. In addition, Manhattan's gradient seems much more sensitive to the business cycle—falling in years in which the economy is growing, and moving closer to zero in the years the economy is in recession or depression. For example, the 1930s to early 1940s, shows the coefficients moving closer to zero, then dropping until the mid-1960s. Another “spike” toward zero occurs in the mid-1970s and the 1990s. The FAR's movements over the course of the business cycle suggests that land values are quite sensitive to economic activity at the national level.

Figure 3 shows the coefficient estimates versus distance from the Empire State Building. The results of each borough are presented in separate graphs. The overall pattern shows that the coefficients very close the Empire State Building are quite large (in absolute value) and moving away they get closer to zero. In general they flatten out, between mile 5 and 15. Then after that there are two areas, one at mile 15 and one at mile 20 where the coefficients go above zero. This suggests that in these two areas there are smaller subcenters, on the fringes of the city. We have more to say about the subcenters in section 5 below. Figure 3 suggests that OLS estimates are misleading with regard to the shape of the coefficients across the city.

**{Figure 3a-d: LWR coefficients vs distance from ESB by borough}**

Figure 4 presents a type of intensity map for the distance coefficient estimates (Fotheringham, 2002). Each point on the map is a t-statistic equal to the coefficient estimate divided its standard error. It shows the relative magnitude of the coefficients. Here we see concentric bands of coefficients; with the regions of positive coefficients. The dark red dots show the largest t-stats (in absolute value) and they are a semi-circular area around the Empire State Building.

The next semi-circle around that has smaller t-statistics, but all above 10 in absolute value. Two clusters of black dots (positive t-statistics) occur in three locations (the one in south-western corner of Staten Island is not shown on the map). One is located in Jamaica, Queens; the other is Far Rockaway, Queens. These suggest local “centers of gravity.” Jamaica is a local transportation hub for the Long Island Railroad; Far Rockaway, perhaps, attracts business near John F. Kennedy Airport. The third cluster is in south west Staten Island, across the river from Perth Amboy, New Jersey (not shown on map).

**{Figure 4: T-stats map for LWR Coefficients}**

Since the LWR estimates give the slope of the density gradient, we compare them to the slope coefficients from OLS. In particular, we first took a moving average (25) of the LWR coefficients versus the distance to the ESB and plotted the scatter plot in Figure 5. Also presented is the slope of the estimated coefficients from the OLS regression equation (4) Table 4. In particular, we graph

$$\partial \ln \hat{FAR} / \partial (DESB) = -.215 + 2(.019)DESB - 3(0.001)DESB^2.$$

Figure 5 shows the results. Over the graph suggests a kind of glass-half-full/glass-half-empty results. On average, the OLS slope coefficients share similar movement compared with the LWR coefficients; however, the LWR coefficients are able to capture more subtle movements in the density landscape.

Finally, we reran the LWRs without the year to see if its omission dramatically changed the distance to the ESB coefficients. We found that it did not. In fact, the correlation coefficient for the two sets of coefficients was .99, and a regression of coefficients without the year on the coefficients with year gave an estimated slope coefficient of 1.01 and p-value=0.00. This suggests that LWRs might offer an “antidote” to the problem of omitted variable bias.

**5. Subcenter Identification**

As a method to identify possible subcenters in New York City, we used the residuals from equation (4), table 4. From this list of residuals we then mapped the clusters of residuals that (a) were greater than 1.47 (two standard deviations away from 0), and had more than 15 of these residuals within a quarter mile of each other. From this procedure we identified 6 centers or subcenters in order of size (based on size of cluster). Figure 6 shows the results.

**{Figure 6: Map of Subcenters}**

In Manhattan the area is north of Grand Central Station (Park and 53<sup>rd</sup> Street) and Wall Street. In Brooklyn, there is downtown Brooklyn, and in Queens there is Flushing and Jamaica, and in the Bronx there is The Hub neighborhood (at East 149<sup>th</sup> and Third Avenue). The process did not yield any centers for Staten Island. We note that technically midtown and downtown are not

subcenters, but actual centers in their own right, but for exposition we refer to them as subcenters because of the way we identify them in this section.

A word is in order about the criteria we used. We recognize there is some arbitrariness in determining the subcenters across the city. However, our aim is to find the largest and most important ones. If we reduced either one of the thresholds, we risked the possibility of including false positive identifications, in the sense that a cluster of positive residuals might simply reflect, for example, a public housing development rather than a true concentration of structural density.

In the end the rule we chose seemed to be a reasonable balance between identifying subcenters while not being overly liberal. The OLS regressions bear this out in the sense that the coefficient estimates for the distance to subcenters are statistically significant, but even including the largest ones don't increase the  $R^2$  by a large amount. Also note that we obtained the exact same centers when positive residuals greater than one standard deviation, and 45 or more were clustered within a quarter mile of each other.

We also note that work by McMillen (2001) has used LWRs to identify subcenters. With our data set, we found that we were able to identify the same subcenters when using the LWR residuals. In particular, when we took positive LWR residuals that were one standard deviation away and had 15 or more clustered within a quarter mile of each other, the same six subcenters appeared.

Lastly, we also included measures of the distance to the closest airport. New York City has two airports, LaGuardia and John F. Kennedy. Distance to these might also affect density, since they are transportation hubs. In the end, we found that the best specification was to divide the distance variable into two. The first variable is the distance to the closest airport times a dummy variable that takes on the value of one if the distance is less than five miles, and zero otherwise. The second variable is the distance to the airport times a dummy variable that takes on the value of one if the distance is between five and ten miles away, and zero otherwise. The results show that moving further away the effect of the airports diminishes. For locations close the airport the FAR density gradient is close to 0.06 on average. For the next group it falls to about 0.014, on average.

## **6. The Effect of Plot Size Across the City**

In both the OLS regressions and LWRs we included the plot size as an explanatory variable. The OLS results show that, on average, there is a negative relationship between the lot size and the FAR, though the functional form appears nonlinear. Figure 7 shows a scatter plot of the plot area estimated coefficients versus the distance from the Empire State Building. Here we can see that the LWRs paint a more subtle picture as compared to the OLS results. Each borough is given a different color to see how the coefficients vary across the city.

The results show that for most of Manhattan and the western portions of Brooklyn and Queens, the coefficient estimates are positive, on average. After about four miles away, the average becomes negative, and slowly decreases, so that by 10 miles away virtually all of the coefficients are less than zero. As well the magnitude of the coefficients (in absolute values) steadily becomes larger as one moves away from the center.

While we leave a more detailed treatment of this result for future work, the relationship is most likely due to three factors: land values, the types of businesses, and zoning. Because land values are much higher closer to the center, each plot of land is likely to be used more intensively. Having a larger plot of land allows the developer to overcome the problems associated with elevators. Since a skyscraper requires that a large fraction of its internal space is devoted to elevator shafts, a larger lot can allow a developer to build a taller building and reap a greater return (Barr, 2012).

Moving away from the center, as land values drop, there is less economic pressure to use the plot more intensively, and our results show that, in fact, at some point, larger plots are associated with less structural density. This negative effect might also be related to the types of businesses that are likely to locate further out from the center. In particular, in the outer boroughs there are more likely to be retail services that cater to the neighborhood populations, including supermarkets, shopping centers, and automobile repair shops. These types of stores mostly likely prefer a flatter, rather than taller, configuration because it is easier for shoppers or workers to navigate through the space.<sup>5</sup>

Lastly, it is also likely that zoning rules play a role. First if the zoning laws reduce the FAR limits in the suburban parts of the city, it will legally promote the relationship we see in Figure 7. Second, if the zoning rules require developers to provide on-site parking, then this will force a less-intensive use of space, all else equal. Where land values are relatively cheap, developers prefer to provide grade-parking, rather than decks or underground garages, because of the additional expense.

## **Conclusion**

This paper explores a less commonly investigated component of urban spatial structure—the Floor Area Ratio (FAR), which is a measure of the capital-land ratio. In particular, our goal is to investigate the FAR gradient across both time and space. We focus on New York City from 1890 to 2009, incorporating practically every extant commercial building in the city—some 40,000 structures completed over the last 120 years. By controlling for the age of the structures, we are able to determine the FAR gradient over time, with little concern for possible vintage effects.

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<sup>5</sup> Consider that even in Manhattan most supermarkets are on one floor, and occasionally, only in the most busy districts do you sometimes find a supermarket with a second level.

We estimate the FAR gradient by both ordinary least squares (OLS) and locally weighted regressions (LWRs). We find that the LWRs are better able to better capture the changes in the gradient over time, as compared to OLS. In particular we find that the gradient steepened in the early part of the 20<sup>th</sup> century, and then began to flatten in the mid part of century, with a plateau around 1945.

We also find a very different gradient pattern over time in Manhattan, relative to the other boroughs. In particular, Manhattan's FAR gradient is much steeper, as would be expected, but it also appears to be very sensitive to the business cycle—flattening during downturns and becoming steeper during boom times. This most likely reflects the sensitivity of Manhattan's land values to the general level of U.S. output.

Next we compare the LWR gradient coefficients to the slope of the OLS coefficients. We find that while a cubic functional form for OLS is a reasonable measure of the FAR gradient, it does not capture the more subtle patterns across space. In particular we find that in some locations in the outer boroughs the gradient with respect to the center is positive.

This suggests then that there are other “centers of gravity” throughout the city. To explore this in more detail we identify possible subcenters by looking at positive clusters of OLS residuals. This procedure identifies six subcenters (two in Manhattan, one in Brooklyn, one in the Bronx and two in Queens). We then rerun the OLS equations with distance to nearest subcenter and distance measures to the city's airports. We find that while these additional controls are statistically significant, they do not appreciably increase the  $R^2$ , suggesting that beyond Manhattan, subcenters are not as important.

Finally, we investigate the relationship between the plot area coefficients from the LWRs and distance from the center. We find that close to the center, the coefficients are positive, suggesting that large plots allow land to be used more intensively there. But moving away from the center the relationship becomes negative, on average, suggesting large plots are used less intensively further away from the center. We leave further exploration of this relationship for future work, but we hypothesize that it is related to land values, the mix of businesses in different parts of the city, and zoning regulations.

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## Tables

<b>Building Type</b>	<b>Count</b>	<b>Percent</b>
Stores	16,726	40.4
Garages/Gas Stations	6,738	16.3
Offices	5,959	14.4
Warehouses	5,240	12.7
Factories/Industrial	3,644	8.8
Lofts	1,287	3.1
Hospitals/Health	987	2.4
Hotels	662	1.6
Theaters	154	0.4
<b>Total</b>	<b>41,397</b>	<b>100</b>

**Table 1: Distribution of Building Types across NYC (excludes residential buildings, asylums and nursing homes, houses of worship, condominiums, parks buildings, and utility properties)**

<b>Borough</b>	<b>Frequency</b>	<b>Percent</b>	<b>Cumulative</b>
Brooklyn	13,942	33.68	33.68
Bronx	5,407	13.06	46.74
Manhattan	6,857	16.56	63.3
Queens	12,447	30.07	93.37
Staten Island	2,744	6.63	100
<b>Total</b>	<b>41,397</b>	<b>100</b>	

**Table 2: Distribution of Commercial Structures in the Five Boroughs of NYC**

<b>Borough</b>	<b>Mean</b>	<b>Std. Dev</b>	<b>Min.</b>	<b>Max.</b>	<b>Nobs.</b>
BK	1.38	1.20	0.01	23.96	13,567
BX	1.13	0.94	0.01	12.14	5,132
MN	5.84	5.87	0.02	87.67	6,831
QN	1.20	1.37	0.01	37.6	11,781
SI	0.65	0.50	0.01	6.03	2,642
NYC	2.00	3.18	0.01	87.76	39,353

**Table 3: Descriptive Statistics for FAR across the Five Boroughs of NYC \* difference is nobs. are due to missing FAR values.**

	(1)	(2)	(3)	(4)
Dist. to Empire State	-0.129	-0.507	-0.053	-0.215
	(109.10)**	(64.98)**	(37.60)**	(22.65)**
(Dist. to ESB) <sup>2</sup>		0.044		0.019
		(42.67)**		(16.87)**
(Dist. to ESB) <sup>3</sup>		-0.001		-0.001
		(34.13)**		(15.41)**
Ln(Lot Area)			-0.168	-0.177
			(3.14)**	(3.32)**
Ln(LotArea) <sup>2</sup>			0.005	0.005
			(1.48)	(1.63)
Year			-0.46	-0.477
			(20.25)**	(21.05)**
Year <sup>2</sup>			0.0001	0.0001
			(20.22)**	(21.02)**
Brooklyn Du mmy			0.353	0.424
			(20.06)**	(22.48)**
Bron x Du mmy			0.305	0.366
			(16.16)**	(18.00)**
Manhattan Dummy			1.27	1.163
			(52.03)**	(46.23)**
Queens Dummy			0.266	0.309
			(15.14)**	(16.84)**
Constant	1.05	1.79	452.1	468.9
	(109.35)**	(106.49)**	(20.35)**	(21.16)**
# Observations	39953	39953	39944	39944
R <sup>2</sup>	0.26	0.31	0.42	0.42
Building Type Du mmies			Yes	Yes
P-val for Du mmies			0.00	0.00

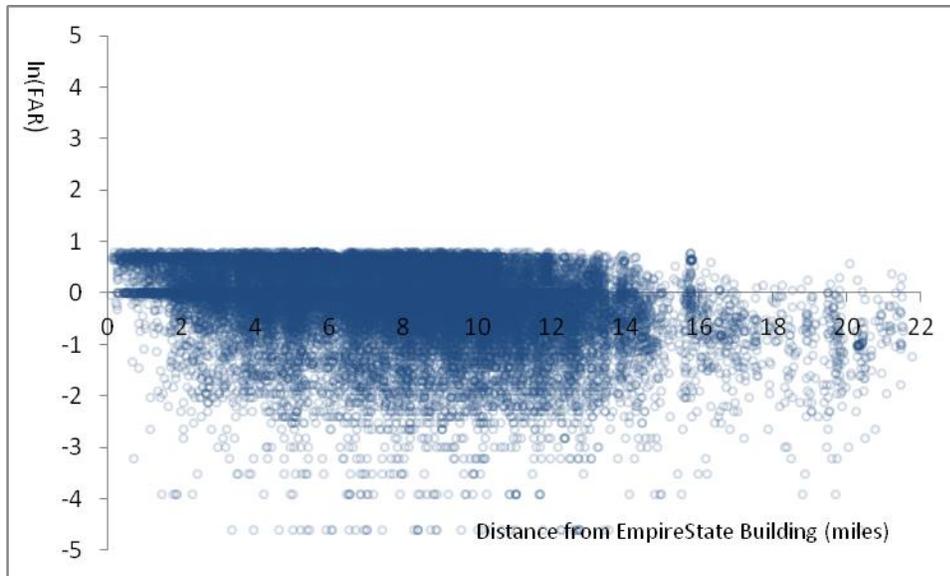
**Table 4: OLS Regression Results. Dependent Variables is ln(FAR) for commercial structures. \*\* Stat. sig. at 99% ; \*Stat. sig. at 95% . Absolute value of robust t-statistics below coefficient estimates.**

<b>Variable</b>	<b>Mean</b>	<b>St. Dev.</b>	<b>Avg. St. Err.</b>	<b>Min.</b>	<b>Max.</b>	<b># Obs.</b>
<b>New York City</b>						
Dist. ESB	-0.11	0.12	0.02	-1.27	1.77	39944
Ln(Area)	-0.06	0.22	0.03	-1.68	1.30	39944
Year	-0.01	0.03	0.01	-0.83	2.38	39944
<b>Brooklyn</b>						
Dist. ESB	-0.10	0.09	0.01	-0.55	0.35	13566
Ln(Area)	-0.10	0.11	0.03	-1.03	1.30	13566
Year	-0.01	0.01	0.00	-0.68	1.00	13566
<b>Bronx</b>						
Dist. ESB	-0.09	0.05	0.02	-0.80	0.76	5132
Ln(Area)	-0.08	0.10	0.04	-1.19	0.62	5132
Year	-0.01	0.02	0.00	-0.23	0.41	5132
<b>Manhattan</b>						
Dist. ESB	-0.23	0.13	0.02	-0.67	0.25	6829
Ln(Area)	0.32	0.15	0.03	-1.41	0.49	6829
Year	0.00	0.05	0.01	-0.10	2.38	6829
<b>Queens</b>						
Dist. ESB	-0.09	0.13	0.02	-1.27	1.77	11780
Ln(Area)	-0.15	0.13	0.03	-1.68	0.73	11780
Year	-0.01	0.02	0.01	-0.83	0.66	11780
<b>Staten Island</b>						
Dist. ESB	-0.08	0.13	0.04	-1.26	0.56	2637
Ln(Area)	-0.32	0.11	0.06	-1.00	0.96	2637
Year	0.00	0.02	0.01	-0.59	0.40	2637

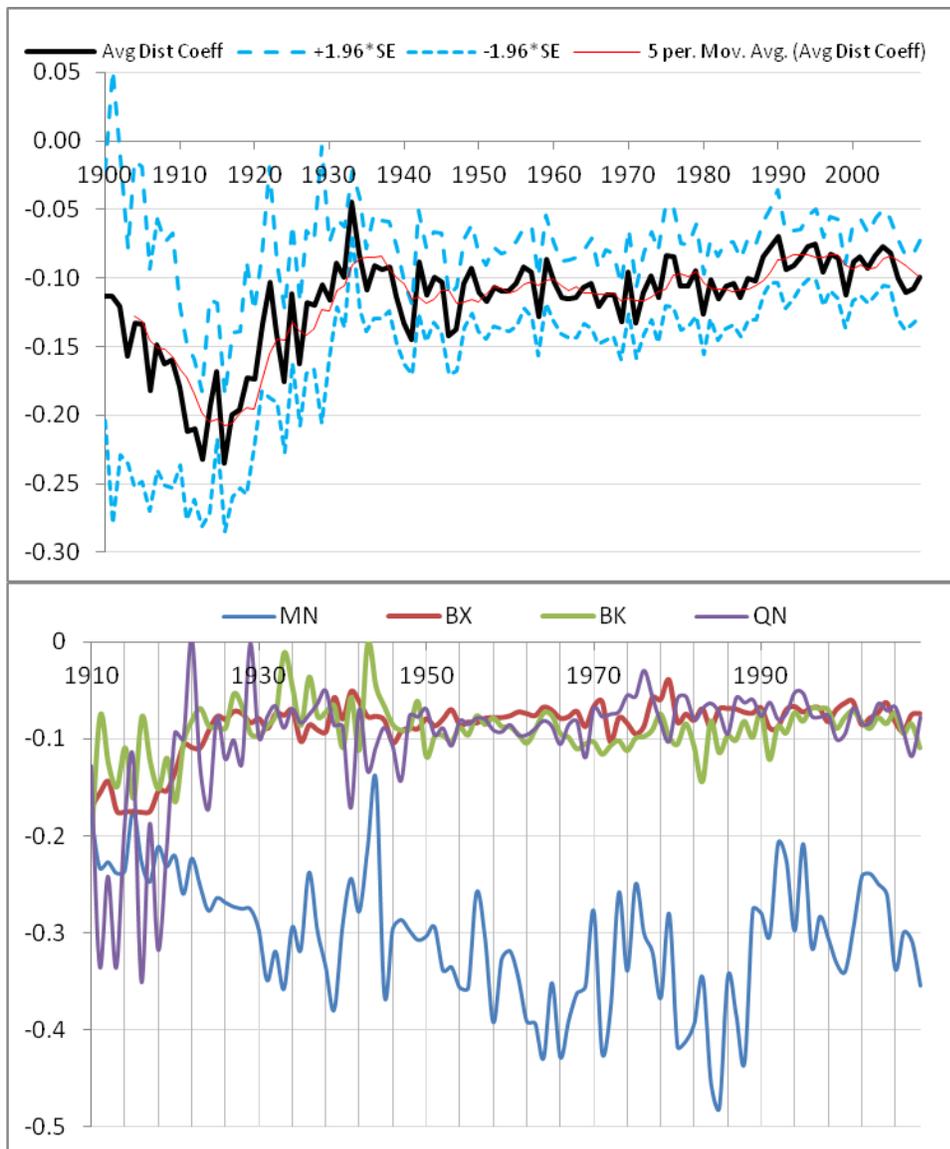
**Table 5: Descriptive statistics for coefficient estimates from the locally weighted regressions.**

	(1)	(2)	(3)	(4)
Dist. to Empire State Bldg.	-0.215	-0.238	-0.203	-0.213
	(22.86)**	(18.71)**	(21.34)**	(16.76)**
(Dist. to ESB) <sup>2</sup>	0.019	0.026	0.017	0.022
	(17.54)**	(13.97)**	(15.67)**	(12.01)**
(Dist. to ESB) <sup>3</sup>	-0.001	-0.001	-0.0004	-0.001
	(13.78)**	(12.18)**	(11.75)**	(10.48)**
Ln(Area)	-0.19	-0.14	-0.198	-0.145
	(3.60)**	(2.65)**	(3.73)**	(2.74)**
Ln(Area) <sup>2</sup>	0.006	0.003	0.006	0.003
	(1.91)	(1.00)	(2.10)*	(1.15)
Year	-0.454	-0.453	-0.455	-0.452
	(20.24)**	(20.38)**	(20.28)**	(20.37)**
Year <sup>2</sup>	0.0001	0.0001	0.0001	0.0001
	(20.21)**	(20.34)**	(20.25)**	(20.33)**
Brooklyn Dummy	0.239	0.579	0.274	0.627
	(11.50)**	(21.75)**	(12.42)**	(22.83)**
Bronx Dummy	0.105	0.458	0.212	0.594
	(4.40)**	(15.64)**	(8.41)**	(19.44)**
Manhattan Dummy	0.872	1.193	0.93	1.27
	(30.56)**	(37.03)**	(31.97)**	(38.81)**
Queens Dummy	0.018	0.411	0.138	0.571
	-0.78	(14.03)**	(5.76)**	(18.79)**
Dist. to Closest Subcenter	-0.064	-0.211	-0.072	-0.237
	(21.04)**	(20.67)**	(23.30)**	(23.07)**
(Dist. to Subcenter) <sup>2</sup>		0.026		0.03
		(12.76)**		(14.51)**
(Dist. to Subcenter) <sup>3</sup>		-0.001		-0.001
		(6.24)**		(7.71)**
Dist. Closest Airport x Less than 5 Miles			-0.057	-0.064
			(16.35)**	(18.31)**
Dist. Closest Airport x (5 – 10 Miles)			-0.015	-0.013
			(9.34)**	(8.61)**
Constant	446.4	444.8	447.0	443.9
	(20.37)**	(20.50)**	(20.42)**	(20.50)**
R-squared	0.43	0.44	0.43	0.44

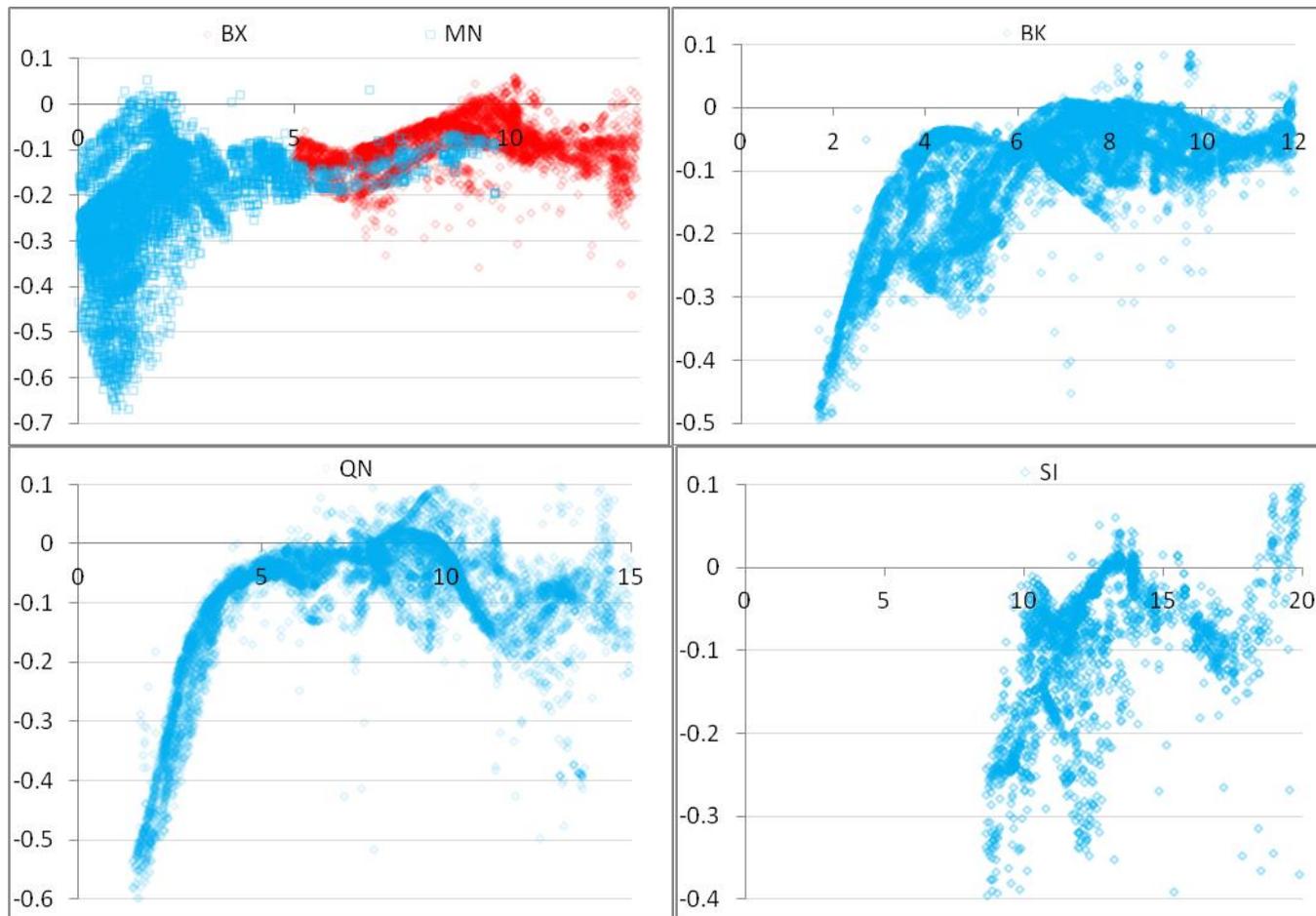
**Table 6: OLS regressions with distance to closest subcenter and airport. Robust t-statistics in parentheses. \*\* Significant at 99% ; \* significant at 95% . Note all regressions have 39,944 observations; all include building types dummies (with p-values =0.00).**



**Figure 1: Scatter plot of  $\ln(\text{FAR})$  versus distance from the Empire State Building for Commercial Structures.**



**Figure 2. Top (2a): average LWR coefficients over time for NYC, 1900-2009. Bottom (2b): average coefficients over time for each borough (Staten Island Not shown), 1910-2009.**



**Figure 3: LWR coefficient estimates vs. distance from the Empire State Building (miles). Top left (3a): Manhattan and Bronx. Top right (3b): Brooklyn. Bottom left (3c): Queens. Bottom Right (3d): Staten Island. Note vertices may have different lengths across graphs.**

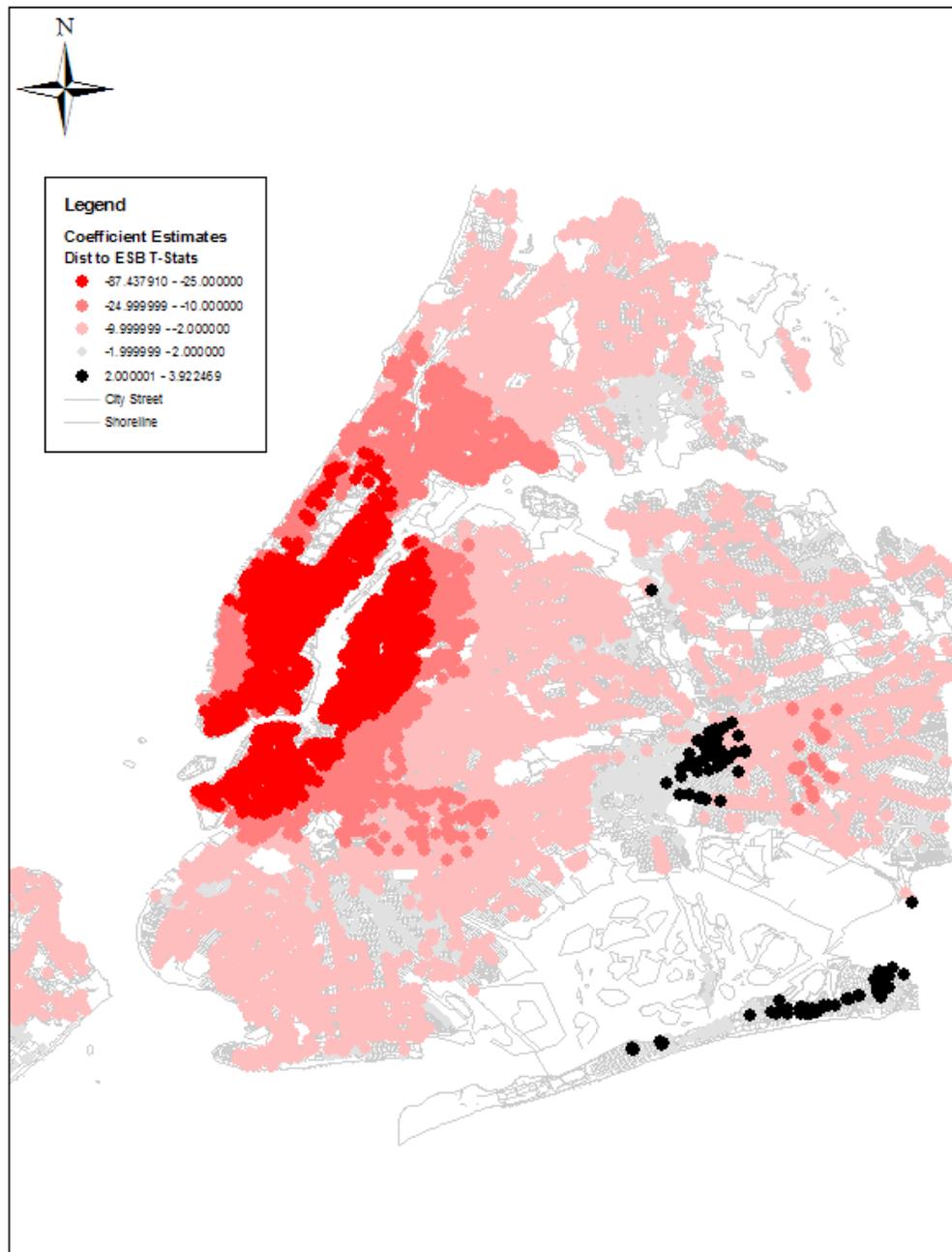
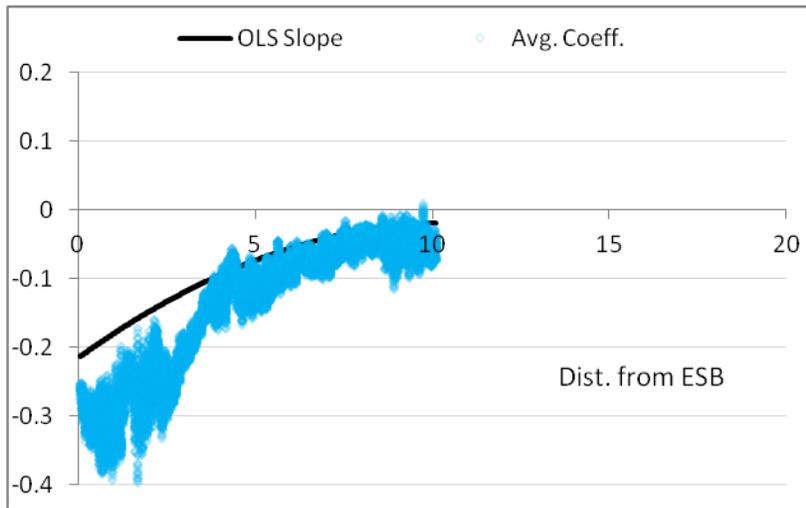
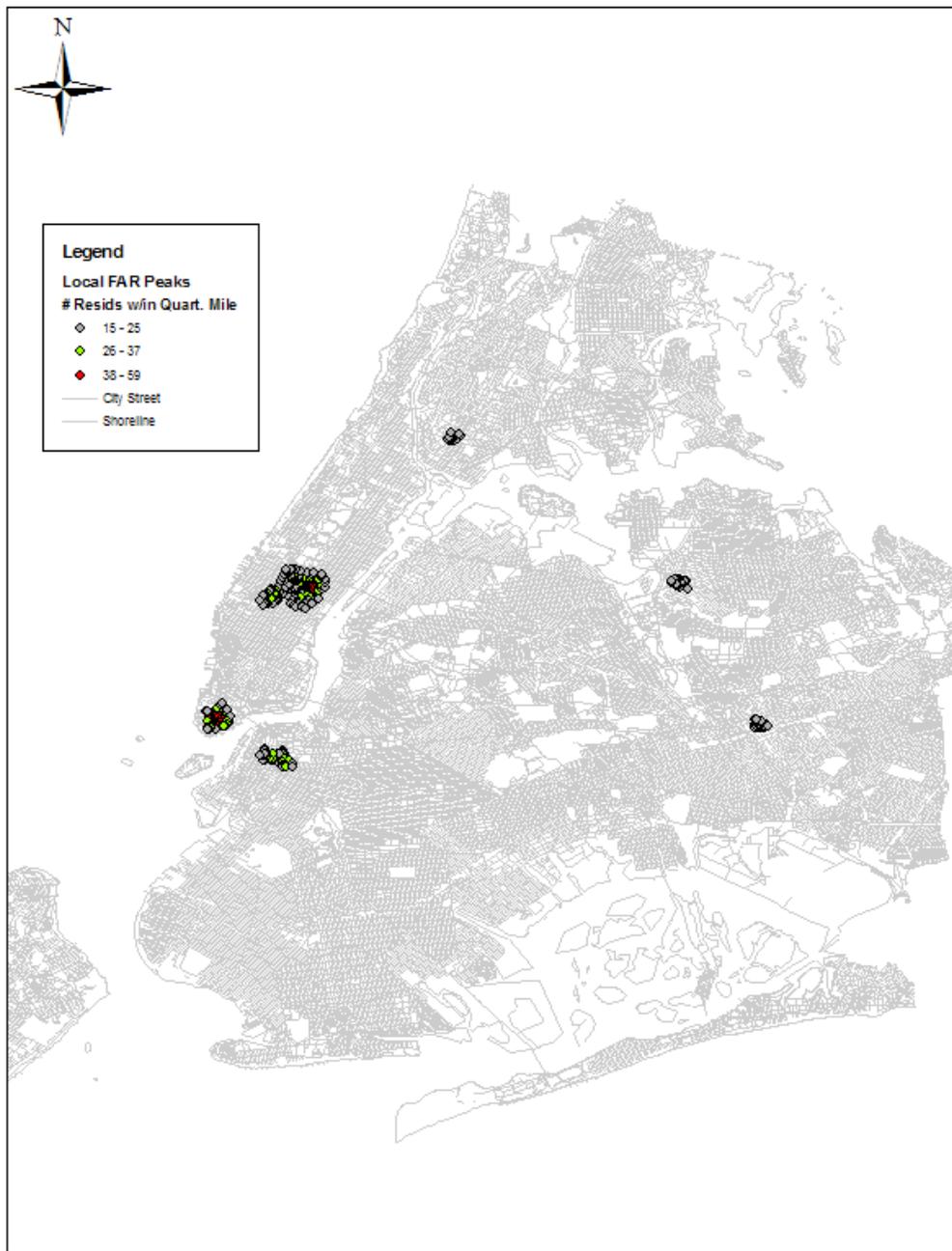


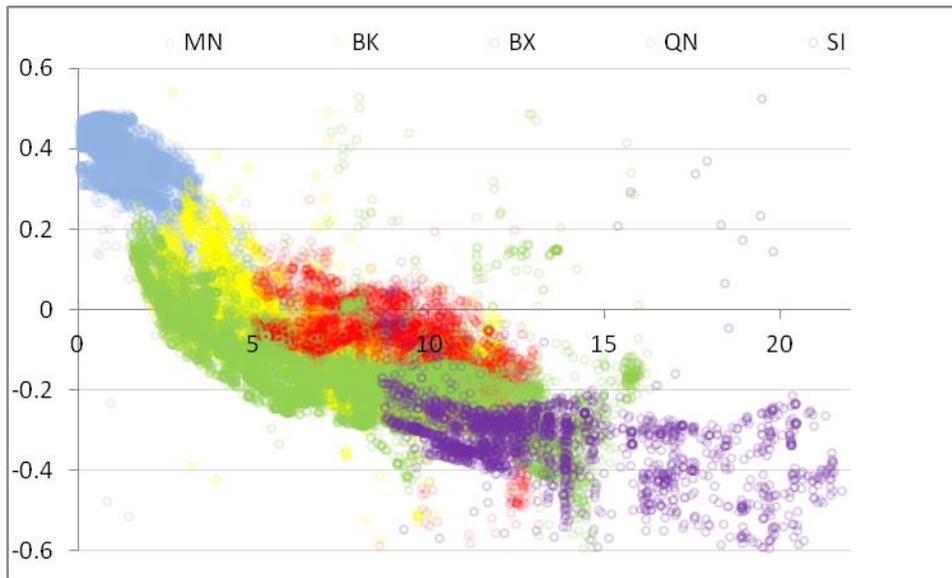
Figure 4: Map of t-stats of GWR distance to ESB coefficients. Note Staten Island note shown.



**Figure 5: Moving Avg. (25) of GWR distance coefficient estimates vs. slope from OLS regression (Table 4, equation (4)).**



**Figure 6: Clusters of positive residuals used to identify sub-centers in New York City.**



**Figure 7: Scatter plot of plot area coefficients from GWRs versus distance from the Empire State Building**