Why are Skyscrapers so Tall? Land Use and the Spatial Location of Buildings in New York

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Abstract

Many major cities in the U.S. and throughout the world, including New York City, have areas where clusters of skyscrapers are present. Why do builders choose to build real estate with such height? And, how does the choice of height depend on characteristics of nearby buildings, demographics, and other spatial factors? Using a data set consisting of detailed information for 458 skyscrapers in New York City completed between 1895 and 2004, we investigate the factors that have determined building height. Our estimation strategy is to use geographically weighted regressions (GWR), which generates a separate parameter estimate for each data point. That is to say GWR gives specific coefficient estimates for each building, so that we can investigate how very local factors have driven building height. We find that the two different business districts (downtown and midtown) generally have different sized coefficient estimates for three important variables: plot size, distance to core and depth to bedrock. In addition we find some interesting coefficient differences within midtown in regard to plot size and distance to Grand Central Station. The widely-cited fact that bedrock depths influenced the skyline is not borne out by the results.

Key Words: skyscrapers, New York City, geographically weighted regression
JEL Classification: C14, R14, R33

1. Introduction

The most recognizable use of urban land is the skyscraper. At its most basic level, the skyscraper is a "machine that makes the land pay" (Gilbert, 1900, p. 643). That is to say, building height is a solution to an economic problem about how to maximize the returns from a given piece of land.

A typical newly-constructed office tower in New York City will have more than one million square feet of rentable space. With 52 stories, the newly rebuilt 7 World Trade Center (2006), for example, contains a gross area of 1.64 million square feet on a plot size of 47,250 square feet.[1]

Because vertical transport via elevator is faster and cheaper than the same horizontal distance travelled, tall buildings can reduce transportation costs and enhance agglomeration effects. As such, the number and location of skyscrapers can have an impact on the productivity of a city.[2]

Furthermore, taken together skyscrapers generate a new entity, the skyline, which can be thought of as a separate good unto itself. The skyline and the skyscrapers that constitute it serve to advertize the city itself and the builders who construct them.

However, even a cursory glance at a skyline will show that there are dramatic differences in building height across space, even in the densest business districts. As such it's natural to ask what is driving building height at the building level.

Figure 1 shows the variation in building height in Manhattan, focusing only on the tallest of the tall skyscrapers (100 meters or taller). The map shows that there is no uniform pattern to building height per se—though there is some spatial autocorrelation.[3] There is virtually no pattern whatsoever in the location of the tallest of the tall.

The work of Barr (forthcoming) shows that, in general, an ordinary least squares regression with important supply and demand variables can account for a large fraction of the variation in skyscraper height. But here we probe deeper into the causes of height. Specifically we use geographically weighted regression (GWR), which allows for separate coefficient estimates for each building for important explanatory variables.

The advantage of using this estimation strategy is that we do not impose the same statistical model on every building. In particular, we can look to see how sensitive each building is to important land-use-related variables. Here we focus on three: plot size, bedrock depths and distance to the urban core. These are three variables whose influence on building height is not likely to be uniform over space.

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[1] Consider a "typical" 2000 square foot suburban house on a 0.25 acre plot. This gives 8000 square feet per acre. 7 WTC sits on a little bit more than one acre of land.
[2] No work to date has explored how skyscrapers may affect urban growth, though Barr (2010) studies how growth can affect skyscrapers.
[3] Depending on the weight matrix used, the Moran's I coefficient ranges from 0.011 to 0.028, which is statistically significant at the 95% level or greater.

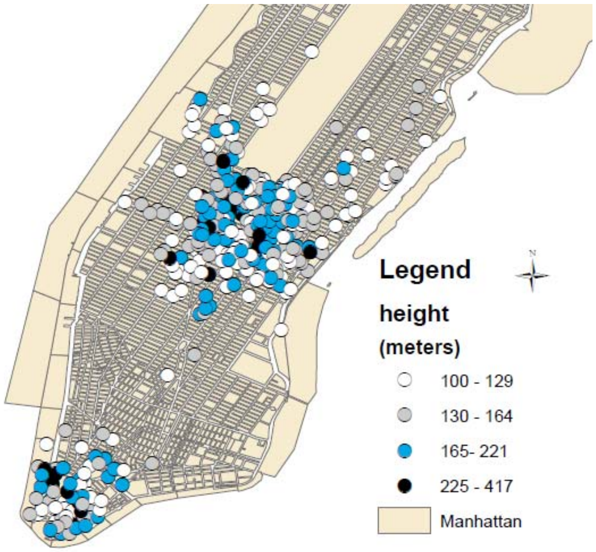

Figure 1: Distribution of Skyscraper Height in Manhattan

The effect of plot size on building height and more broadly on the provision of real estate remains understudied. Several studies have looked at how parcel size affects land values, but little known work has been done on how parcel size affects building height in dense urban areas. If the nature of land use affects the growth and health of cities, and plot size affects land use, then there is a connection between plot size and urban growth.

Willis (1995), for example, has hypothesized that the small plot sizes generated by New York's 1811 Grid Plan indirectly created "plot scarcity" for developers because of problems related to assemblage and hold outs. If this is the case, then it may have indirectly increased New York City's performance over the 20th century, by promoting more skyscraper development and potentially increasing the agglomeration effects that come from building tall.

Another underexplored aspect of urban development relates to geology. While New York and Chicago are famous for their geological conditions, little known work has directly explored how this geology may have shaped the urban landscape. Skyscrapers generally have to be anchored to bedrock, and if the bedrock is far down below the surface, this might act as a deterrent against building skyscrapers. Previous work on the role of bedrock depths has shown little overall effect on height (Barr, forthcoming; Barr, et al. 2010). However, as we show here, the average bedrock effect measured in those works may not capture the heterogeneity of geological conditions as it affects height.

Lastly, while land values are clearly an important influence of land use, average land values or a simple distance to core variable may not capture important variations that relate to a building's location within the city.

Using Geographically Weighted Regressions (GWR) we do indeed find a fair degree of spatial heterogeneity in regard to the three variables studied here. In regard to plot size, we find that though all estimated plot size coefficients (elasticities) are greater than zero, they show a large degree of variation across space. In some neighborhoods of Manhattan, the elasticities with respect to height are low as 0.06 and in other areas they are as high as 0.2.

Similarly with regard to the distance to the core variable, while all coefficients are negative, the size of this coefficient varies widely across space, with the lowest effect (in absolute value) of -0.038 to the largest effect (in absolute value) of -0.23 (where the distance is measured in miles).

Lastly, with regard to bedrock depths, we do see a fair degree of spatial variation. Non-stationarity tests, however, do not reject the null hypothesis of stationarity of coefficients across space. In certain regions we see negative coefficients while in other regions we see positive ones, which suggests at the margin, geology can affect height. But overall the results confirm that geology has had a modest effect on the skyline.

The rest of this paper proceeds as follows. The next section reviews the relevant literature. Section 3 gives a discussion of our estimation strategy—Geographically Weighted Regression (GWR). Section 4 discusses the data set. Next, section 5 presents the estimated from OLS and GWR. The following section presents maps of the coefficient estimates. Finally, section 7 offers concluding remarks. An appendix describes the data sources and preparation methods.

2. Related Literature

2.1 Skyscrapers and New York City

Barr (2010; forthcoming) has investigated the determinants of building height using OLS and spatial regressions. Barr (forthcoming) finds evidence for height competition among builders, who positively react to the height of surrounding buildings; but the degree of competition becomes greater during boom times, when presumably the opportunity cost of height competition is lower. Helsley and Strange (2008) provide a game theoretic model of skyscraper competition to show that the "positional" nature of skyscrapers can result in buildings that are economically "too tall."

Another important issue relates to the role of geology. Because skyscrapers need to be anchored to prevent settling, the geological conditions below a city can impact construction. Barr et al. (2010) show that, overall, geology had a modest impact on the placement of skyscrapers within the city. As well, Barr (forthcoming) finds that bedrock depths do not affect the height of skyscrapers on average. These findings suggest that the historiography of NYC might be wrong, since the claim that bedrocks depths have affected the skyline is a widely-cited belief (Schuberth, 1968).

In addition, it has been assumed that geological variables can affect agglomeration economies (Rosenthal and Strange, 2008). For Manhattan, Barr et al. (2010) have shown that this assumption must be made with caution because geological effects do appear to be important. This paper can shed more light on this issue. By investigating variation in the bedrock depths coefficient, we can get a sense of where on the island depth may have affected height (and hence agglomeration effects).

Finally, Anas, et al. (1998) show that areas of urban development have fractal dimensions (between 1.55 and 1.85 across cities). This is to say that the spatial outlines of cities have dimensions somewhere between a line and a rectangle. However, to the best of our knowledge, fractal "volumes" for cities have not been estimated. Our work here in some sense can provide some initial measurements in this regard, as we aim to estimate how determinants of building height varies across space.

2.2 Parcel Size and Urban Economics

To the best of our knowledge, no work beyond Barr (forthcoming) has investigated how plot size and shape directly influence building height. This work shows a positive and strongly significant effect of plot size on height and a negative effect from plots that are not perfectly rectangular or square.

Presumably, the larger the plot, the lower are the marginal costs to building height (Clark and Kingston, 1930). Smaller plots would also impose a more acute "elevator problem" in that if a builder wants to add extra floors, at some point, the building would need to contain an extra elevator shaft, which would then diminish the total rental space.

The effect of plot size on land values has been well-studied, with the general finding that of an S-shaped relationship. That is to say, for small plots there is a convex relationship with value, but after some size the relationship becomes concave (Lin and Evans, 2000; Colwell and Sirmans, 1978; Thorsnes and McMillen, 1998)

Furthermore, Colwell and Munneke (1997) demonstrate that imposing a constant relationship between plot size and land values is tantamount to introducing omitted variable bias, when estimating the effects of distance from the core.

Colwell and Sheu (1989) study the problem of optimal lot size and configuration for profit maximization by a developer. This is an important issue for urban development since presumably there exists a plot size, given the zoning regulations, will maximize the returns to development. They demonstrate how optimal configuration changes with the frontage and depth parameters, which may be affected by technological change and infrastructure development. For example, an increase of the frontage elasticity causes profit maximizing frontage to increase, depth to decrease and lot area to increase. This model could be extended to understand how lot area and dimension affects the building decision in dense urban areas. Colwell and Sheu, however, assume a building height of one floor and thus do not explore how this issue affects height.

Brooks and Lutz (2010) study the market for land assemblages in Los Angeles County. In dense urban neighborhoods assemblages, presumably, allow builders to build taller with a lower marginal cost. They find, however, inefficiencies in the assemblage market in Los Angeles County. While we do not study assemblages here, we implicitly explore the effect of assemblages on height. Because virtually all plots in Manhattan were originally designated to be 25' wide by 100' deep, skyscraper developers had to rely on assemblages to construct their tall buildings. By looking at how plot size affects height, we can gather some evidence on how builders respond to different plot sizes, providing evidence on which sizes are the most efficient from a development point of view.

2.3 Nonparametric Methods in Urban Economics

Recent work in non-parametric or semi-parametric estimation methods allow for more "smooth" and precise estimates of the local factors that drive important variables, compared with some other approaches (such as fixed-effects). For example, McMillen and Redfearn (2010) estimate nonparametric hedonic housing price equations for Chicago. They conclude that the effect of the distance to the EL train can be negative or positive depending on the spatial location of properties within the city. In wealthier neighborhoods, distance to the EL is positive, presumably because it reduces commuting times. In poorer neighborhoods, distance to the EL is negative, because presumably any benefits from lower commute times are offset by the negative impact that the EL lines have on property values in lower income neighborhoods (because of such things as noise, congestion, etc).

McMillen (1996) uses locally weighted regression 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 with approaching the city center. However, LWR estimation shows that by the early twentieth century, land values take on a much more diverse picture, with multiple and smaller peaks throughout the city. By 1990 the land value gradients are quite varied throughout the city. A standard OLS approach would have difficulty in capturing this complex pattern.

McMillen and McDonald (2004) put forth a locally weighted ordered probit model estimation approach. They estimate their model in the context of density zoning in Chicago. They find that the locally weighted ordered probit model does better at correctly predicting the actual zoning, compared with a regular (i.e., standard) ordered probit model. They also present some Monte Carlo simulations, which imply greater accuracy for the locally weighted ordered probit model opposed to the standard ordered probit model. The locally weighted model is also computationally easier than an ordered probit model that is parametric in the spatial dimension.

Cohen and Coughlin (2010) assess the impacts of various demographic variables on the noise levels surrounding the Atlanta airport. They estimate a locally weighted ordered probit model, as in McMillen and McDonald (2004). Cohen and Coughlin find that in some neighborhoods, higher minority populations lead to greater probability of additional noise, and in other neighborhoods they find the opposite effect. This is in contrast to their findings in a "regular" ordered probit context, where each demographic variable associated with every property only has a one-directional effect and constant magnitude on the probability of additional noise exposure.

As is clear from the GWR literature in the context of urban economics, estimation with GWR can add explanatory power by allowing parameter estimates to vary for each unit of observation. With this feature in mind, we proceeded to estimate our model of skyscraper height determinants with GWR.

3. Estimation Strategy

To estimate our GWR model, we use a version of weighted least squares, as suggested by McMillen and McDonald (2004). The estimation of the model implies that the estimated parameter vector for each observation (i.e., skyscraper), given by β_i, is:

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

where X_j is a matrix of explanatory variables for all observations except i; Y_j is a vector of the dependent variables (building height) for all observations except i; w_{ij} is the weight that building j is given for building i; and the summations given by Σ are taken over all buildings, j. Since $w_{ii} = 0$ (because d_{ii}=0), this effectively eliminates observation i in each of the summations for β_i.

It is noteworthy that for the weights, the routine we used in a STATA software package assumes a variation of the Gaussian weight function. Namely, the code assumes $w_{ij}=exp(-d_{ij}/b)^2$, where d_{ij} is the distance between two buildings, i and j; and b is the bandwidth parameter, which is automatically selected by the software package. Note that this weight matrix is slightly different than the Gaussian specification selected by McMillen and McDonald (2004), and Cohen and Coughlin (2010). Their Gaussian specification is given as $w_{ij} = \Phi(d_{ij}/sb)$, where Φ is the standard normal density function, b is the bandwidth, and s is the standard deviation of the d_{ij}, taken over all possible buildings j for each building i. McMillen and McDonald note that different weighting functions should not produce dramatically different estimation results. They also note that most popular weights "are similar in that they place high weight on nearby observations and low weight on distant observations." To run the GWRs, we used the "gwr" command in Stata 10.[4]

4. The Data

Here we investigate the determinants of height for 458 skyscrapers completed in Manhattan south of 96th street between 1895 and 2004. Here a "skyscraper" is a building that is 100 meters (about 30 floors) or taller. 100-meter buildings have been common since 1895 and they represent the tallest of the tall for New York City. Table 1 gives the descriptive statistics for the data.

{TABLE 1 ABOUT HERE}

For each building, we have data on the size of the plot, the depth to the bedrock and the distance to the closest core.[5] In Manhattan there are two cores: one centered at Grand Central Station and one centered at the corner of Wall Street and Broadway. We also include a dummy variable if the building is a residential rental apartment building or not. Previous work suggests that these buildings are less tall (Barr, forthcoming).

[4] See http://www.staff.ncl.ac.uk/m.s.pearce/stbgwr.htm

[5] Barr (forthcoming) via Hausman tests does not find evidence of plot size endogeneity with respect to height.

Furthermore we have three zoning-related variables. One is a dummy variable that takes on the value of one if the building was completed after zoning rules were in effect (from 1916 onwards), 0 otherwise. Secondly, for buildings completed under 1916 zoning rules, we include the setback multiple (which ranged from 1.5 to 2.5 in the commercial areas).[6] For buildings completed under the 1961 rules, we include the maximum allowable floor area ratio (FAR).

We also include four time series variables (lagged two years): the real interest rate, an index of real building materials costs, the New York City metropolitan population and the fraction of the U.S. workforce employed in the Finance, Insurance and Real Estate sector. These variables are meant to capture the city-wide and national variables that drive the supply and demand for height.

5. Regression Results

5.1. OLS Results.

Table 2 presents ordinary least squares results as the benchmark case. The dependent variable is the height in logs. The results generally confirm expectations. The plot is positively related to height with an elasticity of about 0.13 (i.e., a 10% increase in plot size is associated with a 1.3% increase in building height). The estimated "height gradient" is about 9.5% (i.e., each mile away from the core height is lower about 9.5%). The regressions also confirm no "bedrock effect" on average. Rental apartment buildings are about 8% smaller than other types. Further the zoning variables and time series variables also show expected signs as well.

{TABLE 2 ABOUT HERE}

5.2 Geographically Weighted Regressions

5.2.1 Nonparametric variables only

First, table 3 presents results for the OLS regression of the log of height on four variables: log of plot, the distance to the core, the depth to bedrock and also the year of completion. Table 4 presents the descriptive statistics for the GWR results. Table 5 presents the results for non-stationary tests.

{TABLES 3 – 5 ABOUT HERE}

5.2.2. Parametric and nonparametric results

Tables 4 and 6 give the descriptive statistics for the GWR results for two specifications. The means generally show the expected signs, but the standard deviations show wide relative variations. Looking at table 6, for example, we see that distance has a coefficient of variation of 0.54. Plot size has the lowest CV equal to 0.27, and depth to bedrock has the largest equal to 7.8. This suggests that there is the greatest relative variation in the bedrock coefficients. Section 6 shows the maps of the spatial distribution of the coefficients.

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[6] The 1916 rules stated that building floors had to be set back based on some given multiple of the street length. For example, "In a two times district no building shall be erected to a height in excess of twice the width of the street, but for each one foot that the building or a portion of it sets back from the street line four feet shall be added to the height limit of such building or such portion thereof" (Building Zoning Resolution, 1916, Section 8(d)).

6. Mapping

6.1 Bedrock Depths

Figure 2 shows the variation in the actual bedrock depths across the island (below each building in our sample). The blue dots indicated relatively large depths, with the darkest blue dots indicating bedrock very deep below the surface. The deepest bedrock generally lies closer to the City Hall area of downtown. In midtown the bedrock is relatively close to the surface.

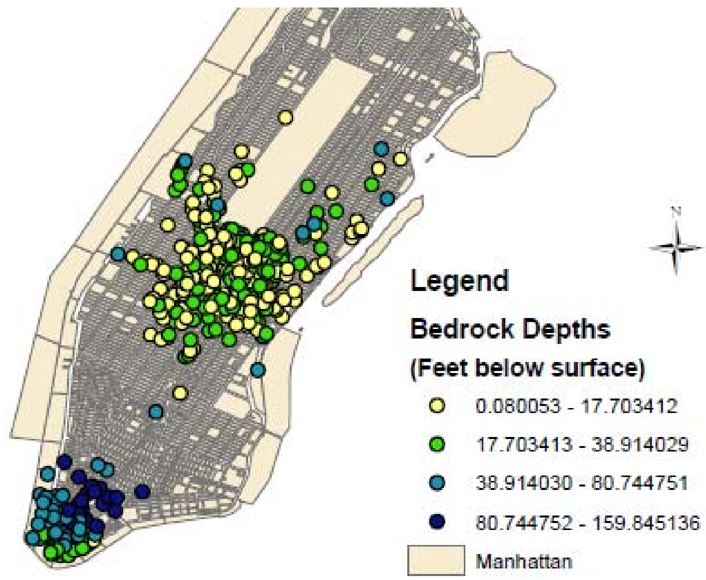

Figure 2: Bedrock Depths Below Skyscrapers.

The question then is: how do these changes in access to the bedrock affect building height. Presumably because of the highly varied nature of the geology there is no one global effect on height, if any.

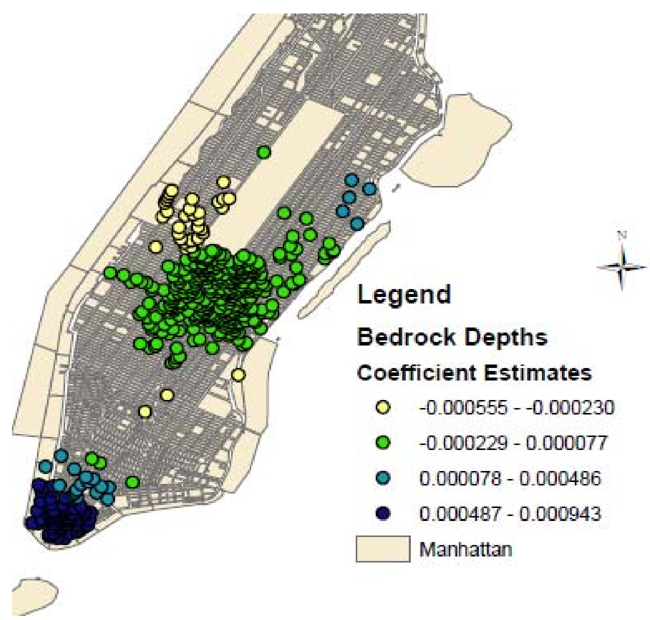

Figure 3: Bedrock Depth Coefficients.

Figure 3 shows that generally in midtown the effect of bedrock depths is relatively small and close to zero. However the downtown effect is largely positive. The reason for this may be that bedrock depths downtown are generally deeper than midtown. If anchoring a building to bedrock is a fixed cost (i.e., if the foundation preparation costs are generally independent of height), then this would suggest a positive effect, since the greater the fixed cost the greater the incentive to build taller to lower the average costs of construction.

Figure 4 presents the distance to the core coefficients. Here we see an interesting amount of spatial variation. Since the variable is negative, the lighter colors represent a greater effect (in absolute value).

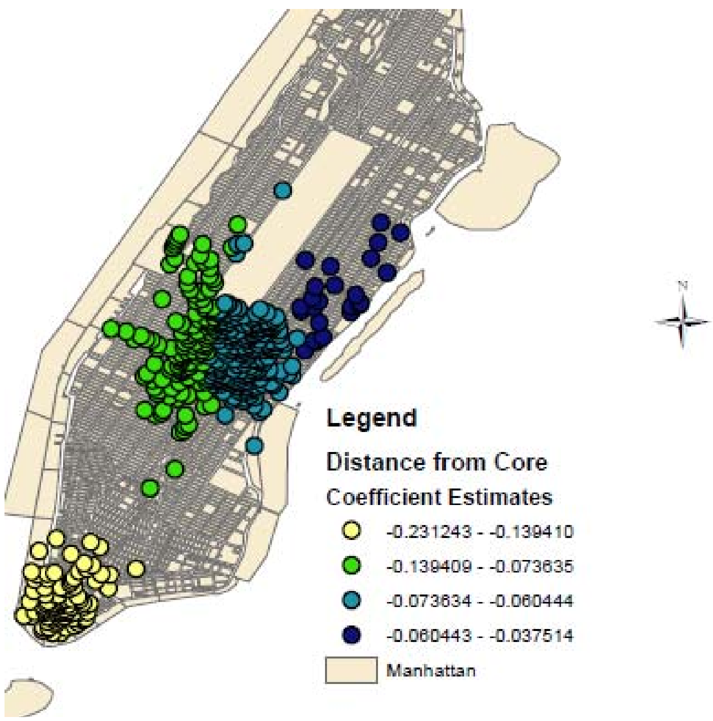

Figure 4: Distance to Core Coefficients

The figure shows that largest coefficients for downtown. That is to say, buildings downtown show the greatest height effect as we move away from Wall Street. This seems plausible given the degree to which firms downtown are finance and services based. The greater the distance from the core the greater the transportation costs due to distance and the less are agglomeration effects.

In midtown, we see basically two "distance" effects. The first is on the west side of midtown and the second is on the east side. The stronger effects are the west side. This stronger east side effect may be due to the relative ease of transportation to the core, which is also on the east side (Grand Central Station). Given the structure of the subway system, the core is fairly easily accessible from the east side, but for people located on the west side, a transfer is required on the "Shuttle" line to take passengers across town. Builders who realized the transport costs to the core were lower on the east side may have chosen to build larger buildings on the east side, since it would be less costly to populate these larger buildings with businesses and residents, on the east side. Since the west side was more costly to access, there may have been less incentives for businesses and residents to locate on the west side, and as a result the marginal impact on building height due to greater distance from the core on the west side was lower.

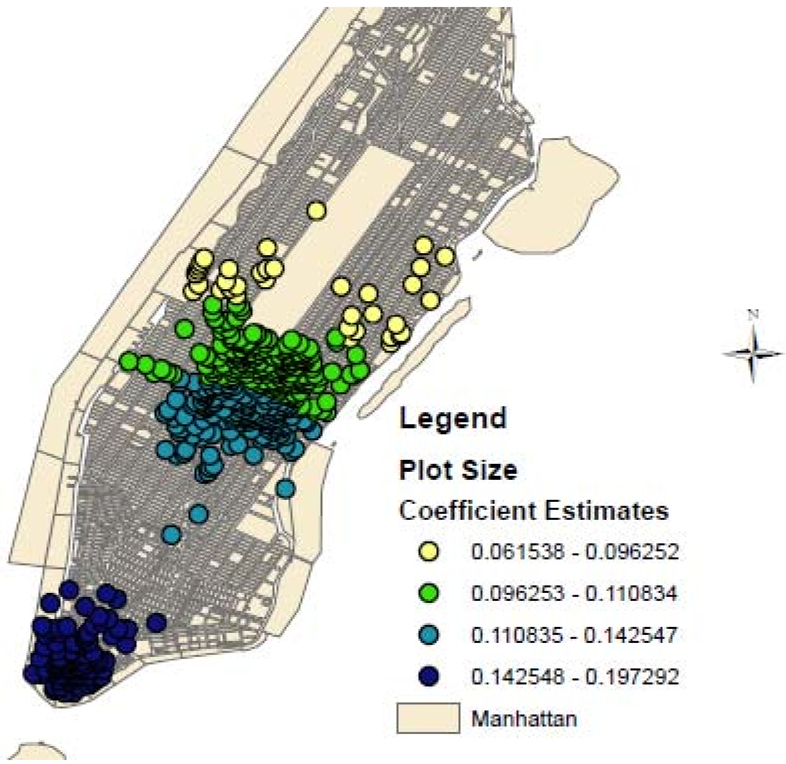

Figure 5: Coefficients for Plot Size

Figure 5 shows the coefficient results for plot size. In generally the greatest elasticity is for buildings in lower Manhattan. Unlike the distance variable, in midtown there is a north and south split in the responsiveness to plot size, with the south being relatively more responsive than north midtown. It is also noteworthy that for the largest 3 quartiles of coefficients, most buildings with similar coefficients are located near each other (with the exception of a few outliers). This may give some support for the notion that skyscrapers nearby each other may be competing with each other in height as a result of the marginal effect of plot size having roughly the same impact on height for nearby buildings.

7. Conclusion

This paper uses geographically weighted regression estimation to analyze skyscraper height in Manhattan. Using a sample of 458 skyscraper (100 meters or tallest), we specifically investigate how the coefficients of three important variables vary across space. We analyze how the coefficients for plot size, distance to the core, and bedrock depths vary across space. The first result is that the lower Manhattan business district centered at Wall Street has different coefficients than the midtown business district, centered at Grand Central Station. In general we find that downtown has larger effects for the distance to core (in absolute value), plot size and bedrock depths as compared to midtown.

Within midtown we find different coefficient patterns in different neighborhoods. For instance, with regard to plot size, we find a north-south split, with the buildings south of Grand Central Station having a large plot size effect than those north of the train station. For the distance to the core variable, however, we find an east-west split, with a greater plot size affect from those buildings further away from the train station. Finally with regard to bedrock, we find that in midtown there is virtually no bedrock effect, with the variation in coefficients being very small.

This paper is a first attempt to understand how aspects of the land—plot size, geology and relative location—determine building height. In general we find support for the argument that the "one size fits all" statistical model of ordinary least squares is not appropriate when analyzing the determinants of the skyline.

Further we find support for a modest effect of New York's geology on the skyline. This finding suggests that the conventional wisdom for the rise of New York's skyline is wrong and needs to be reevaluated.

This paper represents a work in progress and we aim to explore the robustness of the results, the statistical significance of the results and what these finding suggest about theories of urban growth over space.

Appendix A: Data Sources

1. *Skyscraper Height, Number of Floors and Year of Completions*: Emporis.com.
2. *Plot size*: NYC Map Portal (http://gis.nyc.gov/doitt/mp/Portal.do); Ballard (1978); http://www.mrofficespace.com/; NYC Dept. of Buildings Building Information System, (http://a810-bisweb.nyc.gov/bisweb/bsqpm01.jsp).
3. *Distance from Core*: For each building I obtained the latitude and longitude from http://www.zonums.com/gmaps/digipoint.html. I calculated the distance for each building i = 1, ..., 458, , where latitude and longitude were initially measured in degrees. The degrees to miles conversion is from http://jan.ucc.nau.edu/~cvm/latlongdist.html. In NYC, there are two cores: the intersection of Wall Street and Broadway (downtown) and Grand Central Station (42nd Street and Park Ave.). All buildings south of 14th street belong to the downtown core; all buildings on 14th street or above belong to the midtown core.
4. *Depth to Bedrock*: For each building, elevation from sea level (in feet) comes from http://www.zonums.com/gmaps/digipoint.html. Depth to bedrock from sea level (in feet) comes from maps provided by Dr. Klaus Jacob, Columbia University. The maps are based on hundreds of borings throughout Manhattan. The depth to bedrock was calculated by subtracting the depth of bedrock from sea level from the elevation from sea level.
5. *1916 Height Multiples*: Original zoning maps in effect at the time of completion for each building. The maps were provided by the New York City Department of City Planning.
6. *1961 Maximum Allowable FAR*: Original zoning maps in effect at the time of completion for each building. The maps were provided by the New York City Department of City Planning.
7. *Real Construction Cost Index* (1893–2004): Index of construction material costs: 1947–2004: Bureau of Labor Statistics Series Id: WPUSOP2200 “Materials and Components for Construction” (1982=100). 1893–1947: Table E46 “Building Materials.” Historical Statistics (1926=100) (1976). To join the two series, the earlier series was multiplied by 0.12521, which is the ratio of the new series index to the old index in 1947. The real index was create by dividing the construction cost index by the GDP Deflator for each year.
8. *GDP Deflator* (1893–2004): Johnston and Williamson (2007). (2000=100).
9. *Finance, Insurance and Real Estate Employment (F.I.R.E)/Total Employment* (1893–2004): 1900–1970: F.I.R.E. data from Table D137, Historical Statistics. Total (non farm) Employment: Table D127, Historical Statistics. 1971–2004: F.I.R.E. data from BLS.gov Series Id: CEU5500000001 “Financial Activities.” Total nonfarm employment 1971–2004 from BLS.gov Series Id: CEU0000000001. The earlier and later employment tables were joined by regressing overlapping years that were available from both sources of the new employment numbers on the old employment numbers and then correcting the new number using the OLS equation; this process was also done with the F.I.R.E. data as well. 1893–1899: For both the F.I.R.E. and total employment, values were extrapolated backwards using the growth rates from the decade 1900 to 1909, which was 4.1% for F.I.R.E. and 3.1% for employment.
10. *Real Interest Rate* (nominal rate minus inflation) (1893–2004): Nominal interest rate: 1893–1970: Table X445 “Prime Commercial Paper 4–6 months.”Historical Statistics. 1971–1997 http://www.federalreserve.gov, 1998–2004:6 month CD rate. 6 month CD rate was adjusted to a CP rate by regressing 34 years of overlapping data of the CP rate on the CD rate and then using the predicted values for the CP rate for 1997–2004. Inflation comes from the percentage change in the GDP deflator.
11. *Population NYC, Nassau, Suf folk, and Westchester Counties* (1893–2004):1890–2004: Decennial Census on U.S. Population volumes. Annual data is generated by estimating the annual population via the formula popi,t = popi,t−1exp(βi ,), where i is the census year, i.e., i element of {1890, 1900, ..., 2000}, t is the year, and βi is solved from the formula, popi = popi−1e10∗βi . For the years 2001 - 2004, the same growth rate from the 1990’s is used.

References

Anas, A., Arnott, R and Small, K. A. (1998). "Urban Spatial Structure." *Journal of Economic Literature*, 36, 1426-1464.

Barr, J (forthcoming). "Skyscraper Height." *Journal of Real Estate Finance and Economics*.

Barr, J. (2010). "Skyscrapers and the Skyline: Manhattan, 1895-2004." *Real Estate Economics*, 38(3), 567-597.

Barr, J. Tassier, T. and Trendafilov, R. (2010). "Bedrock Depth and the Formation of the Manhattan Skyline, 1890-1915." Fordham University Economics Discussion Paper, 2010-09.

Brooks, L and Lutz, B. (2010). "Sclerosis of the City: Inefficiency and the Assembly of Urban Land. Mimeo.

Clark, W.C. and J.L. Kingston. 1930. *The Skyscraper: A Study in the Economic Height of Modern Office Buildings*. American Institute of Steel Constructions: New York, NY.

Cohen, J. P. and Coughlin C. C. (2010). "Spatial Heterogeneity and the Geographic Distribution of Airport Noise." Working Paper.

Colwell, P. F. and Sirmans, C. F. (1978). "Area, Time, Centrality and the Value of Urban Land." *Land Economics*, 54(4), 514-519.

Colwell, P. F. and Munneke, H. J. (1997). "The Structure of Urban Land Prices*." Journal of Urban Economics*, 41, 321-336.

Gilbert, C. (1900). "The Financial Importance of Rapid Building." *Engineering Record*, 41.

Helsley, R. W. and Strange W. C. (2008) A Game-theoretic Analysis of Skyscrapers*." Journal of Urban Economics,* 64(1), 49-64.

Lin, T-C and Evans, A. W. "The Relationship Between the Price of Land and Size of Plot When Plots are Small." *Land Economics*, 76(3), 386-394.

McMillen, D. P. and Redfearn, C. L. (2010). "Estimation and Hypothesis Testing for Nonparametric Hedonic House Prices Functions." *Journal of Regional Science*, 50(3), 712-733.

McMillen, D.P. and McDonald. (2004). "Locally Weighted Maximum Likelihood Estimation: Monte Carlo Evidence and an Application." Chapter 10, in *Advances in Spatial Econometrics: Methodology, Tools and Applications*, Anselin, L., R. Florax, and S. Rey, eds., Berlin: Springer.

McMillen, D. P. (1996). "One Hundred Fifty Years of Land Values in Chicago: A Nonparametric Approach." *Journal of Urban Economics*, 40, 100-124.

Rosenthal, S. S. and Strange, W. C. (2008). “The Attenuation of Human Capital Spillovers.” *Journal of Urban Economics*. 64(2), 373-389.

Schuberth, C. J. (1968). *The Geology of New York City and Environs*. The Natural History Press: Garden City.

Thorsnes, P. and McMillen, D. P. (1998). “Land Value and Parcel Size: A Semiparametric Analysis.” *Journal of Real Estate Finance and Economics*, 17(3), 233-244.

Willis, C. (1995). *Form Follows Finance: Skyscrapers and Skylines in New York and Chicago*. Princeton Architectural Press: Princeton.

TABLES

Variable	Mean	Standard Dev.	Minimum	Maximum	# Obs.
Height (meters)	149.43	43.04	100.00	417	458
Plot size (feet^2)	446670	63663	4000	681600	458
Bedrock Depth (feet)	26.99	25.97	0.080	159.8	458
Distance to Core (miles)	0.612	0.449	0.0160	2.55	458
Rental Dummy	0.131				458
Zoning Dummy	0.950				458
1916 Multiple	1.94	0.373	1.25	2.5	165
1961 FAR	12.71	2.58	3.44	15	270
Real Interest Rate	3.02	3.90	-8.77	23.9	86
Real Materials Cost Index	1.34	0.269	0.862	1.70	86
Metro. Pop. (million)	9.01	2.53	3.01	11.8	86
% FIRE/Emp.	4.68	1.41	1.76	6.57	86

Table 1: Descriptive Statistics for New York City Skyscrapers, 1895-2004.

Ln(Plot)	0.131
	(8.6)**
Rental dummy	-0.079
	(2.4)*
Depth to bedrock	-0.003
	(0.8)
Distance to core	-0.095
	(3.6)**
Zoning Dummy	-0.452
	(4.1)**
Multiple, 1916	0.113
	(3.5)**
FAR, 1961	0.021
	(4.8)**
FIRE/Emp.$_{t-2}$	0.099
	(5.0)**
Population$_{t-2}$	0.022
	(1.4)
Materials Costs$_{t-2}$	-0.365
	(4.3)**

Interest Rate$_{t-2}$	-0.009
	(2.3)*
Constant	3.7
	(23.0)*
Observations	458
R-squared	0.35

Table 2: Dependent Variable: ln(height). OLS estimates. Robust t-statistics below estimates. * significant at 5%; ** significant at 1%

Global Model

```
      Source |       SS       df       MS              Number of obs =     458
-------------+------------------------------           F(  4,   453) =   35.5
       Model |  6.98892299     4  1.74723075           Prob > F      =  0.0000
    Residual |  22.2942075   453  .049214586           R-squared     =  0.2387
-------------+------------------------------           Adj R-squared =  0.2319
       Total |  29.2831305   457  .064076872           Root MSE      =  .22184

-------------------------------------------------------
    lnheight |      Coef.   Std. Err.      t    P>|t|
-------------------------------------------------------
Dist to core |  -.1412221   .0242974    -5.81   0.000
      lnPlot |   .1252181   .0127949     9.79   0.000
bedrockdepth |   -.000085   .0004105    -0.21   0.836
        year |   .0018935      .0004     4.73   0.000
        cons |   .0495016     .78626     0.06   0.950
```

Table 3: Global Model for 4 variables.

	distance	lnplot	depth	year	constant
Mean	-0.152	0.144	0.0003	0.0019	-0.261
Median	-0.123	0.138	0.0006	0.0019	-0.281
St. Dev.	0.101	0.056	0.0009	0.0010	1.704
Min.	-0.346	-0.087	-0.0032	-0.0021	-3.834
Max.	0.072	0.244	0.0060	0.0044	9.859
Coeff. Var.	0.6635	0.3900	2.9502	0.5368	6.5344

Table 4: Means and Standard Deviations of Coefficients for GWR results

Variable	Si	P-Value
Constant	1.7038	0.242
distcoremiles	0.1007	0.001**
lnPlot	0.0562	0.000**
depthbedrock	0.0009	0.230
year	0.0010	0.075

Table 5: Significance Tests for Non-Stationarity

	distance	lnplot	depth	year	constant
Mean	-0.098	0.125	0.0000	-0.0003	-0.715
Median	-0.074	0.112	-0.0001	-0.0002	-0.737
St. Dev.	0.053	0.035	0.0003	0.0003	0.352
Min.	-0.231	0.062	-0.0006	-0.0009	-1.701
Max.	-0.038	0.197	0.0009	0.0003	0.077
Coeff. Var.	0.538	0.277	7.864	1.191	0.492

Table 6: Means and Standard Deviations of Coefficients for GWR results

Significance Tests for Non-Stationarity

Variable	Si	P-Value
Constant	0.3515	0.720
Dist Core (miles)	0.0525	0.015*
lnPlot	0.0347	0.012*
Depth to bedrock	0.0003	0.435
year	0.0003	0.400

Table 7: Significance Tests for Non-Stationarity