Stringency of Land-Use Regulation: Building Heights in US Cities

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Abstract

This paper explores the stringency of land-use regulation in US cities, focusing on building heights. Stringency is substantial when regulated heights are far below free-market heights, while stringency is lower when the two values are closer. Using *FAR* (the floor-area ratio) as a height index, theory shows that the elasticity of the land price with respect to *FAR* is a proper stringency measure. This elasticity is estimated for five US cities by combining CoStar land-sales data with *FAR* values from local zoning maps, and the results show that New York and Washington, D.C., have stringent height regulations, while Chicago's and San Francisco's regulations are less stringent (Boston represents an intermediate case).

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1. Introduction

The effects of land-use regulation have been extensively studied by urban economists. Gauging these impacts requires measurement of the scope of local regulation, and such measures have been generated by a number of different surveys of local governments, which tally the various types of regulations in place. The first such survey, by Glickfeld and Levine (1992), focused on California and produced a count of the number of different land-use regulations used in a city. The count included regulations such as density restrictions (including building height limits), limitations on the number of building permits, the presence of an urban growth boundary, and many others. Ihlanfeldt (2007) conducted a similar survey for Florida, generating another regulation count measure, and Jackson (2018) carried out a new California survey, generating an index more sophisticated than a simple regulation count but similar in spirit. Gyourko, Saiz and Summers (2008) carried out a nationwide survey of local land-use regulation. By applying factor analysis to the results, they generated the Wharton Residential Land Use Regulatory Index, which has also been used by many other researchers.[1]

While information on the scope of land-use regulation is valuable, it does not provide an answer to a different important question. The question concerns the *stringency* of land-use regulation. A stringency measure gauges the degree to which regulations cause land-use characteristics *to diverge from free-market levels*. For example, in the case of building heights, the focus of the present paper, a stringency measure would capture the degree to which regulated heights fall short of those that would be chosen in the absence of regulation. If regulated heights are much lower than free-market heights, then regulation is highly stringent, whereas stringency is lower when regulated heights are close to free-market levels.

The literature offers two different approaches to measuring the stringency of land-use regulation. The first is due to Glaeser, Gyourko and Saks (2005), who identify the gap between the price per square foot of housing and construction cost per square foot as a measure of stringency. This gap, which they call the "regulatory tax," should be absent in an unregulated market, and its existence implies that regulations are restricting the supply of housing. Glaeser and coauthors compute the regulatory tax for Manhattan, showing that it is appreciable, but their method does not require them to identify the particular supply-restricting regulations that generate the tax.[2]

The second approach, which is applied in the present paper, exploits the relationship between the value of vacant land and the extent of a particular regulation to gauge the regulation's stringency. The approach, which is based on a precise theoretical result, relies on the intuitive notion that relaxing a stringent regulation raises land value per square foot by more than relaxing a less-stringent one (with changes measured in percentage terms). Since building-height regulation constrains development options, thereby reducing the developer's willingness-to-pay for the land, it follows that relaxation of a stringent height constraint will raise WTP by more than relaxation of a mild constraint, a conclusion that is established formally in section 2. Thus, to identify stringency, the log of land value per square foot is regressed on the log of the regulated building height and other covariates, and the resulting height coefficient (which is an elasticity) constitutes the stringency measure. Using extensive data on leasing (effectively sales) of vacant land in China, a study by Brueckner, Fu, Gu and Zhang (2017) applied the method to compare the stringency of height regulations across Chinese cities, made possible by allowing city-specific elasticities.

To apply the method in a context more familiar to Western readers, the present paper carries out the same exercise for several major US cities. As in Brueckner et al. (2017), the focus is on regulations that limit a building's floor-area ratio (FAR), which equals the ratio of total square footage of floor space in the building to the area of the lot, effectively capturing building height.[3] Land-value information comes from data on vacant land sales available from the CoStar Group's commercial real estate website, and digital zoning maps are used to assign an FAR value for each sale transaction. The study includes land sales over the 2000-2018 period for five major US cities: New York, Chicago, Washington, D.C., Boston and San Francisco.

The results allow the stringency of building-height regulation to be compared across these cities, while also showing how stringency varies across locations within each city.

The results are important because building-height regulations can distort urban form and raise housing prices. As shown by Bertaud and Brueckner (2005), height restrictions reduce housing supply, pushing up prices and reducing housing affordability while creating inefficient urban sprawl as the city attempts to accommodate its population, effects that are all more pronounced the greater the stringency of the height limit. Height regulations have various justifications, including the worthy goal of keeping skyscrapers away from the White House and U.S. Capitol building in Washington D.C. and, in earlier days, the goal of limiting interior light reduction from building-induced shadows, an issue that modern lighting has eliminated (see Barr (2016)). In addition, by curbing population density, height limits can also reduce demands on urban infrastructure (streets, water, gas, sewage), a consideration that may have motivated the draconian FAR limits in India, which are studied by Brueckner and Sridhar (2012).[4]

It is not always clear that imposition of height restrictions is carried out with appropriate attention to the potential downsides of such regulations. Glaeser et al. (2005) and Barr (2016), for example, argue that by blocking further densification of Manhattan (a place that is already very dense), height limits impose a cost on New York residents by limiting housing supply. Given such concerns, it is important to know how the stringency of height regulation varies across cities. Cities with the most stringent restrictions could then be candidates for looser regulation. However, such a verdict must be viewed as incomplete since information about the offsetting benefits from height limits is missing, not being generated by the present methodology.

Measurement of the stringency of height regulations must confront a serious identification problem, a consequence of the fact that the FAR value for a land parcel is chosen by the local zoning authority. To see the problem, note that an attractive vacant parcel, with favorable values of unobserved attributes, will tend to have a high price of floor space once developed and thus a high land value, leading to a large value for the error term in a land-value regression. But since the zoning authority will tend to allow intensive development of attractive parcels, the assigned FAR value will tend to be larger for parcels with favorable unobserved attributes. The upshot is that FAR will be positively correlated with the error term in a land-value regression, leading to an upward biased FAR coefficient.

With instruments for FAR hard to find, Brueckner et al. (2017) addressed this bias issue by grouping observations (which were not geocoded) into clusters of parcels located on the same street.[5] Unobservable attributes within clusters were then captured by cluster fixed effects, an approach that reduces the correlation between FAR and the error term in the land-value regression. When cluster fixed-effects were used, the estimated FAR coefficient dropped in magnitude, reflecting a reduction in upward bias.

A related clustering approach is used in the present paper. With the observations all geocoded, several different clustering strategies are used. The first is simply to include zipcode fixed effects in the land-value regressions. Since the observations are from dense central cities, zip codes are spatially small, ensuring that the parcels within a zip code are fairly homogeneous. An alternative approach is to group parcels into circular clusters with a fixed radius and land areas smaller than the average zip code. Clusters with radii of 1/8, 1/4, and 1/3 miles are created in alternate specifications, with the appropriate cluster fixed effects included in the regressions.

As in the Chinese study, inclusion of cluster fixed effects reduces the estimated FAR coefficients in all cities, indicating a reduction in upward bias. Nevertheless, the amount of remaining bias is impossible to judge. Even if some bias is still present, however, a comparison of regulatory stringency across cities (from comparing FAR coefficients) can still be carried out as long as cities share the same degree of coefficient bias, a pattern that would appear plausible.

The plan of the paper is as follows. Section 2 presents a theoretical argument demonstrating that the elasticity of land value with respect to FAR is a measure of regulatory stringency. Section 3 discusses the data, and Section 4 presents results for the five sampled cities. Section 5 offers conclusions.

2. Theory

The connection between land values and *FAR* can be demonstrated using the standard urban land-use model (see Brueckner (1987), Duranton and Puga (2015)).[6] Let r denote the price per unit of land and p denote the price per square foot of real estate (housing or office space), which depends on a vector Z of locational attributes, including distance to the CBD, that affect the attractiveness of the site (thus, $p = p(Z)$). This function can be treated as exogenous with respect to land-use decisions on individual parcels, which have a negligible effect on the city's overall housing supply. Let $h(S)$ denote square feet of real-estate output per unit of land as a function of structural density S, which equals real-estate capital per acre (h is concave, satisfying $h' > 0$ and $h'' < 0$). This function is the intensive form of a production function H that has separate capital and land arguments. The housing developer's profit per unit of land is then equal to

$$\pi \;=\; ph(S) \;-\; iS \;-\; r, \tag{1}$$

where i is the cost per unit of capital. In the absence of an *FAR* limit, the first-order condition for choice of S is $ph'(S) = i$, and the S satisfying this condition is denoted S^*. The land price is then given by the zero profit condition:

$$r \;=\; ph(S^*) \;-\; iS^*. \tag{2}$$

An *FAR* limit imposes a maximal value for $h(S)$, denoted $\overline{h}$, which in turn imposes a maximal value of S. This value is denoted $\overline{S}$, and it satisfies $h(\overline{S}) = \overline{h}$ and $\overline{S} < S^*$. Consider first the effect of $\overline{S}$ on the land price r, with the link between $\overline{h}$ and r analyzed later. Given the *FAR* limit, developers will set $S = \overline{S}$, and the land price will be given by

$$r \;=\; ph(\overline{S}) \;-\; i\overline{S}. \tag{3}$$

The derivative of the land price with respect to $\overline{S}$ is

$$\frac{\partial r}{\partial \overline{S}} \;=\; ph'(\overline{S}) \;-\; i \;>\; 0, \tag{4}$$

with the inequality holding because $\overline{S} < S^*$. In addition, because $\partial r/\partial Z = (\partial p/\partial Z)h(\overline{S})$, the land price will depend on the vector Z. A higher value of a favorable parcel characteristic j such as access to jobs, for which $\partial p/\partial Z_j > 0$, will raise the land price.

Consider now the elasticity of the land price with respect to $\overline{S}$, which equals

$$E_{r,\overline{S}} \quad \equiv \quad \frac{\partial r}{\partial \overline{S}}\frac{\overline{S}}{r} \quad = \quad \frac{[ph'(\overline{S}) - i]\overline{S}}{ph(\overline{S}) - i\overline{S}}. \tag{5}$$

With concavity of h implying $h'(\overline{S})\overline{S} < h(\overline{S})$, it follows that $E_{r,\overline{S}}$ in (5) is less than unity, so that the elasticity of the land price with respect to $\overline{S}$ is less than one.

To put (5) in a more useful form, $ph'(S^*) = i$ can be used to eliminate i in (5). The expression then becomes

$$E_{r,\overline{S}} \quad = \quad \frac{\left[h'(\overline{S}) - h'(S^*)\right]\overline{S}}{h(\overline{S}) - h'(S^*)\overline{S}}, \tag{6}$$

showing that $E_{r,\overline{S}}$ depends on S^* as well as $\overline{S}$ (observe that p cancels). It is now fruitful to impose a standard functional form for h. If the underlying production function H is Cobb-Douglas, then the intensive form satisfies $h(S) = S^\beta$, with $\beta < 1$, and (6) reduces to

$$E_{r,\overline{S}} \quad = \quad \frac{\left[\beta\overline{S}^{\beta-1} - \beta(S^*)^{\beta-1}\right]\overline{S}}{\overline{S}^\beta - \beta(S^*)^{\beta-1}\overline{S}} \quad = \quad \frac{(S^*/\overline{S})^{1-\beta} - 1}{\frac{1}{\beta}(S^*/\overline{S})^{1-\beta} - 1}. \tag{7}$$

Therefore, the elasticity of the land price with respect to $\overline{S}$ depends on the ratio of S^*, the developer's optimal S, to the restricted level, $\overline{S}$. In addition, differentiation of (7) shows that

$$\frac{\partial E_{r,\overline{S}}}{\partial(S^*/\overline{S})} \quad > \quad 0, \tag{8}$$

indicating that elasticity is large when the restricted S lies far below S^* (making $S^*/\overline{S}$ large). In other words, the increase in land price from relaxing a very tight $\overline{S}$ limit is greater than the increase from relaxing a looser limit, a conclusion that matches intuition.

Since $h(\overline{S}) = \overline{h}$ implies $\overline{S}^\beta = \overline{h}$, it follows that $\overline{S} = \overline{h}^{1/\beta}$. Therefore, the elasticity of the land price with respect to $\overline{h}$, denoted $E_{r,\overline{h}}$, equals $E_{r,\overline{S}}/\beta$. Like $E_{r,\overline{S}}$, $E_{r,\overline{h}}$ is therefore increasing in $S^*/\overline{S}$, so that the increase in the land price from relaxing a tight *FAR* limit is greater than the increase from relaxing a loose one. Note that, since both $E_{r,\overline{S}}$ and β are less than 1, the elasticity $E_{r,\overline{h}}$ can be larger or smaller than 1, in contrast to $E_{r,\overline{S}}$.

The empirical model generates an estimate of $E_{r,\overline{h}}$, denoted θ. Treating θ as a known value and assuming a value for β, (7) can be solved for the ratio $\overline{S}/S^*$, which then allows the ratio of the *FARs* to be computed. The solution is

$$\frac{h(\overline{S})}{h(S^*)} \quad = \quad \left(\frac{1-\theta\beta}{1-\theta}\right)^{-\frac{\beta}{1-\beta}}. \tag{9}$$

Therefore, using the estimated θ and a value for β, the ratio of the regulated and free-market *FARs* can be derived. This is a remarkable conclusion given that the free-market *FAR* is unobserved.

It should be noted that, while the housing-price function $p(Z)$ is properly treated as exogenous in evaluating the link between the land price and $\overline{S}$ for individual parcels, the city's overall regulatory policy may affect housing supply and thus the general level of the p function, which in turn determines the level of land prices. This broad effect will be captured in the city-specific intercept in the land-value regression, with the elasticity θ continuing to be identified by variation in land prices and FAR values *across* the city's parcels.

3. Empirical model and data

3.1. Empirical model

The basic regression used to evaluate regulatory stringency is

$$\log(r_{ict}) \quad = \quad \alpha_c \; + \; \delta_t \; + \; \theta \log(FAR_{ict}) \; + \; \epsilon_{ict}, \tag{10}$$

where i denotes the land parcel, c denotes the cluster to which the parcel belongs, t denotes the year of sale, and ϵ is the error term. The year fixed effect is δ_t, and the cluster fixed effect is α_c, with clusters being either zip codes or smaller circular areas, as described above. This equation is estimated separately for the different cities. Given New York's large size, (10) is amended to allow the FAR coefficient to differ across the city's five boroughs (Manhattan, Brooklyn, Bronx, Queens and Staten Island), which is done by interacting $\log(FAR)$ with borough dummy variables.

Another variation on the regression in (10) allows the FAR effect to depend on location, in particular on the parcel's distance from the CBD. Letting x denote the CBD distance, this specification (without clusters) is written

$$\log(r_{it}) \;=\; \alpha \;+\; \delta_t \;+\; \theta\log(FAR_{it}) \;+\; \gamma\, x_i \;+\; \lambda\, x_i \log(FAR_{it}) \;+\; \epsilon_{it}. \tag{11}$$

The FAR elasticity is now distance-dependent, equal to $\theta + \lambda x_i$. In addition, the effect of distance on land value is FAR-specific, equal to $\gamma + \lambda\log(FAR)$.

3.2. Data

While the CoStar Group's website is mainly devoted to providing data on sales of the commercial buildings, it also includes data on vacant land sales for cities across the US. A wealth of information is provided, including the size of the parcel, its sale price and sale date, address, latitude and longitude coordinates, and the zoning code for the parcel. In addition, one data field gives "improvements" to the site, which is usually blank but often includes descriptors such as "finished lot." Sometimes, however, existing buildings are listed under site improvements, presumably indicating a situation where the acquisition of the underlying land is the goal of the purchase, with demolition of the existing structures planned. Because costly demolition is likely to depress the land's selling price, observations with existing buildings are dropped in creating the samples. Another common improvements designation is "previously developed lot," but conversations with CoStar indicated that this descriptor refers to a site that previously contained a building but is vacant when sold.[7]

A possible concern about vacant land sales within built-up cities is that they may include "bad" parcels, which have been passed over for development. The fact that many vacant parcels were previously developed reduces this concern. Moreover, the maps of sold parcels (see Figures 1, 3–6) show a broad distribution of sales across each city, a pattern that would not emerge if sales were concentrated in undesirable areas. In gathering data on vacant land sales for construction of a Manhattan land price index, Barr, Smith and Kulkarni (2018) also address the issue of the potential unrepresentativeness of such parcels, discounting it in several different ways.

Since the FAR value is specified in the zoning code for a parcel, the site's FAR follows directly when the zoning code for the parcel is present in the CoStar data. When the code is missing, the parcel's latitude and longitude values are used to find its location on the city's digital zoning map and thus its FAR. The appendix provides links to the digital zoning maps used for the FAR data.

Another data-manipulation step involves the creation of the circular clusters. The procedure is to rank the parcels in order of increasing distance from the mean latitude and longitude of parcels in the city. The first parcel on this list is chosen as the center of the first cluster, and parcels within the given radius (1/8, 1/4, or 1/3 mile) of the parcel are grouped with it and all are removed from the parcel list. Then, the first parcel in the remaining list is the center of the second parcel, and parcels within the given radius are grouped with it and all are removed from the list. The process continues until all parcels are assigned to clusters. For New York, this algorithm is carried out for each borough separately, while for the other cities (which have fewer total observations), it is carried out on the entire city sample.

Since, with cluster fixed effects, the FAR coefficient is identified by within-cluster FAR variation, observations in clusters containing a single parcel contribute nothing, with their deletion from the sample having no effect on the estimated FAR coefficient. The coefficient's standard error does fall slightly with these deletions, but since this change has no effect on the significance of any of the estimated FAR coefficients, all observations are retained regardless of cluster size.

Variation of FAR within areas such as zip codes or smaller clusters can arise for a number of reasons. The border between two zoning areas that specify different $FARs$ may pass through a cluster, with FAR values changing across the border. Alternatively, negotiations between parcel owners and the zoning authority may alter $FARs$ for some parcels within a cluster while leaving those for others unchanged (see below for further discussion). In pursuit of particular land-use goals, the zoning authority itself may initiate such piecemeal changes in FAR, leading to variation within small areas.

4. Results

4.1. New York

The New York sample has 5173 parcel observations divided across the five boroughs, as seen in Table 1. The observation map in Figure 1 shows that the parcels are widely distributed across the city. The mean price per square foot for the entire sample is \$582, the mean FAR is 4.43, and the mean straight-line distance from Times Square is 6.5 miles. The borough means show that price per square foot and FAR are highest on average in Manhattan (at \$1836 and 7.83) and that the price per square foot is lowest in the Bronx (at \$105) and FAR lowest in Staten Island (at 1.59). The table also shows the number of zip codes in each borough.[8]

The New York regressions include land-use categories (residential, commercial and manufacturing), which are derived from the zoning codes and add two additional dummy variables to the regression (the dummies are absent from (10) because they are not used in other cities; see below). Although categories are not shown in Table 1, they are predominantly residential and commercial.

Table 2 shows the first set of results for New York, with the year fixed effects not reported. The regression in column (1) includes only FAR and the land-use categories as covariates (residential, the default category, is omitted). The FAR coefficient of 0.875 is highly significant, showing that an increase in the regulated FAR raises the land price. Manufacturing land sells at a discount to residential land while commercial land sells at a premium. Column (2) shows the effect of adding zip code fixed effects, which reduces the FAR coefficient by more than 50% (to 0.323, still strongly significant), while eliminating the commercial price premium. The smaller FAR coefficient shows that, by controlling for unobservables common to parcels within a zip code, the inclusion of zip code fixed effects reduces upward bias in the FAR coefficient. Naturally, the R^2 of the regression almost doubles, to 0.627. Since potential error correlation across parcels within a zip code may lead to understatement of the FAR coefficient's standard error despite the use of robust standard errors in columns (1) and (2), column (3) shows the effect of error clustering at the zip code level. The resulting increase in the coefficient standard error is slight, leaving the estimate strongly significant.

The regression in column (4), which again includes zip code fixed effects, allows the *FAR* coefficient to differ across New York boroughs.[9] As can been seen, the Staten Island *FAR* coefficient is insignificantly different from zero, indicating that the *FAR* limits in that borough are not binding. Comparing the sizes of the remaining *FAR* coefficients within the regression yields the first major lesson of the analysis. In particular, the Manhattan *FAR* coefficient is larger than the coefficients for the other boroughs, indicating that *FAR* regulation is more stringent in Manhattan than elsewhere in New York City. Thus, even though regulated *FAR* values are larger in Manhattan than in the other boroughs from Table 1, they *fall short of free-market FARs to a greater extent* than elsewhere. In other words, if *FAR* regulation were removed in all the boroughs of New York, building heights would rise by more in Manhattan than elsewhere.

When the errors are clustered by zip code, the four *FAR* coefficients that are significant in column (4) remain significant, as seen in column (5). Note that the commercial and residential coefficients are similar to those in column (2).

The regressions in columns (6)–(11) use the circular parcel clusters instead of zip codes, with each cluster having its own fixed effect. Note that the number of clusters within each borough is shown at the bottom of the table, numbers that are much larger than the zip code counts by borough shown in Table 1. For each cluster radius, the second regression has borough-specific *FAR* coefficients, while the first has a common coefficient. As can be seen in columns (6) and (7), where the cluster radius is 1/3 mile, the results are very similar to those in columns (2) and (4), with the common *FAR* coefficient and the borough-specific *FAR* coefficients just slightly smaller than in the previous regressions.

In regressions with a smaller cluster radius of 1/4 mile, shown in columns (8) and (9), the results are similar to those in columns (6) and (7). Note, however, that some of the borough-specific *FAR* coefficients increase while others decrease. Moving to the smallest cluster radius of 1/8 mile, which typically more than doubles the number of clusters compared to the 1/3 mile radius, the previously significant *FAR* coefficient for Bronx becomes insignificant. On the one hand, the reduction in the cluster size presumably makes the included parcels more homogeneous, better controlling for unobservables and thus reducing upward coefficient bias. On the other hand, a smaller size, by reducing the number of observations per cluster, also reduces the within-cluster variances of FAR, making it harder to estimate the effect of FAR on land prices (identification of the FAR effect comes solely from this within-cluster variation). This pattern is shown in the rows near the bottom of Table 2, where the number of New York zip codes (clusters) is shown, along with the number of observations per zip code (cluster). Also shown is the average squared FAR deviation from the zip code (cluster) mean, with the deviation computed for each zip code (cluster) and then averaged across the city. As can be seen, observations per zip code (cluster) falls as cluster size decreases, leading to a monotonic decline in the average squared FAR deviation within clusters. This decline makes precise estimation of the FAR effect harder as cluster size falls.

If credence is given to bias reduction from a smaller cluster size, the emergence of zero FAR coefficients with small clusters would imply that the true FAR effect is zero, implying that FAR regulations are not binding in the Bronx. However, it is more likely that a zero FAR coefficient arises because of the difficulty of estimating FAR effects with little intra-cluster FAR variation.[10] Finally, it is to note that regressions (7), (9), and (11) again imply that the stringency of FAR regulation is highest in Manhattan. This key conclusion thus survives the use of a much finer division of parcels into clusters than occurs under zip code fixed effects.

Table 3 shows regressions where borough-specific FAR coefficients are replaced by an FAR effect that is allowed to depend on distance from the CBD, following the specification in eq. (11). In columns (1) and (2), Times Square is treated as the New York CBD, with zip code fixed effects added in column (2). As can be seen in column (1), the FAR coefficient is positive, the distance coefficient is negative, and the distance-FAR interaction coefficient is also negative but smaller in absolute value than the FAR coefficient. This pattern of coefficients implies that the FAR effect (equal to $\theta + \lambda x_i$ from (11)) starts out positive at the CBD and decreases with distance, implying that FAR regulation is most stringent near the CBD. This conclusion mirrors the earlier finding that stringency is greatest in Manhattan. Figure 1 shows a graph of the FAR effect as a function of distance, along with 95% confidence intervals. Note that the confidence intervals cover zero starting at a distance of 13 miles, suggesting that FAR limits may no longer be binding beyond that distance.

Because both the distance and interaction coefficients are negative, the distance effect on the land price (equal to $\gamma + \lambda \log(FAR_{ict})$ in (11)) is also negative in standard fashion, being stronger where FAR is large.[11] When zip code fixed effects are added to the regression, the distance coefficient becomes insignificant but the previous qualitative conclusions remain. Note that, because FAR can vary across zip codes that lie at a common distance but in different directions from the CBD, the FAR effect is identified even with distance held constant.

Recognizing that New York in effect has two CBDs, one at Manhattan's Midtown and one at Wall Street, columns (3) and (4) of Table 3 set distance to the CBD equal to the minimum of the distances to Times Square and Wall Street. As can be seen, the pattern of coefficients, and the resulting conclusions, are identical to those from columns (1) and (2) (the distance coefficient with zip code fixed effects regains significance). Note the coefficients of the commercial and manufacturing land-use categories in Table 3 follow the pattern seen in Table 2.

As explained in Barr (2016), FAR values in New York can be open to negotiation between developers and the zoning authority, a possibility that might affect the interpretation of the preceding results. Barr's discussion details how developers can secure an FAR "bonus" by taking steps that are viewed as desirable by the authority. For example, by providing a public plaza adjacent to a building, the developer can gain permission to exceed the site's FAR limit, as specified in the zoning code. Responding to Barr's description of this process, Bertaud (2018) argues that the New York zoning authority is exerting inappropriate control over land-use in the city by channeling development in specific directions that it deems desirable. Given this policy, the FAR limits in the data may be viewed as somewhat flexible by developers, which might undermine the interpretation of the FAR coefficient as a measure of stringency. However, if developers view the effective FAR as equal to some factor τ times the de facto FAR , with τ greater than but close to 1, then the estimating equation (10) would change only slightly. The replacement of $\theta \log(FAR\ )$ by $\theta \log(\tau FAR)$ would simply add the term $\theta \log(\tau)$ to the constant term in the regression. With the de facto FAR still determining stringency of the regulation (up to the constant τ), the interpretation of the regression results is unchanged.

Note also that, if developers only rarely take steps to secure *FAR* bonuses, the issue recedes in importance.[12]

In another application of the methodology used in this paper, Moon (2018) studies New York and uses the selling price of "teardown" parcels to generate land value data, following Dye and McMillen (2007). The idea is that land value is well approximated by the selling price of occupied parcels where the building is torn down and replaced within a few years. Using land value data generated in this fashion, and regressing value per square foot on the *FAR* limit for the parcel, Moon finds the highest borough-specific *FAR* coefficient in Manhattan. Therefore, the conclusion Manhattan has more-stringent *FAR* regulation than the other New York boroughs again emerges, even though Moon's land value data come from teardowns.

4.2. Washington, D.C.

Table 4 shows summary statistics for the remaining cities. Note that average price square foot and *FAR* are lower in each city than in New York.

The Washington, D.C. sample contains 720 observations, which are widely distributed within the District of Columbia (see the map in Figure 3). Since Washington's zoning code has mixed-use designations in many areas, assigning parcels a residential, commercial or manufacturing designation is not possible, so that category dummies do not appear in the regressions. Table 5 shows the results for Washington, D.C. In column (1), the only variables are the year fixed effects and *FAR*, which has a strongly significant coefficient. Column (2) adds zip code fixed effects, which cuts the *FAR* coefficient almost in half, following the pattern seen in New York. As seen in column (3), clustering of the standard errors by zip code leaves the *FAR* coefficient strongly significant.

Unlike New York, Washington, D.C. has an explicit building-height limit, and its presence appears to be manifested in the large magnitude of the *FAR* coefficient, indicating substantial stringency of height regulation in D.C. At 0.716, the coefficient is more than twice as large as the comparable New York coefficient of 0.322 from column (2) of Table 2, a regression that has a common *FAR* coefficient across New York boroughs and includes zip code fixed effects. The D.C. coefficient of 0.716 is also larger than all of the New York borough-specific *FAR* coefficients in column (4) of Table 2. These comparisons yield the second major lesson of the paper, namely, that height regulation is more stringent in Washington, D.C., than in New York City. Since this conclusion emerges for a city with a well-known height limit, the credibility of the FAR coefficient as a measure of the stringency of height regulation is strengthened.

Use of circular clusters in place of zip codes, leading to the results in columns (4)–(6) of Table 5, reduces the FAR coefficient more substantially than in the New York case, where the magnitude of the common FAR coefficient hardly changed at all (columns (6), (8), and (10) of Table 2). With 1/3 mile clusters, the Washington coefficient of 0.381 is larger than the corresponding New York coefficient of 0.321, again suggesting greater stringency in D.C. But with 1/4 and 1/8 mile clusters, the relationship is reversed, with the D.C. coefficient of 0.270 and 0.257 slightly smaller than the New York coefficients of 0.313 and 0.322. However, given the different relationships between FAR coefficients with zip code and cluster fixed effects in the two cities (similar vs. substantially different magnitudes in New York vs. Washington), a comparison of regulatory stringency based on the results with zip code fixed effects seems most credible. Therefore, the previous conclusion regarding the greater stringency of building-height regulation in D.C. appears justified.

Note that the rows near the bottom of Table 5 show the same pattern as the corresponding rows of Table 2. Observations per zip code (cluster) fall with cluster size, which reduces the average squared FAR deviation within zip codes (clusters) as size decreases. In contrast to New York, this decline does not prevent estimation of a significant FAR effect even with the smallest (1/8 mile) cluster size.

Columns (7) and (8) of Table 5 show regressions where the FAR effect is allowed to depend on the distance from the CBD (identified as the Washington Monument). In contrast to the New York case, the insignificance of the distance-FAR interaction coefficient implies that the stringency of height regulation is spatially uniform in D.C. This result may make sense given that government employment tends to be fairly evenly distributed over much of D.C., implying that job access is similar at different locations within the district and thus that free-market FAR values for private development would be correspondingly similar across space. This pattern, in conjunction with a uniform height limit, would imply spatially invariance in the stringency of height regulation.

4.3. Chicago

The regressions for Chicago are based on 2,540 observations, with the map in Figure 4 showing that the parcels are widely distributed across the city. As in Washington, D.C., inclusion of land-use categories is not feasible in the regressions, which are shown in Table 6. The regression in column (1) shows a strongly significant FAR coefficient, but the magnitude of the coefficient drops dramatically, to 0.0933 when zip code fixed effects are included, as seen in column (2). While significant at the 5% level, this coefficient is not as strongly significant as those in previous tables, which showed 1% significance. As a result, when standard errors are clustered by zip code, the FAR coefficient loses significance, as can be seen in column (3) of Table 6. This pattern continues for the circular-cluster results, with none of the coefficients in columns (4)–(7) statistically significant. Comparing Table 6 to Tables 5 and 2 shows a possible reason for this lack of significance: fewer observations per cluster in Chicago than in Washington D.C. or New York under 1/3, 1/4 and 1/8-mile cluster sizes. This difference may account for the lower precision of Chicago's estimated FAR effects for these cluster sizes.

Viewing the significant column (2) coefficient as credible, its small magnitude compared to the corresponding coefficients for New York and Washington, D.C., suggests the third main lesson of the analysis: building-height regulation is mild in Chicago, with low stringency compared to that in New York and Washington, D.C. Thus, regulated building heights in Chicago are close to free-market levels.

The regressions in columns (7) and (8) of Table 6 allow the FAR effect to depend on distance, and the coefficient pattern is the same as in New York, with a positive FAR coefficient, a negative distance coefficient, and a negative interaction coefficient that is smaller in absolute value than the FAR coefficient (with and without zip code fixed effects). As before, the implication is that the FAR effect declines with distance to the CBD, and that the effect of distance on the land price (which depends on FAR) is negative in standard fashion.[13] Therefore, the stringency of building-height regulation in Chicago, while low on average, is greatest near the CBD.

4.4. Boston

Boston has fewer observations than the previous cities, with only 299 land sales observed.

The bulk of the observations lie in the city of Boston, but some are in outlying communities (see the map in Figure 5). The results, contained in Table 7, show a strongly significant FAR coefficient in column (1), and a substantial reduction in the coefficient (to 0.239**) when zip code fixed effects are included (column (2)). The significance of the FAR coefficient is reduced to the marginal 10% level when standard errors are clustered by zip code, as seen in column (3), and insignificance persists in the three circular-cluster regressions in columns (4)–(6). Comparison to Table 6 shows that observations per cluster are smaller in Boston than in Chicago (and thus smaller than in New York and Washington D.C.), possibly accounting for this lack of significance.

When the FAR effect is allowed to depend on distance, the coefficient pattern is the same as in New York, with a positive FAR coefficient and negative distance and interaction coefficients, in the regression without zip code fixed effects.[14] But when zip code fixed effects are included, only the FAR coefficient among these three is significant, implying that the distance has no effect on land values and that the FAR effect is independent of distance. The first of these conclusions is anomalous and presumably shows that, with relatively few observations, there is not enough distance variation within zip codes to identify an effect on land values.

Focusing on the coefficient in column (2) for purposes of comparison with the other cities, the results suggest that the Boston's building-height regulation is more stringent than in Chicago, but less stringent than in New York and Washington D.C., a conclusion that constitutes the fourth main lesson of the analysis.

4.5. San Francisco

Like Boston, San Francisco has relatively few observations (291), which are widely distributed across the city (see the map in Figure 6). The regression results are shown in Table 8. The FAR coefficient is positive and strongly significant in column (1), which only contains the year dummies and FAR itself. As before, the FAR coefficient drops substantially (to 0.116 in column (2)) when zip code fixed effects are included, but the estimate is not statistically significant (and remains so with clustered standard errors). Evidently, this outcome is due to the relatively small number of observations, which reduces the number of observations per zip code and thus hinders identification of the FAR effect, which relies on within-zip-code variation in FAR . Similarly, the FAR coefficients in the circular-cluster regressions are all insignificant, as seen in columns (4)–(6) of Table 8 (but as in Boston, observations per cluster are lower than in New York, Washington D.C., and Chicago).

In the regressions that allow the FAR effect to depend on distance from the CBD (columns (7)–(8)), the FAR and interaction coefficients are significantly positive and negative, respectively, as before, but the distance coefficient is insignificant (with and without zip code fixed effects). The FAR effect thus decreases with distance, as in New York and Chicago, and while the distance effect is negative as before, it now emerges solely through the interaction term.

The insignificance of column (2)'s FAR coefficient makes comparing regulatory stringency with other cities tenuous. But based on the insignificant point estimate of 0.116, the conclusion would be that San Francisco's height regulation exhibits low stringency, like that in Chicago. This conclusion might be viewed as surprising given California's reputation as a state with extensive land-use regulation. The finding of low stringency could conceivably be explained by the higher costs of earthquake-resistant construction, which may reduce free-market $FARs$ in San Francisco relative to those in similar earthquake-free cities, making them closer to regulated $FARs$. Alternatively, the burdens of other regulations such as minimum parking requirements may limit the incentives for dense development to an extent that makes existing FAR limits nonbinding.[15]

4.6. Calculation of $h(\overline{S})/h(S^*)$

With estimated values of θ in hand, the ratio of $h(\overline{S})/h(S^*)$ can be computed once a value for the production-function exponent β is assumed, using the formula in (9). This ratio gives the regulated FAR as a share of the free-market FAR. Table 9 shows the calculations for two different values of β, 0.6 and 0.8. Note that, for Washington, D.C., the θ value of 0.381 from the 1/3-mile cluster regression is used in place of the much larger 0.716 value from the regression with zip code fixed effects. As can be seen from Table 9, the calculation implies that regulated building heights are 70–77% of free-market heights in New York and 63–72% of free-market heights in Washington, D.C. In Chicago, regulated heights are 92–94% of free-market heights, reflecting low stringency, and San Francisco's 90–93% value is similar. Boston's heights are 78–84% of free-market values. Thus, the stringency ranking, from greatest to lowest is:

Washington D.C., New York, Boston, San Francisco, Chicago.

The conclusions from Table 9 can be compared to the results of Glaeser et al. (2005), who provide regulatory-tax measures for other cities in addition to New York. Since their results are based on data for detached single-family houses (see footnote 1) and implicitly include all types of land-use regulations as sources of the regulatory tax, the findings are not strictly comparable to the present findings. Nevertheless, the ranking of stringency based on the regulatory tax for the current group of cities is as follows, from most to least stringent: San Francisco, Washington D.C., Boston, New York, Chicago. While this ranking is different from the one based on Table 9, both rankings do count Chicago as a low-stringency city.[16]

Since urban theory shows that building-height limits raise housing prices (Bertaud and Brueckner (2005)), a connection between housing affordability and regulatory stringency might be expected. Among the five current cities, it is well known that Chicago is the most affordable, in line with the stringency ranking from Table 9. However, since the other four cities benefit from coastal amenities, which also affect housing prices, other factors would not be equal in attempting to link affordability to FAR stringency across the five cities. Note, however, that with data on many more cities than the current sample of five, it would be possible to untangle these effects by running a regression relating a city-level housing price index to estimated stringency and other covariates. With such a sample, it would also be possible to explore the determinants of stringency. For example, using regression results for their much larger sample of Chinese cities, Brueckner et al. (2017) found that stringency is greater in cities with many historical-cultural sites (high stringency in Washington, D.C., is the US counterpart to this finding).

In addition to raising housing prices, Bertaud and Brueckner's (2005) analysis shows that a height limit creates urban sprawl and reduces the utility of urban residents. The numerical simulation of their model is based on a draconian height limit that reduces central building height to about 20% of its free-market value, a more stringent regulation than any of those in Table 9. In addition to raising the housing price per square foot by 20-30% throughout the city, the height limit causes the city's radius to grow from 21.4 miles to 23.5 miles, increasing the urban land area by 21% (the height limit binds out to a distance of 11.7 miles). In response to this spatial expansion of the city, the annual commuting cost of the resident living at the city's edge increases by \$945 per year, or 2.2% of income. This resulting reduction in disposable income is an exact measure of the welfare cost of the restriction for each of the city's identical residents.

5. Conclusion

This paper has explored the stringency of land-use regulation in US cities, focusing on building heights. Stringency is substantial when regulated heights are far below free-market heights, while stringency is lower when the two values are closer. Using FAR as a height index, theory shows that the elasticity of the land price with respect to FAR is a proper stringency measure. This elasticity is estimated for five US cities by combining CoStar land-sales data with FAR values from local zoning maps, and the results show that New York and Washington, D.C., have stringent height regulations, while Chicago's and San Francisco's regulations are less stringent (Boston represents an intermediate case). While the stringency verdict for Washington is not very surprising given the city's explicit height limit, the verdict for New York is more noteworthy since it confirms other calls for greater densification of the city, especially Manhattan.

The remarkable aspect of the paper's methodology is that stringency can be measured without knowing free-market building heights, which are obviously unobservable. The method exploits the intuitive proposition that relaxing a tight height limit raises the developer's willingness-to-pay for the land by more than relaxing a loose limit. The method could be applied to any regulation that targets a continuous land-use variable, such as a minimum parking requirement, a minimum lot size, or a minimum street set-back distance. Given that land-use regulations are gaining more attention as a potential cause of high housing prices in the US, the ability to gauge their stringency is an important advancement.

Table 1: Summary Statistics: New York

Variable	Obs	Mean	Std. Dev.	Min	Max
New York (Zip Code count = 172)					
FAR	5173	4.428	2.789	1.000	15.000
Sale Price (in '000s)	5173	6363.601	27862.700	1.000	870000.000
Land Area (in '000s sqft)	5173	26.264	417.746	0.200	29446.560
Price per sqft	5173	581.605	1774.472	0.165	36418.250
Dist. to Wall Street	5173	6.722	3.916	0.126	18.780
Dist. to Times Square	5173	6.532	3.802	0.110	22.392
Min. distance to Times Square or Wall Street	5173	5.365	3.545	0.110	18.780
Brooklyn (Zip Code count = 38)					
FAR	2098	3.621	1.593	1.000	12.000
Sale Price (in '000s)	2098	3393.037	14156.470	3.000	383217.500
Land Area (in '000s sqft)	2098	14.726	44.657	0.200	958.320
Price per sqft	2098	325.293	502.890	1.695	8333.333
Dist. to Wall Street	2098	4.306	2.029	0.609	9.192
Dist. to Times Square	2098	6.569	2.536	2.036	12.921
Min. distance to Times Square or Wall Street	2098	4.284	2.044	0.609	9.192
Bronx (Zip Code count = 25)					
FAR	802	4.171	1.571	1.000	7.200
Sale Price (in '000s)	802	1352.363	2558.830	28.000	45800.000
Land Area (in '000s sqft)	802	21.098	48.383	0.984	580.306
Price per sqft	802	104.956	108.267	1.084	1479.444
Dist. to Wall Street	802	11.545	1.934	8.169	16.192
Dist. to Times Square	802	7.894	1.955	4.437	12.455
Min. distance to Times Square or Wall Street	802	7.894	1.955	4.437	12.455
Manhattan (Zip Code count = 42)					
FAR	1088	7.834	3.207	2.000	15.000
Sale Price (in '000s)	1088	19345.980	54626.150	1.000	870000.000
Land Area (in '000s sqft)	1088	13.722	29.280	0.436	569.600
Price per sqft	1088	1836.249	3514.259	0.165	36418.250
Dist. to Wall Street	1088	4.774	2.860	0.126	12.593
Dist. to Times Square	1088	2.570	1.697	0.110	8.686
Min. distance to Times Square or Wall Street	1088	2.210	1.769	0.110	8.686
Queens (Zip Code count = 55)					
FAR	1021	3.114	2.092	1.000	15.000
Sale Price (in '000s)	1021	3068.671	9352.842	33.504	173539.700
Land Area (in '000s sqft)	1021	25.348	67.835	0.370	927.610
Price per sqft	1021	226.913	339.047	1.703	3735.730
Dist. to Wall Street	1021	9.136	3.266	3.569	16.016
Dist. to Times Square	1021	8.162	4.210	1.767	17.168
Min. distance to Times Square or Wall Street	1021	7.904	3.860	1.767	15.897
Staten Island (Zip Code count =12)					
FAR	164	1.590	0.977	1.000	4.800
Sale Price (in '000s)	164	3257.189	11654.480	60.842	122000.000
Land Area (in '000s sqft)	164	288.048	2322.446	1.600	29446.560
Price per sqft	164	76.153	72.319	1.406	400.000
Dist. to Wall Street	164	11.954	3.894	5.554	18.780
Dist. to Times Square	164	15.519	3.887	9.208	22.392
Min. distance to Times Square or Wall Street	164	11.954	3.894	5.554	18.780

Table 2: Regressions of land price on FAR: New York

	Dependent variable: Log of price per square foot										
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Log FAR	0.875***	0.323***	0.323***			0.328***		0.318***		0.341***	
	(0.0289)	(0.0329)	(0.0484)			(0.0426)		(0.0468)		(0.0659)	
Log FAR * Dummy for Queens				0.484***	0.484***		0.463***		0.366***		0.425***
				(0.0562)	(0.0776)		(0.0797)		(0.0857)		(0.1100)
Log FAR * Dummy for Manhattan				0.607***	0.607***		0.620***		0.558***		0.513**
				(0.1260)	(0.1500)		(0.1610)		(0.1640)		(0.2210)
Log FAR * Dummy for Bronx				0.211***	0.211**		0.207**		0.395***		0.227
				(0.0812)	(0.0960)		(0.0895)		(0.0982)		(0.1770)
Log FAR * Dummy for Brooklyn				0.226***	0.226***		0.200***		0.218***		0.270***
				(0.0482)	(0.0667)		(0.0561)		(0.0650)		(0.0872)
Log FAR * Dummy for staten Island				-0.121	-0.121		0.577		0.0535		-0.663
				(0.2090)	(0.3220)		(0.4040)		(0.4390)		(0.6130)
Dummy for commercial land	0.647***	-0.0343	-0.0343	-0.0559	-0.0559	-0.049	-0.0782	-0.0505	-0.0624	0.00706	-0.00208
	(0.0556)	(0.0501)	(0.0588)	(0.0510)	(0.0572)	(0.0608)	(0.0616)	(0.0649)	(0.0664)	(0.1020)	(0.1030)
Dummy for manufacturing land	-0.0828**	-0.317***	-0.317***	-0.314***	-0.314***	-0.150***	-0.158***	-0.215***	-0.209***	-0.149**	-0.151**
	(0.0393)	(0.0341)	(0.0480)	(0.0343)	(0.0462)	(0.0455)	(0.0455)	(0.0526)	(0.0525)	(0.0761)	(0.0760)
Constant	3.673***	7.426***	7.426***	6.686***	6.686***	3.173***	3.379***	3.327***	3.651***	3.724***	3.051***
	(0.1700)	(0.1780)	(0.2400)	(0.3710)	(0.4400)	(0.2620)	(0.2940)	(0.2740)	(0.7090)	(0.3420)	(0.9700)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zipcode fixed effects included		Yes	Yes	Yes	Yes						
Standard error clustered at zip code level			Yes		Yes						
Cluster fixed effect (1/3rd of a mile)						Yes					
Cluster fixed effect (1/4th of a mile)								Yes			
Cluster fixed effect (1/8th of a mile)										Yes	
Number of zip codes or clusters			172			846		1140		2055	
Number of obs. per zip code or cluster			30.10			6.12		4.54		2.52	
Avg. squared FAR deviation within zip codes or clusters			1.81			0.81		0.72		0.39	
R-squared	0.354	0.627	0.627	0.629	0.629	0.7	0.701	0.724	0.725	0.797	0.798
No. of observations	5,173	5,173	5,173	5,173	5,173	5,173	5,173	5,173	5,173	5,173	5,173

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Regressions of land price on FAR: New York (with respect to CBD)

	Dependent variable: Log of price per square foot			
VARIABLES	(1)	(2)	(3)	(4)
Log FAR	0.986***	0.527***	1.004***	0.435***
	(0.0537)	(0.0764)	(0.0504)	(0.0671)
Log FAR * Distance to Times Square	-0.0870***	-0.0294***		
	(0.0062)	(0.0091)		
Distance to Times Square	-0.0514***	-0.0357		
	(0.0076)	(0.0218)		
Log FAR * min. distance to Times Square or Wall Street			-0.104***	-0.0209**
			(0.0067)	(0.0092)
min. distance to Times Square or Wall Street			-0.0551***	-0.0448**
			(0.0081)	(0.0226)
Commercial	0.284***	-0.0509	0.200***	-0.0441
	(0.0505)	(0.0505)	(0.0505)	(0.0505)
Manufacturing	-0.260***	-0.307***	-0.258***	-0.308***
	(0.0342)	(0.0339)	(0.0331)	(0.0340)
Constant	4.160***	6.934***	4.158***	7.174***
	(0.1740)	(0.2510)	(0.1680)	(0.2310)
Year dummies	Yes	Yes	Yes	Yes
Zipcode fixed effect		Yes		Yes
R-squared	0.481	0.628	0.508	0.628
No. of Observations	5,173	5,173	5,173	5,173

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Summary Statistics for Other Cities

Variable	Obs	Mean	Std. Dev.	Min	Max
Washington, DC (Zip Code count = 24)					
FAR	720	3.720	2.120	0.500	10.000
Sale Price (in '000s)	720	6526.632	13586.700	3.733	136602.600
Land Area (in '000s sqft)	720	38.771	138.215	0.638	3073.859
Price per sqft	720	348.194	504.407	0.986	8186.687
Dist. to CBD	720	2.490	1.307	0.437	6.616
Chicago (Zip Code count = 49)					
FAR	2540	2.679	2.926	0.100	32.000
Sale Price (in '000s)	2540	1852.842	5800.289	1.000	136469.000
Land Area (in '000s sqft)	2540	70.481	598.675	0.600	26136.000
Price per sqft	2540	86.146	149.845	0.164	2062.639
Dist. to CBD	2540	4.915	3.018	0.020	16.756
Boston (Zip Code count = 28)					
FAR	299	2.242	2.081	0.300	11.000
Sale Price (in '000s)	299	7775.499	23178.500	30.000	203750.000
Land Area (in '000s sqft)	299	73.394	207.947	0.476	2199.997
Price per sqft	299	250.493	804.227	3.403	12049.080
Dist. to CBD	299	2.956	2.173	0.121	9.221
San Francisco (Zip Code count = 22)					
FAR	291	3.916	2.858	1.000	18.000
Sale Price (in '000s)	291	6776.412	16889.440	1.812	191816.200
Land Area (in '000s sqft)	291	26.488	81.705	1.171	958.908
Price per sqft	291	364.7446	485.2245	0.143445	4353.691
Dist. to CBD	291	2.241	1.698	0.214	6.233

Table 5: Regressions of land price on FAR: Washington DC

	Dependent variable: Log of price per square foot							
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log FAR	1.217***	0.716***	0.716***	0.381***	0.270**	0.257*	0.731***	0.423***
	(0.0762)	(0.0800)	(0.114)	(0.116)	(0.132)	(0.154)	(0.139)	(0.159)
Log FAR * Distance to CBD							-0.0834	-0.0120
							(0.0577)	(0.0593)
Distance to CBD							-0.500***	-0.737***
							(0.0623)	(0.0967)
Constant	2.933***	4.105***	4.105***	1.919	2.028	1.970	4.774***	5.539***
	(0.187)	(0.189)	(0.174)	(1.303)	(1.311)	(1.401)	(0.251)	(0.298)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zipcode fixed effects included		Yes	Yes					Yes
Standard error clustered at zip code level			Yes					
Cluster fixed effect (1/3rd of a mile)				Yes				
Cluster fixed effect (1/4th of a mile)					Yes			
Cluster fixed effect (1/8th of a mile)						Yes		
Number of zip codes or clusters		24		126	165	277		
Number of observations per zip code or cluster		30		5.71	4.36	2.60		
Avg. squared FAR deviation within zip codes or clusters		2.38		0.61	0.50	0.25		
R-squared	0.328	0.539	0.539	0.697	0.745	0.824	0.504	0.600
No. of observations	720	720	720	720	720	720	720	720

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Regressions of land price on FAR: Chicago

	Dependent variable: Log of price per square foot							
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log FAR	0.608***	0.0933**	0.0933	0.0533	0.0710	-0.00418	0.497***	0.182***
	(0.0390)	(0.0368)	(0.0565)	(0.0431)	(0.0437)	(0.0605)	(0.0540)	(0.0619)
Log FAR * Distance to CBD							-0.0704***	-0.0338***
							(0.0118)	(0.0129)
Distance to CBD							-0.153***	-0.270***
							(0.0110)	(0.0341)
Constant	3.107***	5.766***	5.766***	1.007***	0.984***	1.061***	3.989***	5.770***
	(0.111)	(0.295)	(0.137)	(0.107)	(0.103)	(0.148)	(0.116)	(0.306)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zipcode fixed effects included		Yes	Yes					Yes
Standard error clustered at zip code level			Yes					
Cluster fixed effect (1/3rd of a mile)				Yes				
Cluster fixed effect (1/4th of a mile)					Yes			
Cluster fixed effect (1/8th of a mile)						Yes		
Number of zip codes or clusters		49		580	738	1212		
Number of observations per zip code or cluster		51.84		4.38	3.44	2.09		
Avg. squared FAR deviation within zip codes or clusters		5.35		0.84	0.69	0.32		
R-squared	0.161	0.571	0.571	0.777	0.821	0.886	0.317	0.589
No. of observations	2,540	2,540	2,540	2,540	2,540	2,540	2,540	2,540

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Regressions of land price on FAR: Boston

	Dependent variable: Log of price per square foot							
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log FAR	0.939***	0.239**	0.239*	-0.0581	-0.0337	-0.0676	0.854***	0.327*
	(0.0823)	(0.106)	(0.128)	(0.182)	(0.210)	(0.282)	(0.137)	(0.184)
Log FAR * Distance to CBD							-0.132***	-0.0314
							(0.0345)	(0.0385)
Distance to CBD							-0.191***	-0.0309
							(0.0344)	(0.0986)
Constant	2.929***	4.696***	4.696***	2.302***	1.195***	1.225	3.597***	4.624***
	(0.764)	(0.565)	(0.733)	(0.618)	(0.398)	-	(0.775)	(0.648)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zipcode fixed effects included		Yes	Yes					Yes
Standard error clustered at zip code level			Yes					
Cluster fixed effect (1/3rd of a mile)				Yes				
Cluster fixed effect (1/4th of a mile)					Yes			
Cluster fixed effect (1/8th of a mile)						Yes		
Number of zip codes or clusters		28		109	133	192		
Number of observations per zip code or cluster		10.68		2.72	2.23	1.54		
Avg. squared FAR deviation within zip codes or clusters		1.61		0.41	0.20	0.05		
R-squared	0.380	0.658	0.658	0.803	0.826	0.897	0.460	0.660
Number of obs.	299	299	299	299	299	299	299	299

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Regressions of land price on FAR: San Francisco

	Dependent variable: Log of price per square foot							
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log FAR	0.419***	0.116	0.116	-0.00712	-0.0954	-0.0943	0.741***	0.406***
	(0.125)	(0.108)	(0.137)	(0.147)	(0.188)	(0.254)	(0.128)	(0.154)
Log FAR * Distance to CBD							-0.434***	-0.211***
							(0.0656)	(0.0750)
Distance to CBD							0.143*	-0.0969
							(0.0730)	(0.119)
Constant	4.632***	4.941***	4.941***	4.381***	4.425***	4.306***	4.947***	4.782***
	(0.184)	(0.365)	(0.264)	(0.242)	(0.223)	(0.310)	(0.221)	(0.433)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zipcode fixed effects included		Yes	Yes					
Standard error clustered at zip code level			Yes					
Cluster fixed effect (1/3rd of a mile)				Yes				
Cluster fixed effect (1/4th of a mile)					Yes			
Cluster fixed effect (1/8th of a mile)						Yes		
Number of zip codes or clusters		22		87	105	161		
Number of observations per zip code or cluster		13.23		3.34	2.77	1.81		
Avg. squared FAR deviation within zip codes or clusters		2.57		0.83	0.65	0.13		
R-squared	0.169	0.503	0.503	0.649	0.703	0.802	0.427	0.532
No. of observations	291	291	291	291	291	291	291	291

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Calculation of $h(\overline{S})/h(S^*)$

	estimated θ	$\beta = 0.6$	$\beta = 0.8$
New York	0.322	0.77	0.69
Washington, D.C.	0.381	0.72	0.63
Chicago	0.093	0.94	0.92
Boston	0.239	0.84	0.78
San Francisco	0.116	0.93	0.90

Fig. 1: New York observation map

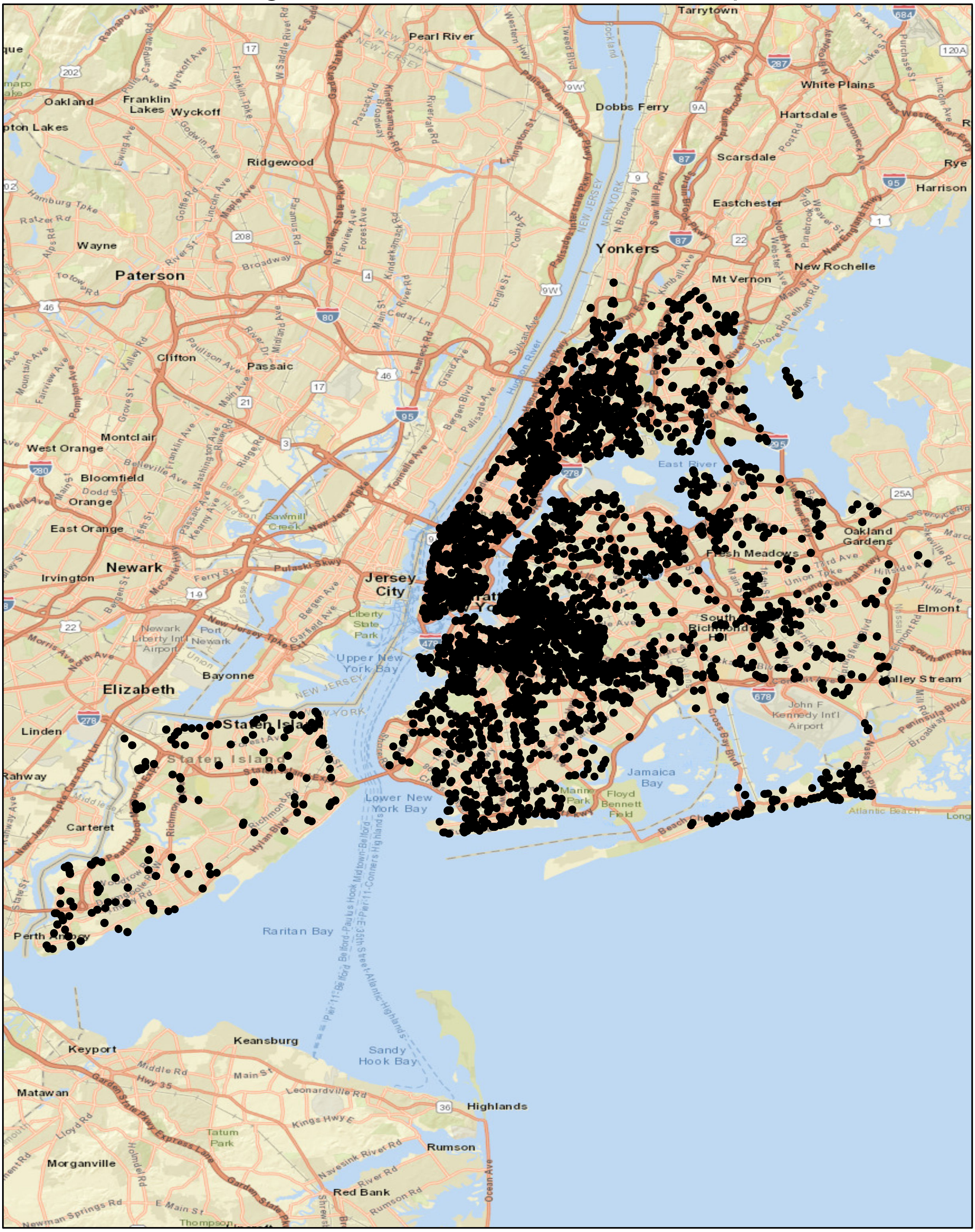


Figure 2: New York FAR effect as a function of distance to Times Square

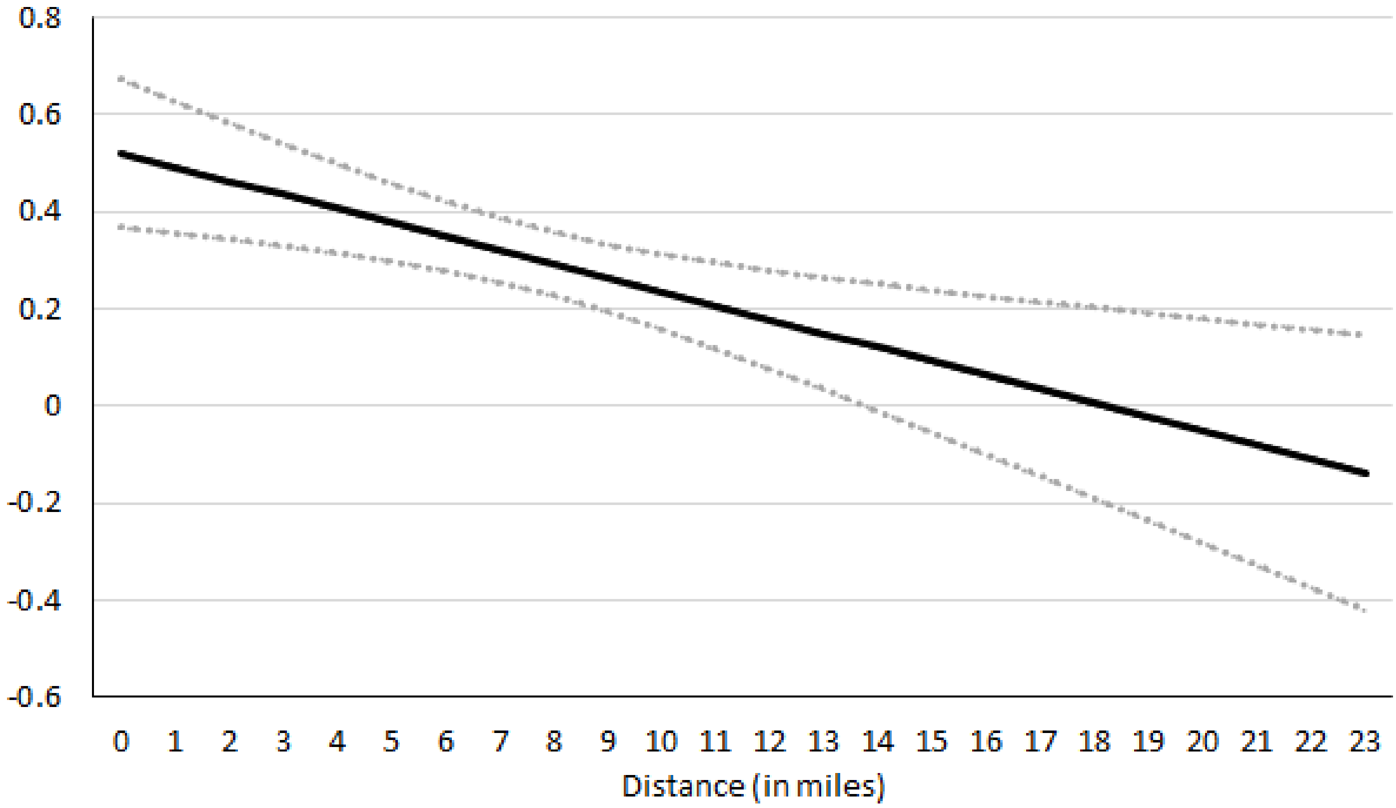


Fig. 3: Washington, DC observation map

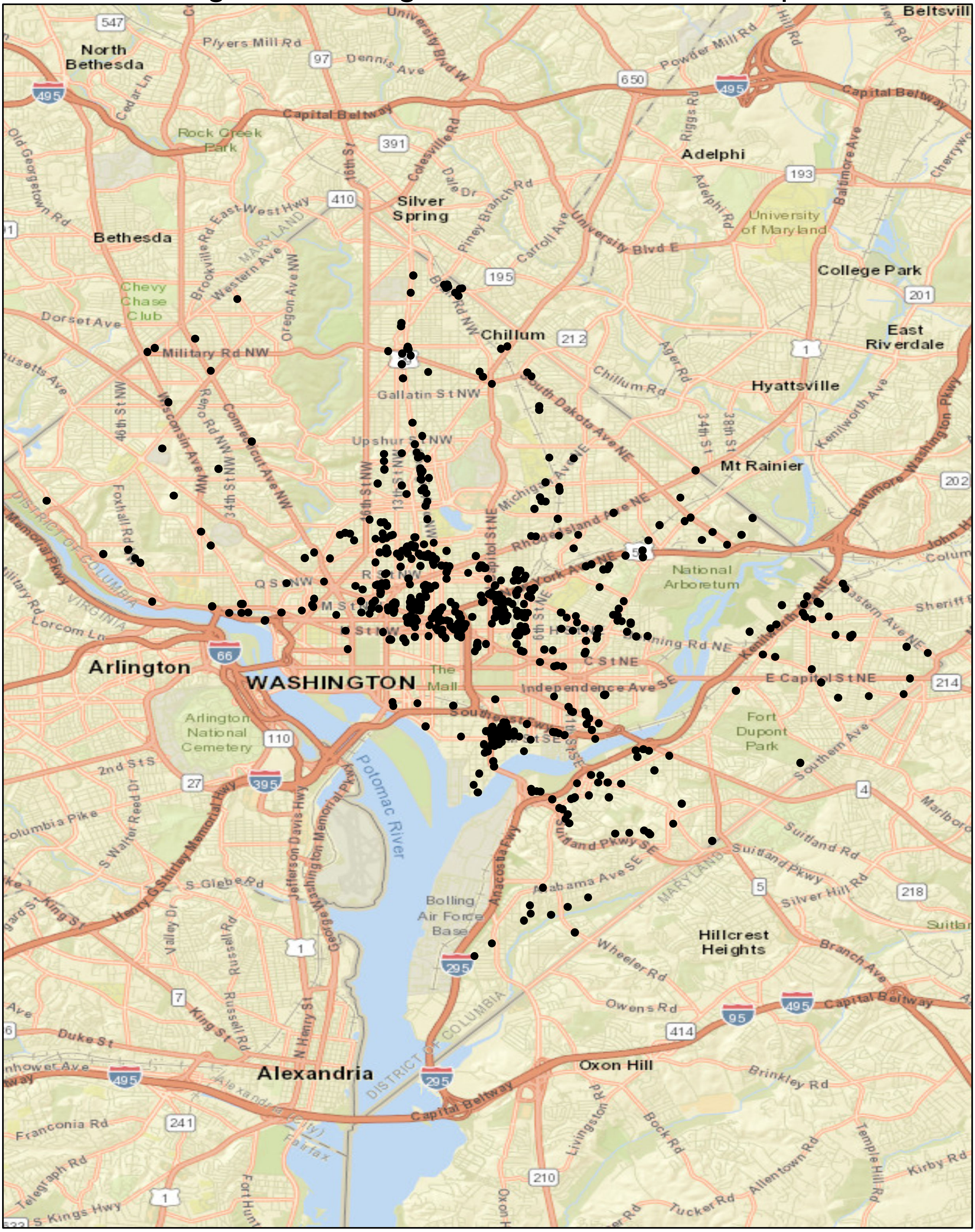


Fig. 4: Chicago observation map

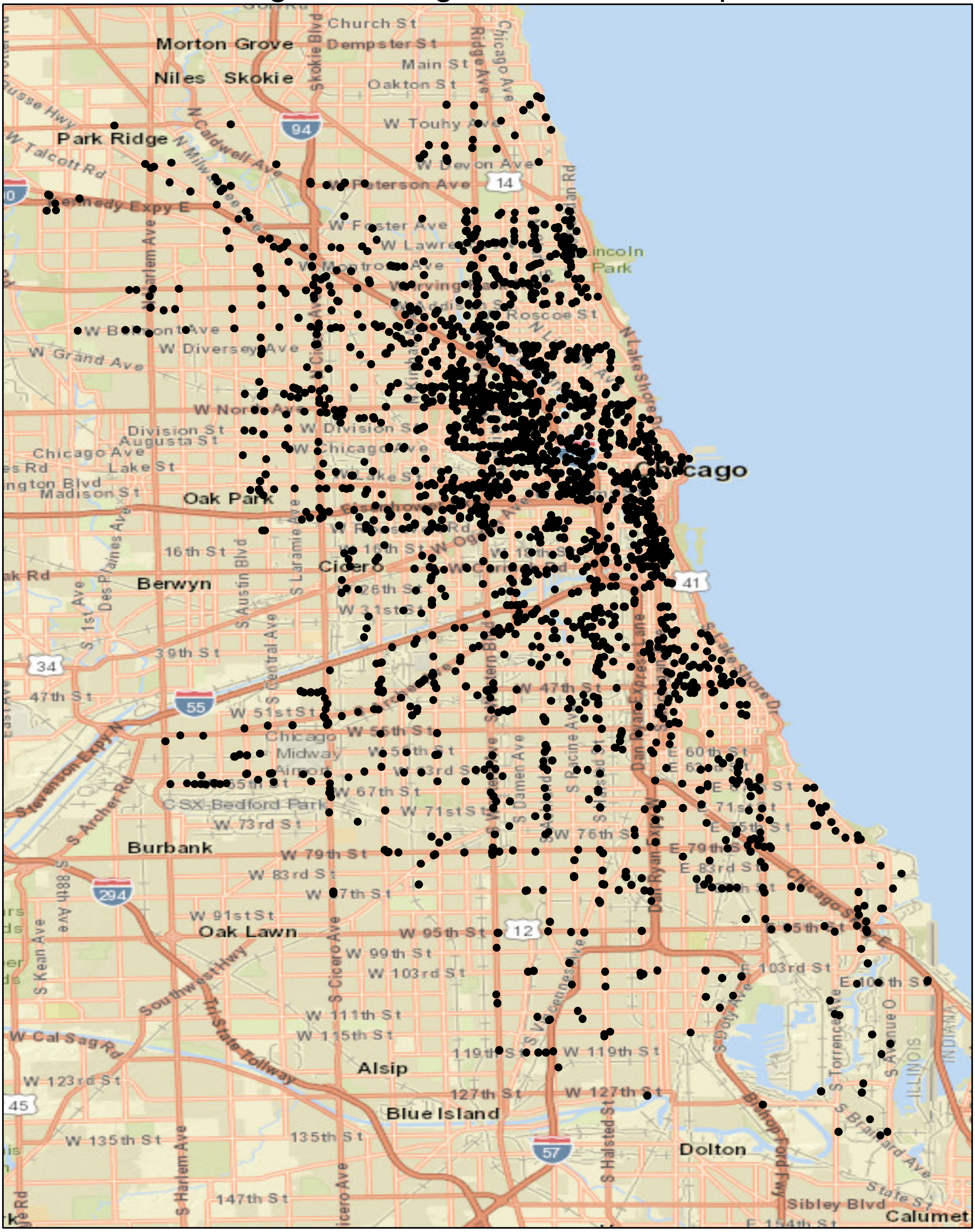


Fig. 5: Boston observation map

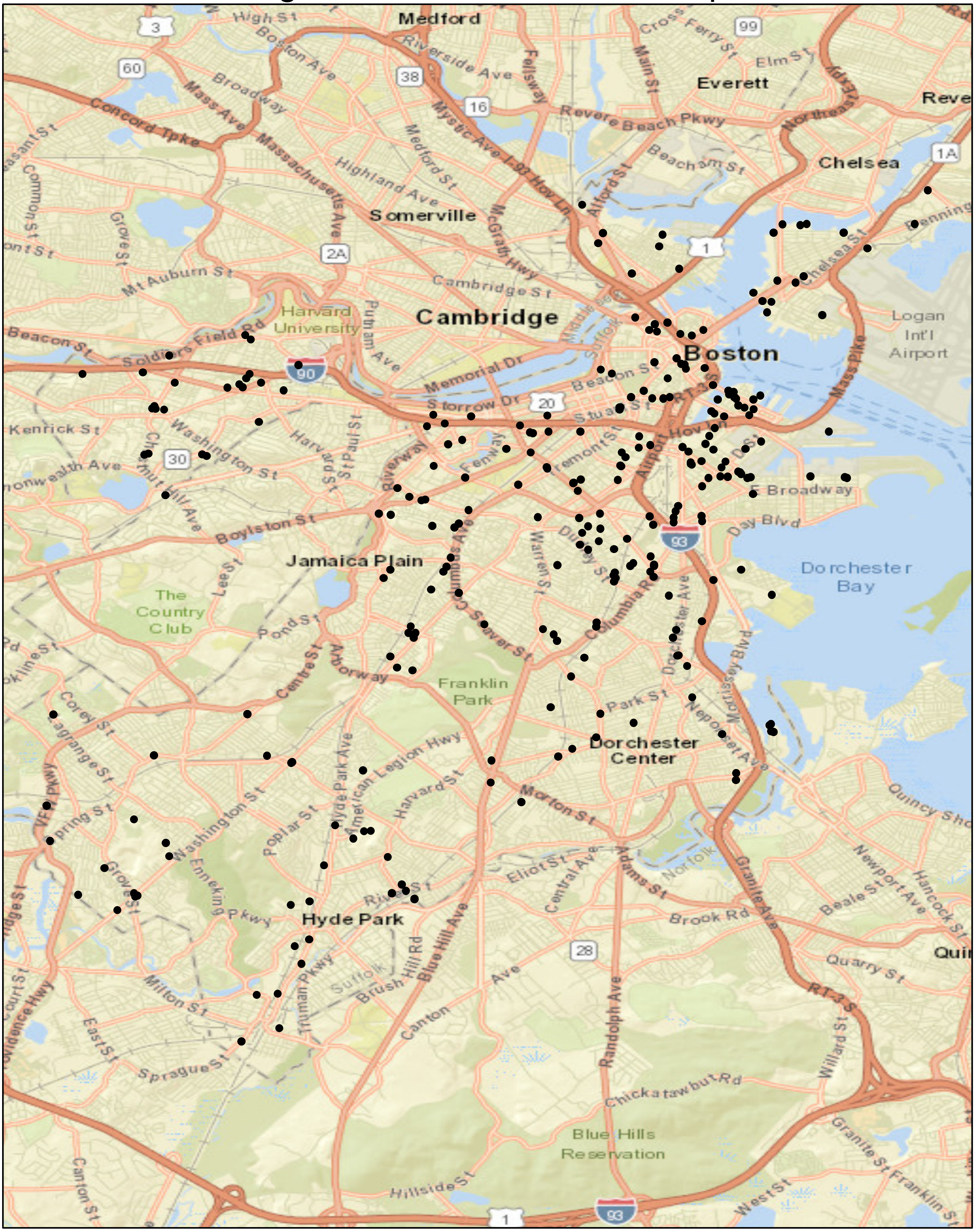
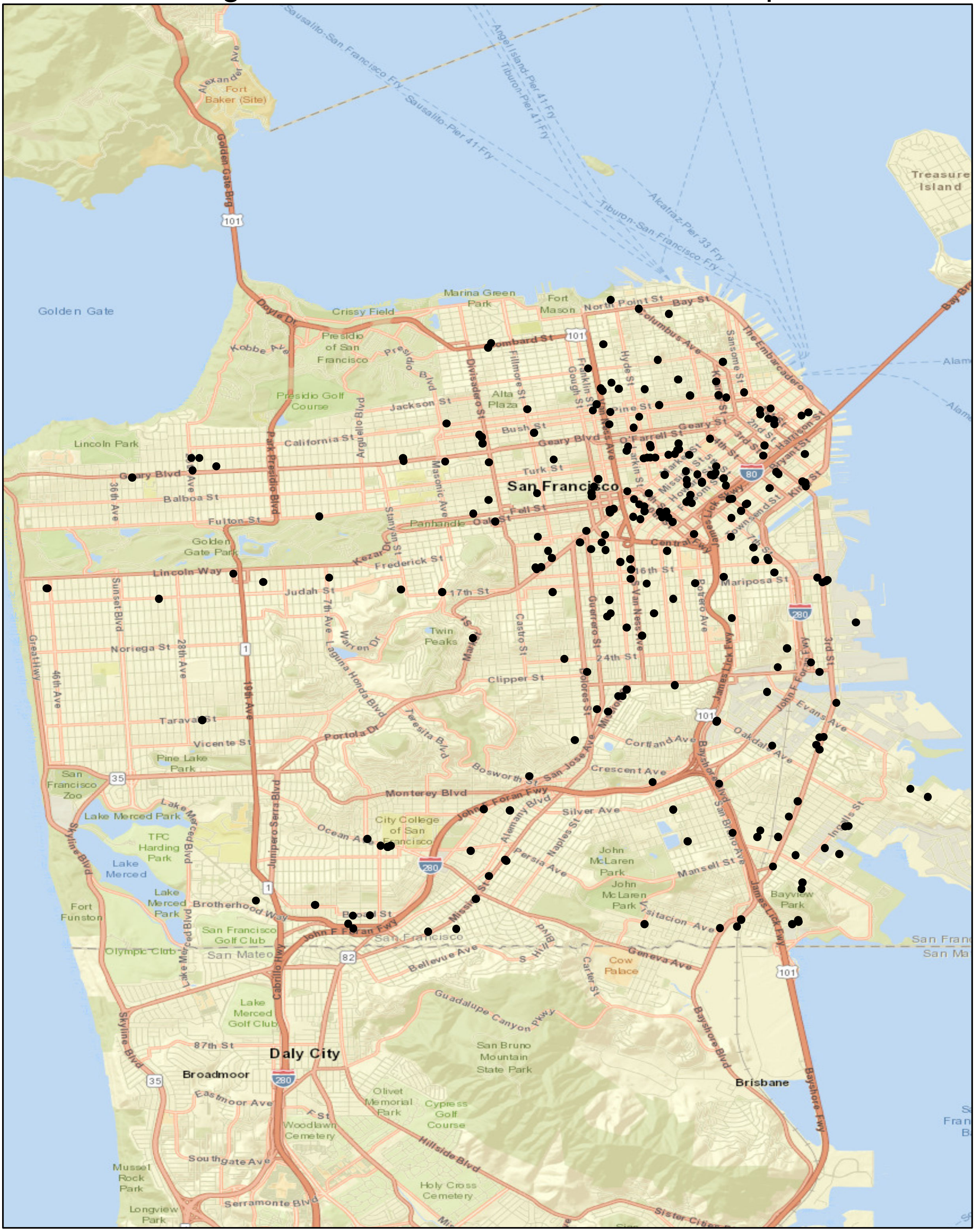


Fig. 6: San Francisco observation map



Appendix: Sources of Zoning Data

New York

http://www1.nyc.gov/site/planning/data-maps/open-data/dwn-pluto-mappluto.page

Washington DC

http://opendata.dc.gov/datasets/planned-land-use-in-2006?geometry=-78.321%2C38.712%2C-75.708%2C39.086

Chicago

https://data.cityofchicago.org/Community-Economic-Development/Boundaries-Zoning-Districts-current-/7cve-jgbp

Boston

http://hub.arcgis.com/datasets/boston::zoning-subdistricts

San Francisco

http://sf-planning.org/zoning-use-district-summaries#crnc

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Footnotes

*We thank CoStar for access to their land sales data. We also thank Jason Barr, Devin Bunten, Jeffrey Brinkman, Edward Coulson, Shihe Fu, Leonard Nakamura, Jeffrey Lin, David Neumark, Chris Severen, Guangliang Yang, Junfu Zhang, and seminar participants at Xiamen University and at the 2018 CURE conference for helpful comments.

[1]The regulatory indexes are typical used to study the impacts of regulation on housing and land prices. Ihlanfeldt (2007) and Jackson (2018) use their indexes in this way, and other recent examples are Turner, Haughwout, and van der Klaauw (2014) and Albouy and Ehrlich (2017) (see Gyourko and Molloy (2015) for a survey of earlier work).

[2]The New York calculation, which applies to residential floor space in high-rise buildings, can ignore land costs, focusing on the cost of per square foot of adding more vertical space relative to the price of such space. The paper also includes calculations of the regulatory tax for detached single-family houses in other metropolitan areas, a calculation that requires consideration of land costs. In the calculation, the excess of house value over production cost (which includes the cost of land, estimated from the lot-size coefficient in an hedonic price function) is expressed as a percentage of house value, with a larger number indicating a greater regulatory tax.

[3]If a building completely covers its lot, then FAR equals the number of storeys in the building, and with partial coverage, FAR equals the number of storeys times the fraction $k < 1$ of lot coverage. Since the k is fairly uniform within cities, FAR is good index of building height.

[4]Brueckner and Sridhar (2012) provide a measure of the welfare cost of the very stringent height limits in India. They use results from Bertaud and Brueckner (2005), which show that welfare cost of a tighter FAR limit can be measured by the sprawl-induced increase in commuting cost for the resident at the edge of the city. Regressing the size of the urban footprint on average regulated FAR, population and other covariates shows the negative effect of a higher FAR on edge-resident commute distance. Using estimates of the time and money costs of commuting in India, the edge-resident's commuting-cost savings from a higher FAR can be computed and aggregated up to the city level to measure the overall benefit from looser regulations. For an average-size Indian city, the aggregate welfare gain from a unit increase in FAR is more than \$1 billion.

[5]The approach is imperfect because, when streets are long, parcels within a cluster may not be close to one another.

[6]The discussion in this section mostly replicates the full derivations in Brueckner et al. (2017)

since leaving out steps would keep the paper from being self-contained.

[7]Other studies using CoStar land-value data include Albouy, Ehrlich and Shin (2017) and Barr (2016).

[8]See Barr and Cohen (2014) for an analysis of the spatial FAR pattern in existing New York buildings. In addition, Barr (2012a,b) analyzes the determinants of building heights in New York.

[9]Specifications that allow the FAR coefficient to differ by land-use category did not yield useful results.

[10]With relatively few observations per cluster, as opposed to the larger number of observations per zip code, clustering the standard errors by circular cluster seems less needed than in the zip code case and therefore is not done.

[11]The distance effect is significantly negative for a wide range of FAR values around the mean.

[12]Although one might expect that buildings would always be constructed up to the relevant height limit in an area, the fact that many buildings predate existing zoning rules can make existing $FARs$ less than regulated levels in many cases. In fact, as explained by Barr (2016), New York rules allow this FAR gap to be sold in the form of "air rights", which allow a developer to exceed a regulated FAR by the amount of a nearby building's shortfall via payment to its owner. See Furman Center for Real Estate and Urban Policy (2013) for further information.

[13]In a graph like Figure 1, the confidence intervals start to cover zero at a distance of 4 miles, suggesting that FAR limits may not bind beyond this distance. As in New York, the distance effect is negative in a range around the mean FAR.

[14]In a graph like Figure 1, the confidence intervals start to cover zero at a distance of 4 miles (as in Chicago), again suggesting that FAR limits may not bind beyond this distance. The distance effect is negative in a range around the mean FAR.

[15]For a cost-benefit analysis of regulations targeted toward earthquake resistance, see Schulze, Brookshire, Hageman and Tschirhart (1987). They assume that such regulation raises construction costs by 3–7%.

[16]The ranking of the current group of cities by the value of the Wharton Residential Land Use

Regulatory Index (Gyourko et al. (2008)) is, from largest to smallest: Boston, San Francisco, New York, Washington D.C., Chicago. This index, however, does not attempt to measure the stringency of regulation.