Is the Rent Too High?
Land Ownership and Monopoly Power*

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Abstract

We investigate the sources, scope, and implications of landowner market power. We show how zoning regulations generate spillovers through increased markups and derive conditions under which restricting landownership concentration reduces rents. Using new building-level data from New York City, we find that a 10% increase in ownership concentration in a Census tract is correlated with a 1% increase in rent. Market power is substantial: on average, markups account for nearly a third of rents in Manhattan. Furthermore, pecuniary spillovers between zoning constraints and markups at other buildings are appreciable. Up-zoning that results in 417 additional housing units at zoning-constrained buildings reduces markups on policy-unconstrained units and generates between 5 and 19 additional units through increased competition.

Keywords: monopolistic competition, market power, concentration, rent, housing demand, zoning

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1 Introduction

Property rights grant landowners exclusive use over parcels of land. Since Chamberlin (1933), and as far back as Adam Smith, economists have considered whether this arrangement endows landowners with monopoly pricing powers.[1] *A priori*, property rights need not generate monopoly power, and it is standard for models of real estate markets to assume competition is perfect.[2] Moreover, the empirical relevance of any potential landowner market power and, as a result, its policy implications are poorly understood.

This paper investigates the economic impact of market power due to land rights. We answer two questions: is this power economically meaningful, and how should this alter our understanding of urban land use policies? Using data on multi-unit residential rental buildings in New York City (NYC), we find that monopoly markups are on average about a third of rental prices. We show how monopoly markups interact with zoning regulations, and examine the possibility that restrictions on land ownership concentration can reduce rents.

Using a model that nests two monopoly power generating mechanisms—vertical and horizontal differentiation—we first explore the theoretical implications of monopoly markups for urban policy. Previous work has focused almost exclusively on a justification of rent control based on landowner monopoly power (Arnott, 1989; Arnott and Igarashi, 2000; Basu and Emerson, 2003). Our framework allows us to explore how monopoly pricing and a larger set of urban policies interact in general equilibrium.[3]

For instance, on the one hand, monopoly power attenuates the impact of up-zoning at up-zoned parcels themselves, as rent and quantity changes revert to monopolistic rather than efficient levels. On the other hand, zoning regulations have an additional impact on rents at other locations through markups, and we show that when the cost function for developing and renting units is nondecreasing, heavier zoning constraints in one parcel always raise rents at other, unzoned parcels by raising markups.

[1]For Smith, that the landowners could rent unimproved land lead him to believe that rent was a "monopoly price" (Smith, 1776). Ricardo (1817) considered land a differentiated factor of production, so that rents reflected differentials in marginal product. Marx argued that monopoly land rents came from three sources: quality differences, markups designed to limit access to land, and extraction of rents from producers selling at markups (Evans, 1991).

[2]See Brueckner (1987) for a unified, formal Alnso-Muth-Mills (AMM) model and Glaeser (2007) for standard modelling of competitive developers.

[3]Diamond, McQuade, and Qian (2019) consider the equilibrium effects of rent controls on landowner entry and exit. Urban policies could also interact with monopoly profits through equilibrium entry and exit. We do not know of any paper that explores this interaction.

We also explore the potential for municipalities to reduce rents by limiting the concentration of land ownership. Restrictions on concentration have been recently proposed by Berlin housing activists (Stone, 2019). We apply the results of Nocke and Schutz (2018a), part of a growing literature on multi-product oligopoly (Affeldt, Filistrucchi, and Klein, 2013; Jaffe and Weyl, 2013; Nocke and Schutz, 2018a), to the impact of zoning on monopoly markups, and show that with non-decreasing marginal cost, landowners with higher concentration always raise markups. Intuitively, landowners with multiple lots can potentially internalize the impact of one parcel's pricing decision on that of their other parcels. When cost-related substitution effects between parcels are sufficiently small, this can lead to higher rents and markups. Furthermore, we extend the results of Nocke and Schutz (2018b), finding conditions under which increased concentration also generates increases in prices for all other products, or, in our case, parcels.

While these theoretical channels may exist, a separate question, over which the literature is silent, is whether they are empirically relevant. The extent to which landowners' market power affect rents will depend on the strength of complementarities between renter and building types, as well as the degree to which consumers see housing at similar buildings as substitutes. To answer this question, we construct a new building-level dataset for multi-unit residential buildings in NYC. We obtain building rental income from a combination of scraped public owner communications and deconstructing formulas used by the NYC Department of Finance (DOF) for calculating tax assessment. Our main results focus on Manhattan buildings, although we probe robustness and derive additional power where necessary from buildings in the Bronx, Brooklyn, and Queens.

First, we find that patterns in the data are consistent with the predictions of our model. In particular, we find that over a seven year period, a 10% increase in Census tract concentration is correlated with a 1-1.6% increase in average building rents. The relationship holds even when fully accounting for time-invariant building characteristics. These correlations are not causal, but they are consistent with the existence of meaningful monopoly power.

Next, we estimate our model in order to ascertain the quantitative scope of markups.[4] The first step in our markup estimation is the estimation of building-level own-price elasticity of demand, accounting for sorting and unobserved building quality. Previous

[4]Our estimation method is based on differentiated product demand estimation developed by Berry, Levinsohn, and Pakes (1995) and Grigolon and Verboven (2014). Within urban housing demand literature, our work is most closely related to Bayer, McMillan, and Rueben (2004), who estimate housing demand and resident sorting within San Francisco. See Kuminoff, Smith, and Timmins (2013) for a literature overview.

housing demand elasticity estimates focus on the housing-consumption trade-off and, as a result, tend to find inelastic results (Albouy and Ehrlich, 2018), which, if taken literally, would be inconsistent with monopoly pricing.[5] However, the relevant elasticity for a landowner's pricing decision is the own-price elasticity that accounts for substitution *between* rival buildings. We estimate this elasticity and find median building own-price demand elasticity of -3.3 in our preferred specification.[6]

An important aspect of our empirical environment is the ubiquity of constraints on prices and quantities in the form of rent restrictions and zoning regulations.[7,8] In order to use our estimated parameters to further estimate markups, we use detailed building characteristics to isolate the set of buildings in our sample which are neither rent stabilized nor constrained by zoning.[9] We call this sample policy-unconstrained. We find that in the policy-unconstrained sample, rents include an average markup over marginal costs of $705 per month, with the mean and median markup being 30% of the rent in our preferred specification. These markups are over "shaddow" marginal costs including amortized purchase and maintenance costs and outside options.

In addition, our model assumes quantity can be set optimally for current-period demand, a condition unlikely to be met in our setting where fixed costs of construction and durable housing stocks make quantity adjustments lumpy. While we show that our model is isomorphic to one with separated developers and landowners with rational expectations, much of the housing stock in our sample was likely constructed (and quantity set) at a time when 21st century demand was unforeseeable. Accordingly, we isolate the subset of the policy-unconstrained sample which were constructed in the last decade of our data, and separately calculate markups for these. We find markups are similarly on average 31-32% of rent for these buildings. In an additional specification, we estimate elasticities and

[5]Using hedonic approaches with building-level data, Gyourko and Voith (2000) and Chen, Clapp, and Tirtiroglu (2011) find elasticities compatible with monopoly pricing, but only the latter notes the connection with monopolistic landowners.

[6]When we estimate the change in aggregate rental demand if *all* building rents increased by 1%, which is closer in spirit to previous estimates, we then find an inelastic result of -0.14.

[7]NYC has two forms or rent regulation, rent control and rent stabilization; we use the term rent stabilization for all rent regulation. Control is now rare as it applies only to buildings built before 1947 for tenants in place before 1971. Stabilization by far more common based on a building having 6+ units and built before 1974 and and may pass between different tenants; stabilized units' rent annual growth set by NYC Rent Guidelines Board.

[8]For zoning constraints, we ask whether a building could add one additional minimum sized residential unit based on floor-area-ratios and density limits.

[9]We calculate that 92% of Manhattan rental buildings with four or more units are either zoning constrained or rent stabilized.

markups using data from the Bronx, Brooklyn, and Queens in addition to Manhattan. We find average markups range by borough between 21-30% for new, policy-unconstrained buildings.

Finally, we use our results to assess the quantitative impact of up-zoning on markups, using the cross-price elasticities generated by our estimates in order to quantify the impact of a marginal relaxation of zoning constraints on rents at policy-unconstrained parcels. As noted by our model's predicted interaction between zoning and markups, the large markups we find may in part reflect the pecuniary spillovers of the (many) zoning-constrained lots on the policy-unconstrained sample. Indeed, we find the ubiquity of zoning constraints appears to have an appreciable impact on rents at policy-unconstrained lots. On average, a policy change resulting in the construction of roughly 417 additional units at zoning-constrained parcels reduces markups by between \$6.72 and \$7.41 per unit at policy-unconstrained buildings, which implies an additional 5-19 units through increased price competition. For context, the magnitude of this spillover on rents at the significantly smaller unconstrained sample is over 10% of what the magnitude of the (first-order) average rent effect on the up-zoned lots themselves would be.

2 Model

We first set up the optimization routines for each agent in our model: landowners endowed with locations and choosing rental rates, and renters endowed with income and choosing residences. We then define and solve the equilibrium in two cases: first, without vertical differentiation in location quality, and, second, without horizontal differentiation. We review how, in each case, the model delivers landowner pricing power.

2.1 Setup

Parcels and Landowners The space, a city, is comprised of a set $\mathcal{A} = \{a_0, a_1, a_2, \ldots, a_J\}$ discrete parcels, which differ according to their underlying quality a, drawn without replacement from a distribution $G_1(a)$. Higher values of a have higher amenity value to renters. We refer to a as "location quality" and differences in a as vertical differentiation in parcels. A location's realized quality a will also be used henceforth to index each location in the set $\mathcal{A}$. We make the simplifying assumption that a is exogenous, while noting that in the data building and parcel characteristics are a mix of endogenously chosen and exogenously given. Additionally, we set a_0 as living out of the city; i.e, an outside-option.

Each parcel has a unique landowner $f \in \mathsf{F}$ who maximizes profits by choosing the rent level at her location. Here, we also assume landowners each own a unique parcel, although we relax this later on.

Landowners provide a mass of renters housing at a positive, differentiable marginal cost $c_a(q)$, where q is the mass of renters the landowner accommodates in equilibrium. Total revenue is rent r collected times q. A given landowner f's profits from parcel a are $\pi_a = r \cdot q - c_a(q)$. Landowners determine the constructed quantity and rental price of units, and subtracting markups from rent backs out a "shadow" marginal costs combining both of these activities. Our estimation will not rely on observing these costs. Appendix B shows that equilibrium prices and quantities are unchanged when we separate the development and rental price problems and the markup is capitalized into the price of the building. In Section 6.3, we discuss how we navigate this assumption in our empirical setting, where landowners are constrained by policy and supply is set in advance.

Renters A mass M of heterogeneous renters, indexed by $i \in N$, draw income-types y from distribution $G_2(y)$. Renter utility is derived from consumption and location amenities. Renters also draw idiosyncratic tastes for each location, $\epsilon_{i,a}$, from a type-one extreme value distribution $G_3(\epsilon)$ with scale parameter σ_ϵ. Utility may vary independently by type as well:

$$U_i(a; y_i) = F(a, y_i - r(a), y_i) + \epsilon_{i,a}, \tag{1}$$

where consumption is equivalent to income minus rent. Renters choose among all locations a to maximize utility taking amenities, rents, and personal income as given.

2.2 Equilibrium

An equilibrium will be defined by a schedule of rents and quantities $\{(r_a, q_a)\}_{a \in \mathcal{A}}$ that maximize landowner profits, assign renters to locations a such that no renter can increase utility by choosing to pay rents at any other parcel, and clear the real estate market. Thus, for each type y, the original density of types y is accounted for across all their chosen locations a and the outside option, $g(y) = \sum_{\mathcal{A}} q_a(y) + q_0(y)$.[10]

We make additional assumptions on the renter's payoff function F and the distributions of types to briefly review each source of landowner monopoly in equilibrium.

[10]We do not consider combinations of $G_2(y)$, cost functions, and $G_1(a)$ which result in the full mass of renters choosing the outside option.

2.2.1 Equilibrium Under Horizontal Differentiation

For the horizontal differentiation case, we set the quality and income distributions as degenerate; i.e., $a_j = a$ and $y_i = y$. This construction delivers standard multinomial logit choice probabilities for market demand:

$$D_a = \frac{\mathrm{e}^{F(a,y-r(a),y)/\sigma_\epsilon}}{\sum\limits_{a'\in\mathcal{A}}\left\{\mathrm{e}^{F(a',y-r(a'),y)/\sigma_\epsilon}\right\}} \cdot M \tag{2}$$

We solve the symmetric pricing equilibrium assuming landowners compete in rents and noting that all amenities are equivalent, which yields an inverse elasticity markup rule:[11]

$$r^\star(a) = mc(D_a) - \frac{D_a}{\partial D_a/\partial r} \implies \frac{r^\star(a) - mc(D_a)}{r^\star(a)} = \frac{-1}{\varepsilon_a}, \tag{3}$$

where ε_a is the own-price elasticity.

The equilibrium rent at each building equals marginal cost plus a markup related to the curvature of demand, which is a function of the marginal utility of consumption, the scale of the idiosyncratic tastes, and substitution behavior of renters.[12] The solution implies strictly positive markups in rents.[13] To close the model, we apply a market clearing condition that the total number of renters housed in and out of the city equals the total number of renters.

2.2.2 Equilibrium Under Vertical Differentiation

For the vertical differentiation case, we assume that the renters' utility function displays increasing complements between renter income y and location quality a and that idiosyncratic draws, $\epsilon_{i,a}$, are all zero. We now suppress individual subscripts i as all differences are based on a and y. The model yields vertical oligopoly as in Shaked and Sutton (1983).

[11]Given the degenerate distribution of amenities, a symmetric solution to the landowner's problem can be reasoned verbally. Suppose all landowners with amenity value a set rent at some equilibrium $r^\star(a)$. Any individual deviation to a higher rent leads to less demand since amenities are equivalent, but any deviation to a lower rent would lead to greater demand.

[12]Caplin and Nalebuff (1991) and Perloff and Salop (1985) show that such an always equilibrium exists.

[13]An economic consequence of the markup is that some renters do not enter though they would if parcels were priced at marginal cost; i.e., $D_a(r^M) < D_a(mc(D_a))$. Thus, there exist renters with a willingness to pay for space greater than their impact on marginal cost, but are nevertheless priced out of the market. See Bajari and Benkard (2003) for more implications from the horizontal discrete choice model.

We assume utility is log-supermodular in renter and parcel type:

$$F(a, y - r, y) = F_1(a, y) \cdot F_2(y - r), \tag{4}$$

where function F_1 is log-supermodular in a and y, and F_2 is an increasing function of consumption (equivalent to income minus rent). Landowners set rents according to individual willingness to pay (WTP). Because $(\mathrm{d}F_1/\mathrm{d}a) > 0$, it's clear that all else equal, all types prefer higher a locations, and therefore that $(\mathrm{d}r_a/\mathrm{d}a) > 0$. Moreover, conditional on rents at other locations, different types y will have different WTP for a given parcel of type a. WTP of type y for location a is

$$WTP(y, a) = \min_{\forall b \in \mathcal{A} \setminus a} F_1(a, y) \cdot F_2(y - r_a) - F_1(b, y) \cdot F_2(y - r_b). \tag{5}$$

The equilibrium is given by a set of rents r_a and cutoffs $y_1, ..., y_{N-1}$. Between any cutoff y_{a-1} and y_a, the willingness to pay of individuals assigned to location a is heterogeneous and single-peaked in type y at some $y_{a,peak} \in [y_{a-1}, y_a]$. In other words, increasing complementarity acts within assignments of continuous types to the discrete number of parcels to create variation in WTP.

The landowner pricing rule chooses q, and effectively y_{a-1} and y_a such that

$$r_a - mc_a(q) = -\frac{G_2(y_a) - G_2(y_{a-1})}{g_2(y_a)\frac{dy_a}{dr_a} - g_2(y_{a-1})\frac{dy_{a-1}}{dr_a}}. \tag{6}$$

Note that $\frac{dy_a}{dr_a} < 0,\ \frac{dy_{a-1}}{dr_a} > 0$, and therefore markups are positive. As landowners adjust rent r_a upwards, they lose renters on two margins, the lowest-type assigned to their parcel, y_a, who flee to the cheaper next-best option $a - 1$, and those near the top of the distribution at their location that spend more for the option $a + 1$.

To close the model, the housing market must clear. Note that cutoffs are continuous, and for any y_1, if y_1 chooses a parcel in the city all $y > y_1$ do as well. If WTP is negative for the lowest type $\underline{y}$ at the lowest location $\underline{a}$, some mass of types will choose the outside option. A parcel is unoccupied if $y_a = y_{a-1}$.

3 Policy Implications: Theory

In this section, we assess the effects of several policies in the context of monopoly markups. First, we discuss the impact of zoning. We show that in the horizontal case, zoning raises rents of parcels that are *not* constrained by zoning, even when marginal costs are constant. Second, we discuss how, under non-decreasing marginal costs, concentration of land ownership raises markups and rents at all parcels. We conclude by discussing the scope for analysis of monopoly power in several other urban policies. Appendix A presents proofs of our propositions.

3.1 Old Policies, New Implications

An immediate implication of the above model is that, even in the absence of spillovers, a policy of no zoning is not first-best. Because a monopolist landowner restricts quantity, the quantity difference between zoning-restricted and an identical, unrestricted parcel with a monopolist landowner is less than the difference between zoning-restricted parcels and a competitively priced parcel. Height minimums could reduce rents.

What happens when zoning constraints are not binding everywhere? To the extent that zoning constrains bind at a particular parcel, the quantity must be restricted beyond the monopoly-optimal quantity, and rents as a result must be higher. However, in a city where only some parcels are constrained by zoning rules, those constraints also impact rents at unzoned parcels by affecting equilibrium monopoly power at unconstrained parcels. In both the vertical and horizontal case, the rent at a given parcel is inversely proportional to rents at other parcels. When we restrict ourselves to the horizontal case, we can state the following:

Proposition 1. *With logit demand and non-decreasing marginal cost, all else equal, the imposition of binding zoning constraints on a given parcel increases the rent at all other parcels, including unzoned parcels and parcels where zoning constraints do not bind. When marginal cost is constant, markups at those parcels go up as well.*

Appendix A presents a proof. By raising rents at competing locations, binding zoning constrains have spillover effects on rents at policy-unconstrained locations through monopoly pricing. Likewise, relaxing zoning constraints at one parcel brings down rents everywhere. Of course, even when units are priced competitively, if marginal costs are increasing, by limiting supply at one location, zoning can impact rents and quantities at other locations. But Proposition 1 points out that monopoly power exacerbates the price effects by changing optimal markups. In other words, even in a world of constant marginal costs, zoning constraints at one parcel would raise rents at all other parcels in the city by increasing monopoly markups. This effect operates through the cross-price elasticities, which, in the multinomial logit case can be signed and compared across any equilibria. In Section 8, we assess the empirical magnitude of this force by considering a marginal, across the board loosening of zoning constraints in Manhattan.

3.2 New Policies, New Implications

Under monopoly pricing, higher rents can generate a positive pecuniary externality on other landowners, and, by increasing demand and affecting elasticity, monopoly markups at one parcel may positively impact markups, rents, and profits at other locations. When landowners own multiple parcels, they internalize these pecuniary externalities, which may result in higher markups and rents overall. Intuitively, monopolists with greater market share may reduce quantity to a greater extent in order to maximize total profits.

In general, however, the impact of changes in land ownership concentration is analogous to mergers in the multi-product oligopoly setting. As in that setting, we cannot make statements on the effects of concentration on the equilibrium without additional assumptions. We extend Nocke and Schutz (2018b) to generate the following proposition:

Proposition 2. *With logit demand and non-decreasing marginal cost, all else equal, landowners with higher market share have higher markups and rents; an increase in the ownership share of one landowner will generate increases in markups and rents at all the landowner's parcels, and increases in rents at all other parcels.*

Because we cannot assume marginal cost is constant, we introduce an even more flexible cost function than those found in Nocke and Schutz (2018b,a). That, in turn, requires an extension to the result on the relationship between own share and others' share on markup and rent. Appendix A provides a proof.

Note that Proposition 2 is only guaranteed to hold when we can exclude the possibilities of scale economies and when there are no systematic variations in individual valuations by individual characteristics; i.e., no sorting. Intuitively, if landowners can raise profits by forcing more individuals into one parcel, generating scale, or if they can affect the sorting equilibrium through manipulations to the rents of multiple parcels, they may find it optimal to reduce, rather than increase rents and markups.

An important implication of this result is that manipulating the ownership structure of parcels affects rents through monopoly pricing. In particular, under specific conditions, reducing ownership concentration will reduce rents. In Section 5, we look for evidence of scope for such policies in our New York City dataset.

3.3 Additional Policies

We close our policy discussion by briefly and informally discussing the potential interactions of monopoly pricing with three other urban policies: rent regulation, inclusionary zoning, and use laws.

Where previously introduced into the housing literature, the concept of monopoly power among landowners has been used to advocate for rent regulation. The intuition is that reducing rents in the presence of monopoly markups can achieve the efficient equilibrium. By contrast, Diamond, McQuade, and Qian (2019), who do not explore monopoly markups, show that rent controls generate an extensive margin impact. While it is beyond the scope of this paper to discuss exit and entry, Appendix B shows how monopoly markups are capitalized into land rents and could impact such decisions.

In this context, inclusionary zoning policies, which mandate affordable housing be included in new developments, can be considered as a policy which moves monopoly quantities to efficient levels similarly to rent controls, but without reducing monopoly profit and therefore without affecting entry decisions.

Finally, we point out that zoning use laws may also operate on monopoly margins. While we only consider markups in a residential market, if demand elasticities vary between residential and commercial markets, use laws may reduce markups by constraining landowners to build in less profitable markets with more elastic demand.

4 Data

Sources Our main data are derived from public administrative building-level records, as well as scraped data, from several New York City departments, including the Departments of City Planning, Finance, and Housing Preservation & Development. Our primary dataset combines the Primary Land Use Tax Lot Output (PLUTO) and the Final Assessment Roll (FAR) for all buildings in NYC, as well as current and historic Multiple Dwellings Registration and Contacts (MDRC) datasets (with prior years graciously provided to us by the NYU Furman Center).[14] The PLUTO provides location, zoning, and building characteristics while the FAR provides market values, land values, and building ownership information.

We merge these with data derived from communications between the DOF and

[14]The MDRC links building owners to shareholders revealing common ownership across buildings.

landowners, scraped off the Property Tax Public Access web portal, which we call the Notice of Property Value (NPV) dataset. It includes information mailed to building owners including gross revenue and cost estimates and the number of rent stabilized units.[15]

We use the 2010 Decennial Census to allocate rental households to buildings to estimate building vacancies.[16] To determine the size of the rental market, we use the total number of NYC renter households that are in buildings with four or more units.[17]

Sample Our data spans from 2008 to 2015. We use all years when analyzing ownership concentration but focus on 2010 for demand estimation.

For demand estimation, we use all private buildings classified as multi-family rental buildings in Manhattan with four or more units, where all units are residential units and there is no missing data. When we construct the instruments based on rival building characteristics, detailed in Section 6.2, we expand the sample to include mixed-use, residential rental buildings. We exclude mixed-use buildings in the estimation because we cannot separate building income due to residential versus commercial tenant sources.[18]

For analyzing rents and ownership concentration, we use a subset of our estimation sample that excludes buildings that are zoning constrained or rent stabilized, which we call the unconstrained sample.[19] For the ownership concentration results, we additionally drop buildings where the listed building owner in the FAR data did not match the MDRC data and buildings with less than six units.[20] For more details, see Appendix C.

For computation and expositional purposes, our main analysis focuses on buildings in Manhattan. For additional power and robustness, we expand our sample to include buildings from Brooklyn, the Bronx, and Queens; we exclude Staten Island due to relatively small number of multi-unit rental buildings.

[15]The NPV dataset was originally web-scraped by a third-party from the DOF's Property Tax Public Access web portal. Full details about this process are available at `http://blog.johnkrauss.com/where-is-decontrol/`.

[16]To allocate rental households, we multiply building residential units by the block level rental occupancy rate. This method assumes that vacancy rates are uniform within Census blocks.

[17]The 2010 Census reports the number of renter households but not stratified by building units, so we scale the 2010 Census value by the ratio of renters in 4+ unit buildings to all renters from the 2010 ACS.

[18]In the context of our demand model discussed later, we do *not* push mixed-use buildings to the 'outside' good; instead, we simply do not include them in the estimation.

[19]Specifically, a building is zoning constrained if the building would not be allowed to create an additional unit based on building floor-area-ratios and minimum unit area requirements, and is rent stabilized if more than 10% of units are rent stabilized.

[20]We are able to match over 80% of all building owners across years. We drop buildings with $\{4, 5\}$ units due to NYC assessment methodology changes for these buildings.

Geographic Units We use Census tracts as a unit of observation for ownership concentration as well as for nests in one specification of our elasticity estimation. The large number of tracts provides us greater variation in the data. In addition, as discussed in Appendix D, ownership concentration is more easily calculated at the tract level, a feature which will help us in Section 5. An obvious downside to this choice is that markets are likely geographically continuous. Individuals at the borders of tracts are more likely to search at adjacent tracts than in other neighborhoods. The nested logit structure we adopt will not fully capture this, nor will our concentration measures, which will likely attenuate results. We also use an NYC specific geography, Neighborhood Tabulation Areas (NTAs), that is a sub-county collection of Census tracts.

Building Rental Income For 80% of our multi-year sample, we use scraped data from communications between the city and landowners about building income. For the rest of our sample, we rely on public data on assessments records from the DOF, which include methodologies for generating assessments from building income, that allows us to back out income from the assessment data.[21]

In NYC, rental buildings are assessed based on their income generation. The DOF collects annual revenue and cost information for all rental buildings and then applies a statistical formula to translate annual revenue into 'market value' (MV) of the building if it were sold, which is the basis of a building's tax assessment. Importantly, MV is determined by a simple Gross Income Multiplier (GIM) formula:

$$\frac{\text{Market Value}_j}{\text{SQFT}_j} = \text{GIM}_j \cdot \frac{\text{Annual Revenue}_j}{\text{SQFT}_j}, \tag{7}$$

where the GIM is determined by the DOF based on actual sales in a given income decile range and location.[22] The DOF reports MV and SQFT for all buildings in the FAR dataset, and so for 80% of the sample we observe both income and MV. We non-parametrically estimate the GIM term as a function of MV/SQFT, borough, and year based on DOF guidance documents.[23] We assess our procedure by using the estimated GIM and reported MV to calculate a fitted income value for the matched sample, and find a correlation of

[21]See – `nyc.gov/site/finance/taxes/property-assessments.page`.

[22]Effectively, if a building's MV/SQFT is in the q^{th} quantile, then its AR/SQFT is also in that quantile, and all buildings in a given quantile and location will have the same GIM.

[23]For each borogh-year, we estimate the empirical GIM within 50 quantile bins of MV/SQFT (which we observe for all buildings) and then apply this to the unmatched buildings.

0.99 and coefficient of determination of 0.98. For more details, see Appendix E.

Once we have building income for all buildings, we must subset the data to single-use residential buildings due to our inability to distinguish between residential and commercial income. We divide building income by the number of units for average annual unit rent in a building, and again by twelve for average monthly rent. A limitation of this approach is that we rely on building averages as we do not see individual unit income.

Other Variables We link buildings based on their "borough-block-lot" (BBL) identification that is uniquely assigned to real estate parcels, with additional verification based on lot characteristics.[24]

The building-level characteristics that we include are building age, log miles to the central business district (CBD, which we define as City Hall), log miles to nearest subway station, years since the last major building renovation, average unit square-feet, and whether the building has an elevator. We also measure the number of residential buildings, office buildings, retail buildings, and open parks in the Census block group. For location controls we include polynomials of building latitude and longitude coordinates and include location fixed effects.[25] We also use reported land value of parcels, which is constructed by the NYC DOF using a database of building and vacant parcel transactions.

An important limitation of our data is the inability to control for unit-level characteristics. We approach this issue as an omitted variables issue. In our analysis of concentration changes, building fixed effects will be an important control that, together with information on renovations, help us control for these unobservables. In our elasticity estimation, unobsevable unit characteristics will show up as building unobservables and will be an important motivation for our instrumental variable approach.

Summary Statistics Table 1 presents summary statistics for 2010 Manhattan rental buildings. Each column represents a cut of the data that we use. As explained above, the first is used for calculating our instruments, the second is used in our estimation, the third is the set of policy-unconstrained buildings—for which we can calculate markups, and the fourth is a subset of the policy-unconstrained buildings that are 10 years old or less in 2010. Figure 1 plots the total number of households and mean unit rents by Census tract. In Appendix C we plot additional spatial distributions, such as zoning constraints and

[24]Most parcels contain a single building, but large parcels can contain multiple buildings with open space between them. We refer to buildings and BBLs interchangeably throughout.

[25]We use Census tract FEs for the RCL and Neighborhood Tabulation Area FEs for the RCNL.

rent stabilization.

Table 1: Summary Stats:
2010 Manhattan Rental Buildings

	IV Sample	Estimation Sample	Unconstrained Sample	New, Unc. Sample
Total Market Share	26.5%	11.7%	0.7%	0.1%
Res.Units per Building	25.3	21.1	20.5	46.3
Households per Building	24.9	20.0	19.4	43.4
Vacancy Rate	5.4%	5.5%	5.7%	5.8%
Percent Mixed-Use	47%	0%	0%	0%
Percent Rent Stabilized	63%	60%	0%	0%
Percent Zoning Constrained	77%	80%	0%	0%
Median Monthly Rent*	–	$1,309	$2,071	$2,247
Median Rent by Median Income*	–	30%	48%	52%
Median Monthly Land Value per Unit	$2,989	$2,520	$5,314	$2,381
Years Since Construction	94	95	87	4
Years Since Renovation	48	48	35	4
log(Distance CBD)	1.34	1.58	1.45	1.32
log(Distance Subway)	-1.94	-1.89	-1.96	-1.72
Avg Unit Sqft	769	752	1,135.11	1,339
Buildings	17,828	9,484	566	53

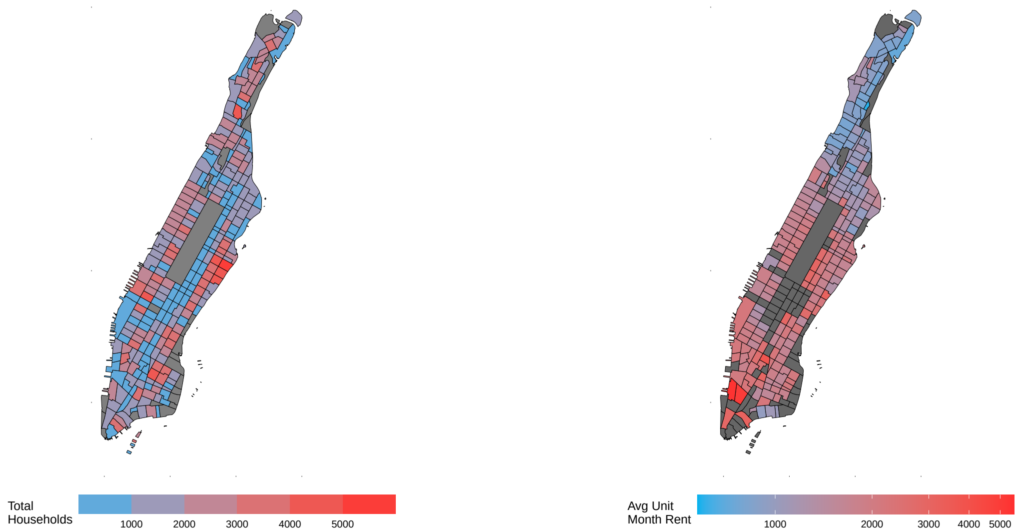
Note: The table reports summary statistics for our main samples using Manhattan buildings with four or more residential units. The first column, IV Sample, includes mixed-use buildings. The second column, Estimation Sample, includes buildings with only residential units. The third column, Unconstrained Sample, includes buildings with no rent-stabilized units and which are able to add an additional unit according to zoning regulations. The New, Unconstrained Sample (last column) is hte subset of the Unconstrained Sample which were constructed between 2001-2010. Building data from PLUTO, NPV, and FAR files. Market share is the sum of total households in all buildings by large building total renter population in NYC. Households are allocated to buildings based on building units and 2010 Decennial Census and American Community Survey. The vacancy rate is one minus the total households in building divided by total building units. A building is mixed-use if the building has positive commercial area. A building is considered rent stabilized if more than 10% of units are rent stabilized. A building is zoning constrained if the building would not be allowed to create an additional unit based on building floor-area-ratios and minimum unit area requirements. Monthly rental income is building income divided by total units divided by 12. Median income in 2010 for NYC is $ 50,711. Monthly land value per unit is [Land Value / (12 x Residential Units)]. Years since construction and renovation equal 2010 minus the construction year and most recent major renovation year. Geodesic distances are in log miles based on building (lat,lon) coordinates. Avg Unit Sqft is total building area divided by total units.
(*) – Rent data is only available for single use buildings

5 Concentration and Rents in New York City

We now examine the correlation in the data between ownership concentration and rents. We note that results in this section are not causally identified. Nonetheless, we find, reassuringly and in line with predictions of Proposition 2, that increases in concentration are correlated with increases in rents.

To examine whether the data are consistent with the predictions of Proposition 2, we first construct ownership shares at the Census tract level from 2008 to 2015. Section 4 summarizes the trade offs of tract-level analysis, as well as our construction of tract-level ownership data, in tandem with Appendix D. As noted in Section 4, we calculate concentration, which will be a Herfindahl-Hirschman Index (HHI), off of the full sample of buildings in each year but for rents, our outcome variable, we restrict our sample here to unconstrained buildings with matched ownership information. Note that our sample

Figure 1: Distribution of 2010 Manhattan Renters & Rents



Note: The figure displays the geographic distribution of households and rent in the Manhattan data. The map on the left plots total renter households by Census tract in 2010. The map on the right displays the mean monthly unit rent by Census tract in 2010. Missing values are Census tracts where we have insufficient data, in part due to the exclusion of mixed-use buildings. Red tracts indicate higher households and rents respectively, using a log scale. Data from PLUTO, FAR, NPV, and 2010 Census.

differs from our estimation sample in Table 1 because we pool eight years of data and only use buildings with six or more units in each year.[26] Summary statistics for this sample are available in Table A1 in Appendix C. We begin with our main geography, Manhattan, and then extend the sample to equivalent buildings in the whole of New York City to improve power.

Using our constructions of ownership, we calculate tract-level concentration. Let $\mathcal{A}_{f,g,t}$ be the set of buildings owned by landowner f in tract g in time period t, and let $\mathsf{F}_{g,t}$ be the set of landowners in that tract and time. We thus calculate landowner market shares as:

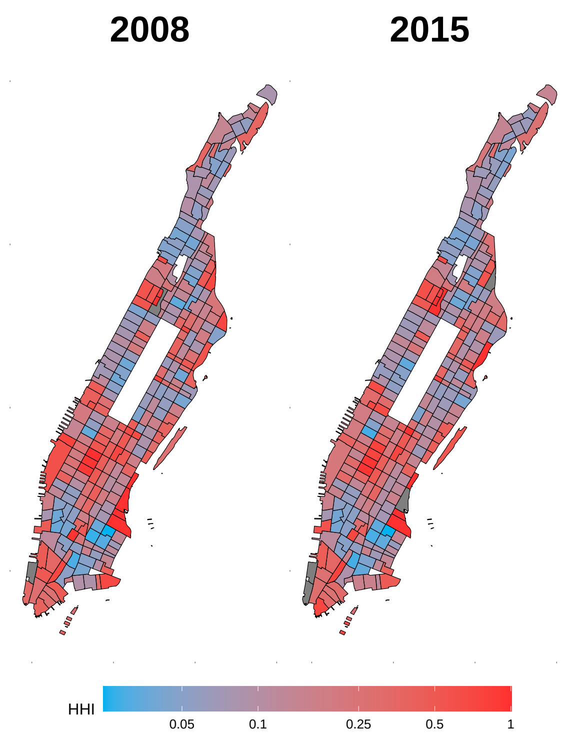
$$s^{f}_{g,t} := \frac{\left(\sum_{j\in\mathcal{A}_{f,g,t}} D_{j,t}\right)}{\sum_{f'\in\mathsf{F}_{g,t}}\left(\sum_{j\in\mathcal{A}_{f',g,t}} D_{j,t}\right)}. \tag{8}$$

Figure 2, plots tract-level HHI measures for Manhattan, where HHI is the sum of squared owners' shares, $\mathsf{HHI}_{g,t} := \sum_{f'\in\mathsf{F}_{g,t}}\left(s^{f'}_{g,t}\right)^2$.

To more closely match the predictions of Proposition 2, which links ownership con-

[26]In Section 7 our results use rental income for buildings with four or five units. These are obtained using DOF assessment procedures linking reported market values to rental income. We cannot use these here because of assessment procedures changes over the course of this panel for this group.

Figure 2: Distribution of Ownership Concentration in Manhattan



Note: The figure plots the tract-level ownership concentration index $\mathsf{HHI}_{g,t}$ in 2008 (left map) and 2015 (right map) on log scales. Reds indicate more concentration. FTC Horizontal Merger Guidelines consider values above 0.25 to be highly concentrated. Sample is all residential buildings with 4+ units in Manhattan. Data from PLUTO, MDRC.

centration elsewhere to rents, we construct a modified "leave-out" HHI index. For each landowner f, we recalculate the market share of a rival landowner, h, as:

$$\tilde{s}^h_{f,g,t} := \frac{\left(\sum_{j \in \mathcal{A}_{h,g,t}} D_j\right)}{\sum_{f' \in \mathsf{F}^{-f}_{g,t}} \left(\sum_{j \in \mathcal{A}_{f',g,t}} D_j\right)}, \tag{9}$$

where $\mathsf{F}^{-f}_{g,t}$ is the set of rivals to landowner f, and then calculate the leave-out HHI for landowner f as the sum of these rival landowners' squared shares: $\mathsf{HHI}_{f(j),g,t} := \sum_{h \in \mathsf{F}^{-f}_{g,t}} \left(\tilde{s}^h_{f,g,t}\right)^2$.[27]

We then test the basic prediction that rent increases in concentration. Our main specification estimates

$$\ln[r_{j,g,t}] = \alpha_0 + \alpha_1 \cdot \ln[\mathsf{HHI}_{f(j),g,t}] + \alpha_2 \cdot X_{j,g,t} + \epsilon_{j,g,t}, \tag{10}$$

where $r_{j,g,t}$ is the average unit rent of building j in tract g at time t, $\mathsf{HHI}_{f(j),g,t}$ is described above, and α_2 is a vector of coefficients on controls $X_{j,g,t}$. We also include $\ln[s^{f(j)}_{g,t}]$ in some specifications to separately test for the impact of owners' shares on rents at their own buildings. Note that while we use general subscripts $\{j, g, t\}$ for $X_{j,g,t}$, in specific specifications some controls will be time variant, e.g., when using building fixed effects.

Column (1) of Table 2 Panel (A) estimates the specification in Equation (9) for Manhattan buildings using year fixed effects, building age, square of building age, the log of distance to nearest subway and the log of distance to the CBD, average square feet of living space per unit, and years since last renovation. The inclusion of year fixed effects treats the data as a repeated cross section, and suffers from clear unobserved variable bias. We refrain from interpreting the small and insignificant resulting coefficient on $\mathsf{HHI}_{f,g,t}$.

In Column (2) of Panel (A), we add tract fixed effects. Here, identifying variation is changes over the course of the panel at the tract level, removing unobserved time-invariant tract-level variation. A 10% increase in tract concentration index is associated with a 1.6% increase in rents. The significant coefficient is consistent with Proposition 2: buildings in tracts where ownership elsewhere in the tract is concentrating experience larger increases in rents.

Column (3) of Panel (A), our most stringent specification, further imposes building fixed effects. Here, building time-consistent controls drop, though years since renovation

[27]In Appendix D, we probe robustness using the more standard construction of HHI and shares in Equation (8).

Table 2: The Relationship Between Ownership Concentration and Rent

	(1)	(2)	(3)	(4)	(5)	(6)
			$\ln[\text{Average r}_{j,g,t}]$			
			Panel (A): Manhattan			
$\ln[\text{HHI}_{f(j),g,t}]$	-0.012	0.161	0.075	0.009	0.162	0.075
	(0.032)	(0.080)	(0.076)	(0.038)	(0.076)	(0.076)
$\ln[s_{g,t}^{f(j)}]$				-0.028	0.002	-0.013
				(0.026)	(0.025)	(0.027)
Year FEs	Y	Y	Y	Y	Y	Y
Tract FEs	N	Y	N	N	Y	N
Building FEs	N	N	Y	N	N	Y
Observations	2,519	2,504	2,393	2,519	2,504	2,393
R^2	0.29	0.63	0.75	0.29	0.63	0.75
			Panel (B): Bronx, Brooklyn, Manhattan, Queens			
$\ln[\text{HHI}_{f(j),g,t}]$	0.047	0.122	0.102	0.043	0.128	0.095
	(0.016)	(0.056)	(0.037)	(0.018)	(0.053)	(0.037)
$\ln[s_{g,t}^{f(j)}]$				0.006	0.006	-0.027
				(0.013)	(0.012)	(0.014)
Borough-Year FEs	Y	N	N	Y	N	N
Tract and Year FEs	N	Y	N	N	Y	N
Building and Year FEs	N	N	Y	N	N	Y
Observations	13,651	13,576	12,743	13,651	13,576	12,743
R^2	0.40	0.64	0.77	0.40	0.64	0.77

Note: The table reports the results from regressions of log of building average unit monthly rent on the log of the 'leave-out' HHI index, calculated at the building level by leaving out the building owner's units. Regressions are at the building-year level and are weighted by building units. Columns (4)-(6) add log of building owner's market share as a control. The sample in Panel (A) are all matched, unconstrained buildings in Manhattan; Panel (B) expands the sample to all matched, unconstrained buildings in NYC. Columns (1) and (3) in Panel (A) use year / Panel (B) borough-year fixed effects, running a repeated cross-section. Columns (2) and (4) include tract and year fixed effects, running a panel at the tract level. Columns (3) and (6), our most stringent specifications, include building and year fixed effects, exploring variation in tract-level concentration while controlling for building-level, time-invariant differences. Building controls for all columns include building age, age squared, years since renovation, indicator if building has an elevator; for columns (1,2,4,5) log distance to CBD and log distance to closest subway (omitted in columns (3,6) due to building FEs. Standard errors in parentheses are clustered two ways by tract and year.

is an important control that remains. Because of the difficulty in observing key building characteristics, this specification ensures that of Column (2) is not identified off of unobserved differences in building quality. The coefficient is positive but insignificant – a motivation for our inclusion of more data in Panel (B) below.

Finally, Columns (4)-(6) introduce controls for building owners' own share of the tract as a control. According to Proposition 2, we expect owners with growing shares and thus market power to increase rents. An important condition in the Proposition is that costs be non-decreasing, which would be violated if there were scale economies in ownership. Across specifications, the coefficient is small but noisy and inconclusive.

Because our most stringent specifications appear to lack power in Columns (3) and (6), we expand our sample to include three more boroughs: the Bronx, Brooklyn, and Queens (with too few observations per tract in Staten Island, we do not include it in our sample). Here, coefficients are generally in the same direction, and in particular, the coefficients on tract HHI in Columns (3) and (6) are now positive, significant, and economically meaningful, with a 10% increase in concentration again associated with a roughly 1% increase in rents.

An important caveat in this analysis is the inability to observe changing tract conditions that are correlated with both rents and ownership concentration. Tracts with improving overall neighborhood qualities may experience rising rents and rising ownership concentration in tandem. We therefore caution against interpreting these coefficients causally, but instead take reassurance from the stylized fact that increases in concentration are correlated with increases in rents. We use this stylized fact as motivation for our identified estimation results.

6 Estimating Elasticities and Markups

To empirically assess the monopoly forces described above, we estimate the building-level demand elasticity for Manhattan rental buildings in 2010. We follow the literature empirically estimating differentiated product models with consumer heterogeneity based Berry, Levinsohn, and Pakes (1995) (BLP) and the citing literature.[28] Below, we describe our empirical model and identification strategy.

[28]In particular, we follow the methodological advice in Dubé, Fox, and Su (2012); Knittel and Metaxoglou (2014); Gandhi and Houde (2018); Conlon and Gortmaker (2020).

6.1 Renter Demand Econometric Model

As in our theoretical model, the urban rental market is made up of all individuals who will choose to live in a rental property.[29] In our main specification, we differentiate the choice set geographically, such that we consider all rental properties in Manhattan as 'inside' goods and all rental properties in the other boroughs as part of an 'outside' good.[30] We then probe robustness using NYC data from four boroughs as separate markets, where the outside goods are smaller buildings in the same borough.

We estimate two versions of our model. Closest to our exposition in Section 2, we estimate a random coefficients logit (RCL) model. Second, we estimate a random coefficient *nested* logit (RCNL) model where nests are Census tracts, which by necessity remove our most stringent location controls—tract-level fixed effects—due to collinearity with our definition of building nests. The RCL model is simpler to estimate and allows greater location controls; however, the RCNL model allows for within-nest preference correlation with nearby buildings at the expense of less robust location controls.

We assume that renter i's utility from choosing unit j is composed of a common vertical differentiation component, μ, and idiosyncratic horizontal components, $\{\psi, \epsilon\}$:

$$U_{ij} = \mu_j + \psi_{ij} + \epsilon_{ij} := \underbrace{\delta_j + X_j\beta}_{\mu_j} + \underbrace{\frac{\alpha}{y_i}r_j + \sum_{h\in H_2}\{\gamma_h v_{ih} x_{jh}\}}_{\psi_{ij}} + \epsilon_{ij}. \tag{11}$$

Equation (11) parameterizes utility as a function of renter income, y, observed covariates and rent, $\{X, r\}$, a scalar unobservable amenity, δ, and covariate-specific taste shifters, v_h. For ease of notation, we express the joint distribution of renter incomes and tastes, $\theta = (y, \{v_h\})$, conditional on observed variables,(X, r), as $F(\theta)$, which we will define empirically when we describe our estimation routine.

For our empirical specifications, building covariates in X include a constant, age, years since last renovation, log distance to CBD, log distance to nearest subway, avgerage unit square feet, and the location controls mentioned in Section 4, including Census tract FEs for the RCL and NTA FEs for the RCNL models.[31]

[29] Our market definition may be better stated as *large* rental properties as we only consider rental properties with four or more units.

[30] This is analogous of comparing utility from a Manhattan property to the average non-Manhattan property for each individual renter.

[31] For the H_2 subset of covariates with random coefficients, we use a constant, age, years since renovation, log distance to CBD, log distance to nearest subway, and avg. unit square feet.

We calculate a building's market demand, D_j, as the aggregation of individual renter demands, d_{ij}. Under the assumption that ϵ_{ij} is distributed Type 1 Extreme Value, the RCL model implies an individual renter's building demand is calculated as:

$$d_{ij} = \frac{\mathsf{e}^{(\mu_j + \psi_{ij})}}{\sum\limits_{k \in \mathcal{A}} \mathsf{e}^{(\mu_k + \psi_{ik})}}. \tag{12}$$

Similarly, under the assumption that $\epsilon_{ij} = \left(\tilde{\epsilon}_{i,h(j)} + (1-\rho)\tilde{\epsilon}_{ijh}\right)$, where $\tilde{\epsilon}_{ijh}$ is distributed Type 1 Extreme Value, the RCNL model implies:

$$d_{ij} = d_{ij|h(j)} \cdot d_{i,h(j)} = \frac{\mathsf{e}^{((\mu_j + \psi_{ij})/(1-\rho))}}{\sum\limits_{k \in h(j)} \mathsf{e}^{((\mu_k + \psi_{ik})/(1-\rho))}} \cdot \frac{\sum\limits_{k \in h(j)} \mathsf{e}^{(\mu_k + \psi_{ik})}}{\sum\limits_{h \in \mathcal{H}} \sum\limits_{k \in h} \mathsf{e}^{(\mu_k + \psi_{ik})}}, \tag{13}$$

where $d_{ij|h}$ is the within-nest building demand and $d_{i,h}$ is the nest demand. The random variable $\tilde{\epsilon}_{i,h}$ introduces taste variation across nests and ρ governs preference correlations within nests.[32]

6.2 Identification and Instruments

There are two endogenous variables for every observation: market share and rent.[33] Our estimation strategy allows us to identify demand parameters while being agnostic to the supply side of the market. While we observe some building amenities directly, rents are likely correlated with unobserved amenities, δ_j. Broadly, these unobervables may either be about buildings' amenities or area amenities not in our data. To identify α, we require an instrument $Z^{(r)}$ that shifts rent but is unrelated to these amenities. To identify the γ coefficients, we require instruments that shift the substitution patterns between products, $Z^{(x)}$. With instruments, $Z = (X, Z^{(x)}, Z^{(r)})$, the identifying moment condition is

$$\mathsf{E}[\delta(X, r, s; \theta) \mid Z] = 0, \tag{14}$$

which leads to our use of $\mathsf{E}[Z'\delta]$ as the empirical moment we wish to minimize.

[32] The parameter is defined over the interval $\rho \in [0, 1)$, where $\rho = 0$ collapses to the RCL model and $\rho = 1$ is inconsistent with utility maximization. The r.v. $\tilde{\epsilon}_{i,h}$ is integrated out, but could be included at the expense of increasing the number of non-linear parameters.

[33] We assume that the building-level characteristics are exogenous and can additionally serve as instruments. For a rigorous discussion of identification, see Berry and Haile (2014, 2016).

We construct $Z^{(x)}$ using functions of rival building characteristics. When creating the rival set $K(j)$, we exclude rivals within a 1km radius of a given building, based on Bayer, McMillan, and Rueben (2004) and Bayer, Ferreira, and McMillan (2007)[34] For the RCNL model, we also create 'local rivals' who are in the same tract (i.e., nest) but not in the same block group. We use "Quadratic Differentiation Instruments" based on Gandhi and Houde (2018). These are a finite order basis function approximation of the optimal instruments in the sense of Amemiya (1977) and Chamberlain (1987). For a given covariate h for building j with rivals $K(j)$, each instrument is defined as:

$$Z_{hj}^{\mathrm{DQ}} = \sum_{k \in \{K(j)\}} (x_{hk} - x_{hj})^2. \tag{15}$$

For $Z^{(r)}$, we use the land value of the building parcel; i.e., the market value of vacant land where the building is located, which captures the opportunity cost of the landowner for renting the space out. The exclusion restriction is violated if constructed land value from sales around the city are correlated with unobservable amenities at the building-level, conditional on building observables and location controls. While actual land value in general may be correlated with nearby building characteristics, our measure is constructed by NYC DOF using sales of similar parcels which are not necessarily close. Furthermore, we control directly for location observables (which include tract fixed effects in our RC Logit specification), and as such the residual measure should not be systematically correlated with local building-level unobservable residential amenities. Appendix G describes further details on instrument construction and other aspects of estimation.

Armstrong (2016) discusses the asymptotics of differentiated product estimation when there are few markets and many products and provides sufficient conditions such that markup converges to a constant. If markups converge to a constant 'faster' than the instrumental variables estimator, then the latter is inconsistent because there is not variation in markups to use.

We address with this issue in three ways. First, our RCNL specification follows Armstrong (2016) by splitting products into nests. Armstrong (2016) shows in this setting that nests effectively bound the number of rival products within in a nest, so neither within-nest shares, $D_{j|h(j)}$, nor markups converge to a constant even if the total number of products in the full market goes to infinity.[35] Second, we use a marginal cost shifter in

[34]The authors use rings of five and three miles, respectively for their instrument construction using homes in the San Francisco bay area.

[35]The median number of buildings per nest is 32, the average is 43, and the maximum is 195.

$Z^{(r)}$ that is valid even if the conditions of Armstrong (2016) hold, as that variation is not due to markups. Third, we perform statistical tests for under-identification of the "BLP instruments" on the model implied markups (Armstrong, 2014), and we also calculate a robust first stage F statistic from a linear regression of the endogenous rents on the instrument vector $(Z^{(x)}, Z^{(r)})$, advocated in Armstrong (2016).

6.3 Estimating Markups in the Presence of Supply-Side Restrictions

While our elasticity estimation is agnostic to the supply side of the market, to derive markups from estimated demand elasticities, we must account for how landowners set rents and quantities in our setting. In particular, our model assumed landowners are (policy-)unconstrained in their ability to set rents by adjusting supply. Two features of our setting are particularly problematic for this assumption: rent and quantity constraints (through rent stabilization and zoning), and constraints on quantity adjustments due to fixed redevelopment costs and the durability of the housing stock.

In particular, constraints on rent in the form of rent control and rent stabilization, and constraints on supply in the form of zoning restrictions mean that the observed pricing and quantity behavior of a constrained landowner will not be reflective of optimally chosen prices and quantities. In addition, the markups in our model do not account for lumpy redevelopment or the durability of the housing stock. Appendix B shows how our model can be extended to a model with separated developer and landowner quantity and price decisions, but clarifies that monopolist quantities, and thus the ability to derive markups from the price elasticity, are only achieved when developers correctly anticipate the demand faced by landowners. In reality, fixed costs may delay redevelopment and the durability of the housing stock means that current quantities may not reflect current demand.

We approach these limitations by subsetting our data twice. First, our main results derive markups only for policy-unconstrained parcels, which could raise rents and adjust quantities unencumbered by zoning constraints or rent regulation. Second, we separately examine the 53 policy-unconstrained buildings that were built in the last 10 years of our 2010 data, where developers will have been more likely to have correctly anticipated contemporary demand and set monopolist-optimal quantities, according to Appendix B.

With those restrictions in mind, we turn to our markup calculation.

6.4 Elasticities and Markup Calculations

Using estimated parameters, θ, we can calculate building-level elasticities and markups that will inform our understanding of monopoly power in the Manhattan market. We calculate the building-level demand elasticities using the analytical derivatives of the demand functions, and we calculate the percent markup assuming landowners solve a Bertrand price competition game:

$$\varepsilon_j = \frac{\partial D_j}{\partial r_j}\frac{r_j}{D_j} = \begin{cases} \left[\int_i \left(\frac{\alpha}{y_i}\right) d_{ij}(1-d_{ij})\mathrm{d}F(\theta)\right]\frac{r_j}{D_j} & \text{if RCL} \\ \left[\int_i \left(\frac{\alpha/y_i}{1-\rho}\right) d_{ij}\left(1-\rho d_{ij|h(j)}-(1-\rho)d_{ij}\right)\mathrm{d}F(\theta)\right]\frac{r_j}{D_j} & \text{if RCNL} \end{cases} \tag{16}$$

$$\mathsf{Lerner}_j = \frac{r_j - mc_j}{r_j} = \left(\frac{-1}{\varepsilon_j}\right) \tag{17}$$

Again, we use Bertrand pricing only for interpretation but not estimation.

Most housing demand literature estimates inelastic demand seemingly incompatible with monopoly pricing (Chen, Clapp, and Tirtiroglu, 2011; Albouy, Ehrlich, and Liu, 2016). We reconcile this by the fact that the relevant elasticity for landowners is the own-price elasticity, ε_j, rather than the "aggregate elasticity," the change in total housing consumed with a change in (aggregate) rents. To connect our setting to previous housing demand estimates, we calculate the aggregate elasticity which provides the responsiveness of renters to a 1% increase in rent for all 'inside' buildings (Berry and Jia, 2010; Conlon and Gortmaker, 2019):

$$\varepsilon^{\text{Agg}} = \sum_{k\in\mathcal{A}} \left.\frac{D_j(\{r_k+\Delta r_k\}_{k\in\mathcal{J}}) - D_j}{\Delta}\right|_{\Delta=1\%}. \tag{18}$$

Foreshadowing results, we will find both monopoly-consistent elasticities ε_j as well as literature-consistent inealistic aggregate elasticity ε^{Agg}.

6.5 Estimation Routine

Here we briefly describe our estimation algorithm. We are guided by methodological reviews (Nevo, 2000; Knittel and Metaxoglou, 2014; Conlon and Gortmaker, 2020) and point interested readers to Appendices F, G, and H for additional details.

We estimate the econometric model using market-level variables on building choice shares, rents, and characteristics, $\{D_j, r_j, X_j\}$. We simulate R renters by drawing $(y_i, \vec{v}_i)$ to calculate the individual demands, and then use pseudo Monte Carlo integration to calculate market demand.[36]

Estimation has four steps, which are iterated until parameters converge.[37] `First`, a non-linear inversion step finds mean product utility, μ, given an initial set of non-linear parameters, $\varphi = (\alpha, \gamma, \rho)$.[38] `Second`, we use linear GMM to estimate mean utility parameters, β, which identify the unobserved mean utility characteristic, δ. `Third`, we use a non-linear minimization routine to estimate the non-linear parameters using the moment condition $\mathsf{E}[Z' \cdot \delta]$. `Fourth`, we update the weight matrix using the residuals from Step 3, and repeat until the parameter vector converges, $\|\varphi^{s+1} - \varphi^{s}\| \approx 0$.

7 Estimation Results

In this section, we report our main results for Manhattan and as a robustness check a similar model using Manhattan, the Bronx, Brooklyn, and Queens as four separate markets.

7.1 Results using Manhattan

Table 3 presents our main empirical results for Manhattan. We estimate utility parameters based on our empirical model, then calculate building-level elasticities. For the unconstrained subset of our sample as well as the "new" subsample, we then calculate the markup share of rent. We present both the Logit and Nested Logit models, both estimated via IGMM and using "Quadratic Differentiation Instruments," as described in Section 6.2. Of our estimated parameters, we only present our estimates of $\{\alpha, \rho\}$ and their heteroskedasticy robust standard errors. Using Equation (16) we calculate the own-price elasticity, Equation (17) the markup share or "Lerner index," and Equation (18) the aggregate elasticity.

The first four rows of Table 3 report our estimates of model parameters α and ρ, with standard errors in parentheses. Our estimates of the rent coefficient, $\hat{\alpha}$, are similar in magnitude between the models with roughly equal standard errors. Our estimate $\hat{\rho}$ is close but statistically different from zero implying only slightly greater within-nest correlation relative to the RCL model. For the full sample, we estimate median own-price elasticities

[36]We use Halton sequences to approximate uniform random draws. Income is simulated by using a log normal distribution with mean and variance based on the ACS 2010 file.

[37]In finite samples the 2-Step parameters depend on the initial weight matrix and can be subject to greater misspecification errors, leading us to use an Iterated GMM approach (Hansen and Lee, 2019).

[38]For the inversion, we use a tolerance of $\|\mu_j^{r+1} - \mu_j^{r}\|_\infty < 10^{-12}$. See Appendix F for more details.

of -2.99 and -3.16 for Logit and Nested Logit specifications, respectively. We calculate but do not interpret the Lerner index for this sample. The model implied building-level own-price elasticities are all elastic, which is consistent with monopoly pricing.

For the unconstrained buildings, the first subset for which we will find meaningful markup results, we find elasticities of -3.40 and -3.30, respectively. We expect these unconstrained landowners have the most control over their rents compared to landowners with rent-stabilized units or pressed against zoning constraints. For the second subset, "new" unconstrained buildings built between 2000-2010, we find elasticities of -3.48 and -3.31.

We find that the median markup share of total rent, the Lerner index, is between 32-33% of total rent for the full sample, with a slightly greater mean (33-35%). For the unconstrained samples the median and mean markup shares are between 29% and 31%. Among the new constructions subset of unconstrained, means and medians range from 29-32%. Overall, were units priced at the marginal cost reflective of the production and maintenance of buildings, we would expect rents to be about 70% of their current levels. Figure 3 plots the full distribution of the own-price elasticities and Lerner Index by building for all three samples and both the RC and RCNL models. All three samples of the nested logit model, drawn in thinner lines, are less dispersed. Figure 4 plots the mean own-price elasticity and the dollar value of markups in monthly rent by Census tract for the full sample only.

Again, we note that our results differ from the literature on the elasticity of housing demand. Our elasticity of interest is conceptually different than that targeted by that literature, which seeks to measure the substitution between quantity of housing and consumption. In that literature, housing demand is typically found to be inelastic. When we estimate the aggregate elasticity in our data, which is more akin to the parameter estimated in the prior housing demand literature, we find similarly inelastic demand with an elasticity is between $(-0.14, -0.16)$. This estimate is slightly lower than the consensus range in the prior literature: $(-0.64, -0.3)$ (Albouy, Ehrlich, and Liu, 2016). This may be due to a differences in setting (Manhattan rental markets) or in methodology as our outside good includes other housing choices in NYC rather than pure consumption.

7.2 Results for Manhattan, the Bronx, Brooklyn, and Queens

In this subsection, we report results using all four NYC boroughs for which we have adequate data, using each as a separate market. Our estimation broadly follows that for

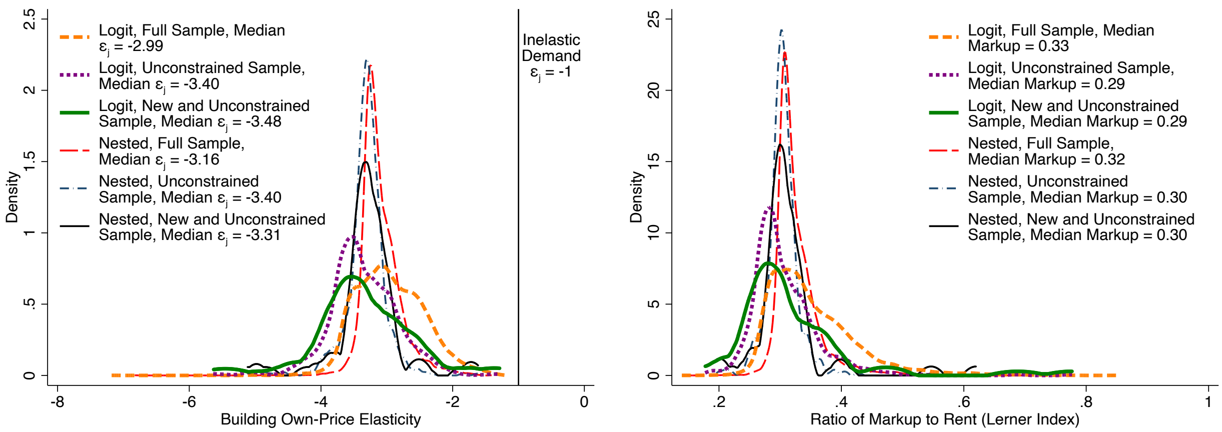
Table 3: Main Estimation Results: Manhattan

	RC Logit	RC Nested Logit
α	-43.79	-34.80
	(11.66)	(11.96)
ρ		0.065
		(0.037)
	Full Sample	
Mean ε_j	-2.95	-3.09
Median ε_j	-2.99	-3.16
Mean Lerner$_j$	35%	33%
Median Lerner$_j$	33%	32%
Percent $\varepsilon_j < -1$	100%	100%
ε^{Agg}	-0.16	-0.14
N	9,484	9,484
	Policy-Unconstrained Sample	
Mean ε_j	-3.36	-3.31
Median ε_j	-3.40	-3.30
Mean Lerner$_j$	31%	30%
Median Lerner$_j$	29%	30%
N	566	566
	New, Policy-Unconstrained Sample	
Mean ε_j	-3.35	-3.29
Median ε_j	-3.48	-3.31
Mean Lerner$_j$	32%	31%
Median Lerner$_j$	29%	30%
N	53	53
BLP F Stat	42.7	24.9
Linear F Stat	94.2	49.9
GMM Obj	10.3	36.3

Note: The table displays results from the Random Coefficient Logit (RCL) and Random Coefficient Nested Logit (RCNL) models using data on Manhattan multi-unit (four or more) residential buildings. Nests for RCNL are Census tracts. The coefficient α corresponds to the marginal utility of consumption and ρ governs within-nest preference correlations. Both models include random coefficients are on a constant, age, log distance to CBD, log distance to nearest subway, avg unit sqft. RCL uses Census tract fixed effects (FEs), and RCNL uses NYC NTA FEs plus additional location controls: measures residential buildings, commercial buildings, and parks in Census block-group and polynomials of latitude and longitude coordinates. Both models estimated using GMM and use "Quadratic Differentiation Instruments" based on Gandhi and Houde (2018), as described in Section 6.2. The own-price elasticity is ε_j, the Lerner index is $-1/\varepsilon_j$, and the aggregate price elasticity, ε^{Agg}, is based on Berry and Jia (2010). Buildings are 'unconstrained' if *not* rent stabilized and *not* zoning-constrained; new buildings were built after 2000. The Robust F statistics are from on regressions of building rent on building characteristics, location controls, and instruments. The BLP-F statistic tests identification of differentiation IVs for the RC model and is based on Armstrong (2014). Standard errors in parentheses are robust to heteroskedasticity.

Figure 3: Distribution of Results

(a) Own-Price Elasticity (b) Markup as a Percent of Rent



Note: The figure plots the kernel density plot of own-price elasticities (Panel (a)) and markups (Panel (b), Lerner Index), for main results using Manhattan buildings. Thin lines plot results from Random Coefficient Nested Logit model. Thicker lines plot results from Random Coefficient model. Orange dashed and red long-dashed lines plot elasticities and markups for the full sample. Purple short-dashed and navy dot-dashed lines plot results for the unconstrained sample. Green and black solid lines plot results for the new and unconstrained sample. Results based on Table 3. The full sample is comprised of all Manhattan single-use residential buildings with four or more units. The unconstrained sample is comprised of all buildings in the full sample that are not zoning constrained and where units are not rent stabilized. The new and unconstrained sample is the subset of the unconstrained sample for which buildings are 10 years old or less. The vertical line in Panel (a) indicates elasticities greater than -1, which would be incompatible with monopolistic pricing. RCL and RCNL models and estimation are described in the text.

Manhattan with some necessary changes. First, for computational reasons, we run 2-step rather than iterated GMM. Second, with four markets, we define the outside option as smaller 1-3 unit NYC buildings. As with Manhattan, we run both RC and RCNL models. Appendix I provides more details on this robustness check and reports summary statistics by borough.

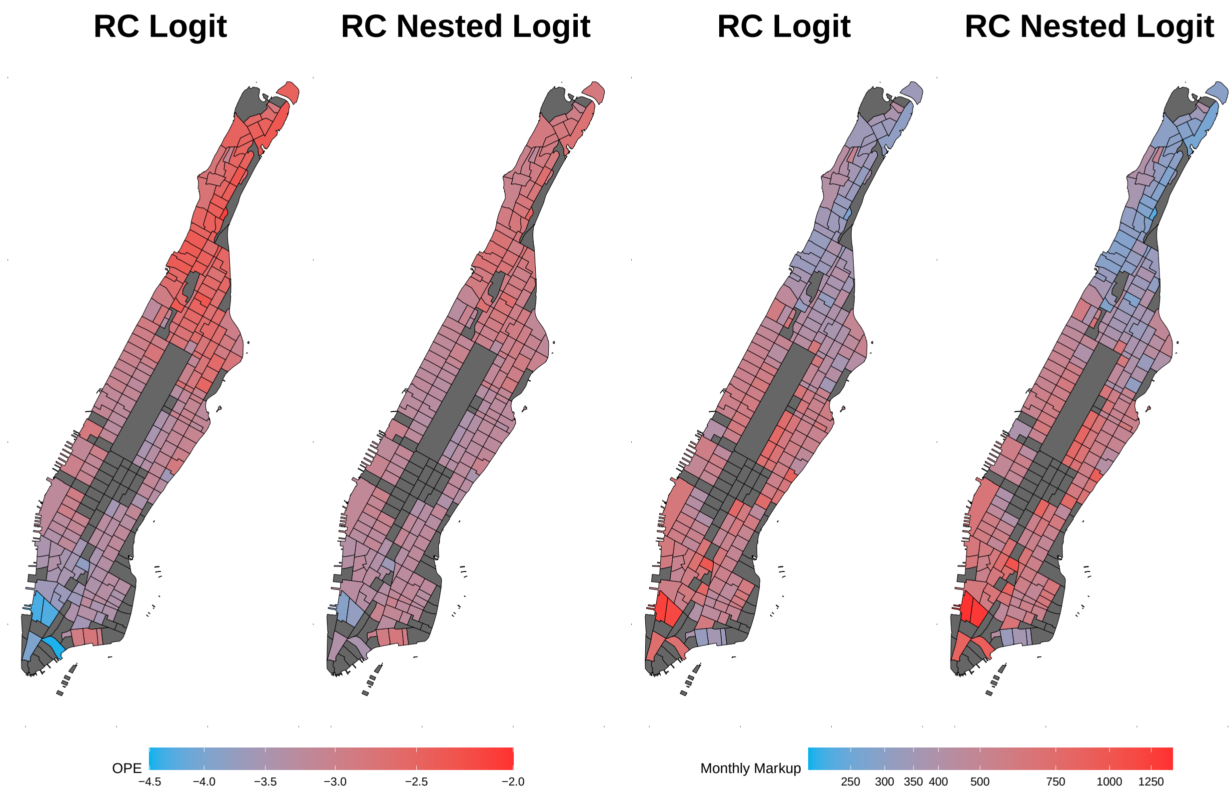
Table 4 reports the models' parameter estimates and Table 5 reports borough-level elasticities and markups. Again nearly all building elasticities are estimated as being consistent with monopoly pricing. Average elasticities and markups for Manhattan are in line with those reported in Section 7.1. Markups in other boroughs vary between 20-30%.

8 Up-Zoning's Spillover Effects Through Monopoly Power

In this section, we use our data and the results of our model to quantify the potential effects loosening zoning restriction. In our setting, additional competition from up-zoning puts downward pressure on the rents of policy-unconstrained buildings. By contrast, were policy-unconstrained buildings to be priced at marginal cost (e.g., if there was no markup

Figure 4: Results for Manhattan

(a) Own-Price Elasticity (b) Monthly Markup in Rent



Note: The figure plots Census tract level average own-price elasticities in Panel (a) and monthly markups (Lerner Index) in Panel (b) for the RCL model (left) and the RCNL model (right). Reds indicate higher own-price elasticities and markups on a log scale. Results based are based on the Full Sample estimation presented in Table 3, which use all 2010 Manhattan single-use residential buildings with four or more units. Missing values are Census tracts where we have insufficient data, in part due to the exclusion of mixed-use buildings. RCL and RCNL models and estimation are described in the text.

in rent), then we would not expect a loosening of zoning constraints in *other* buildings to affect rents of already unconstrained buildings, excepting changes in marginal cost.

To illustrate and quantify the rent effect of up-zoning constrained buildings on policy-unconstrained buildings, we use the model-estimated elasticities to examine the effect of a marginal change in zoning in the form of a 1% across-the-board reduction in zoning quantity constraints. The price effect that we estimate is the change in monopoly markups for the 566 unconstrained buildings given a marginal reduction in zoning constraints for the set of 3,226 zoning-constrained, non-rent regulated residential buildings.[39]

We consider a marginal change in constraints rather than a full counterfactual with

[39]We exclude rent stabilized buildings where estimated own-price elasticities may not reflect rents of additional units on the margin.

Table 4: Model Parameter Estimates for Four NYC Boroughs

	RC Logit	RC Nested Logit
α	-27.80	-23.74
	(13.97)	(4.23)
ρ		0.069
		(0.043)
BLP F Stat	88.0	32.4
Linear F Stat	111.6	121.9

Note: The table presents results for the Random Coefficient Logit (RC Logit, RCL) and Random Coefficient Nested Logit (RC Nested Logit, RCNL) estimations using Manhattan, the Bronx, Queens, and Brooklyn as four separate markets. The coefficient α corresponds to the marginal utility of consumption and ρ governs within-nest preference correlations. Both models include random coefficients are on a constant, age, log distance to CBD, log distance to nearest subway, average unit square feet, and building controls described in the text. The RCL model uses Census Tract fixed effects (FEs) and the RCNL uses NYC NTA FEs and additional location controls described in the text. Both models use "Quadratic Differentiation Instruments" based on Gandhi and Houde (2018), as described in Section 6.2. Both models are estimated using Two-Step Efficient GMM due to computation constraints. The Robust F statistics are from on regressions of building rent on building characteristics, location controls, and instruments. The BLP-F statistic tests identification of differentiation IVs for the RC model and is based on Armstrong (2014). Standard errors robust to heteroskedasticity are in parentheses.

changes in actual numbers of whole units for specific buildings. For example, a one-unit change for five-unit buildings is a 20% change in demand, and such non-marginal changes would require re-solving the monopolist problem. We also assume marginal cost is constant at unconstrained buildings. Increases in marginal costs would dampen the positive quantity and negative price effects we find. In light of these constraints on our exercise, we view this exercise as an illustration of the interactions between zoning constraints and monopoly rents rather than a policy evaluation.

We implement the exercise as follows. `First`, we use the estimated own-price elasticities to calculate the percent change in rents required to increase the market share of all zoning-constrained buildings by 1%, $\{\%\Delta r_k^{\mathsf{cf}}\}_{k\in\mathcal{Z}}$. `Second`, we totally differentiate the monopoly pricing rule with respect to all rents and solve for a given unconstrained building's rent change, $\{\%\Delta r_j^{\mathsf{cf}}\}_{j\in\mathcal{U}}$. `Third`, we manipulate the solution for an elasticity representation that yields:

$$\%\Delta r_j^{\mathsf{cf}} = \sum_{k\in\{\mathcal{Z}\}} \left\{ \frac{\vartheta_k^j \cdot \%\Delta r_k^{\mathsf{cf}}}{\left(\varepsilon_j - \vartheta_j^j\right)} \right\}, \tag{19}$$

where ε is the own-price elasticity and $\vartheta_k^j = \frac{\partial \varepsilon_j}{\partial r_k}\frac{r_k}{\varepsilon_j}$. See Appendix J for a complete derivation.

We also calculate the change in demand for unconstrained buildings from the price and quantity change at constrained buildings: $\%\Delta D_j^{\mathsf{cf}} = \varepsilon_j \%\Delta r_j^{\mathsf{cf}}$. This tells us the first

Table 5: Estimation Results: Four NYC Boroughs

	Manhattan		The Bronx		Brooklyn		Queens	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	RCL	RCNL	RCL	RCNL	RCL	RCNL	RCL	RCNL
	Full Sample							
Mean ε_j	-3.67	-3.41	-5.10	-4.67	-4.40	-4.08	-3.49	-3.28
Median ε_j	-3.76	-3.54	-5.17	-4.75	-4.50	-4.17	-3.54	-3.33
Mean Lerner_j	28%	30%	20%	21%	23%	25%	29%	31%
Median Lerner_j	27%	28%	19%	21%	22%	24%	29%	30%
Percent $\varepsilon_j < -1$	99.9%	99.9%	99.9%	99.9%	99.9%	99.9%	99.9%	99.9%
N	9,484	9,484	7,128	7,128	26,136	26,136	10,573	10,573
	Policy-Unconstrained Sample							
Mean ε_j	-3.75	-3.32	-4.94	-4.60	-4.27	-3.98	-3.51	-3.32
Median ε_j	-3.77	-3.36	-4.99	-4.67	-4.39	-4.07	-3.55	-3.36
Mean Lerner_j	27%	30%	20%	22%	24%	25%	29%	26%
Median Lerner_j	27%	30%	20%	21%	23%	25%	28%	25%
N	566	566	408	408	3,457	3,457	784	784
	New, Policy-Unconstrained Sample							
Mean ε_j	-3.54	-3.35	-4.80	-4.44	-4.01	-3.78	-3.54	-3.35
Median ε_j	-3.58	-3.38	-4.92	-4.59	-4.05	-3.78	-3.58	-3.38
Mean Lerner_j	28%	30%	21%	23%	26%	27%	28%	30%
Median Lerner_j	28%	30%	20%	22%	25%	26%	28%	30%
N	53	53	32	32	261	261	159	159

Note: The table presents results for the Random Coefficient Logit (RC Logit, RCL) and Random Coefficient Nested Logit (RC Nested Logit, RCNL) estimations using Manhattan, the Bronx, Queens, and Brooklyn as four separate markets. Both models include random coefficients are on a constant, age, log distance to CBD, log distance to nearest subway, avgerage unit square feet, and building controls described in the text. The RCL model uses Census Tract fixed effects (FEs) and the RCNL uses NYC NTA FEs and additional location controls described in the text. Both models use "Quadratic Differentiation Instruments" based on Gandhi and Houde (2018), as described in Section 6.2. Both models are estimated using Two-Step Efficient GMM due to computation constraints. ε_j is the own-price elasticity and the Lerner index is $-1/\varepsilon_j$. Sample definitions follow, by borough, those in Table 3; buildings are 'unconstrained' if *not* rent stabilized and *not* zoning-constrained; new buildings were built after 2000.

order effects of the increased competition for residences on the overall quantity of space provided. Note that we exclude cross-price elasticities between policy-unconstrained buildings, as well as higher-order effects on all constrained plots. To the extent that these are negative, our estimates are a lower bound on the result.

Table 6 presents our results. We find that the RC Logit and RC Nested Logit yield roughly similar results in aggregate. A 1% loosening of zoning constraints for rival buildings leads to a mean markup *decrease* of \$7.41 and \$6.72 per unit for the RCL and RCNL models, respectively, on unconstrained buildings. These are over 10% of the first-order price effects on the directly-impacted units. We find small mean elasticities of -0.017 and -0.012, respectively. Loosening the zoning constraints by 1% would yield a direct increase of about 417 households and the spillover effects from increased competition would add 19 and 5 *additional* households through lower rents for the the RCL and RCNL models, respectively—a 0.16% and 0.04% increase at the unconstrained plots.

Table 6: Spillover Effects from Up-Zoning Manhattan Buildings

	RCL	RCNL
Direct Price Effect of Looser Zoning: $\mathsf{E}\left[\mathsf{d}r_k^{\mathsf{cf}}\right]$	-\$59.64	-\$58.55
Spillover Markup Effect of Looser Zoning: $\mathsf{E}\left[\mathsf{d}r_j^{\mathsf{cf}}\vert_{\mathsf{d}mc_j=0}\right]$	-\$7.41	-\$6.72
Implied Spillover Zoning Elasticity: $\mathsf{E}\left[\frac{\mathsf{d}r_j^{\mathsf{cf}}}{r_j}/\frac{\mathsf{d}D_k^{\mathsf{cf}}}{D_k}\right]$	-0.017	-0.012
Net Increase in Households		
Direct and Spillover	436	421
Spillover Only	19	5

Note: The table reports the effects of up-zoning zoning constrained buildings that are not rent stabilized by a marginal amount; i.e., a 1% increase in allowable quantity, which corresponds to a total addition of 417 whole units. Results are presented separately for the Random Coefficient Logit (RCL) and Random Coefficient Nested Logit (RCNL) models described in the text. $\mathsf{E}\left[\mathsf{d}r_k^{\mathsf{cf}}\right]$ is the first-order average annual price effect on buildings k in the set $\mathcal{Z}$ of 3,226 directly impacted buildings. $\mathsf{E}\left[\mathsf{d}r_j^{\mathsf{cf}}\vert_{\mathsf{d}mc_j=0}\right]$ is the average effect on annual rents on the zoning unconstrained buildings j in the set $\mathcal{U}$ of 566 non-zoning constrained, non-rent regulated buildings, assuming constant marginal costs. This number does not include cross-price effects between buildings $j \in \mathcal{U}$ or other higher order effects. The implied spillover elasticity is the average percent change in annual rents at buildings $j \in \mathcal{U}$ given a 1% increase in maximum quantity allowed at buildings $k \in \mathcal{Z}$. For more details, see Appendix J.

Altogether, we interpret these results as additional rationales for easing residential zoning restrictions. Without monopoly power, only changes in marginal cost would affect rent. The price effect we calculate represents *additional* downward pressure on rents that arises purely through the monopoly forces in the model. In addition, these results imply that at least part of the large equilibrium markups on unconstrained parcels we find in our estimation may be a result of spillovers from (the numerous) zoning-constrained parcels.

9 Conclusion

While previous housing and urban literatures have considered the scope for monopoly power, we believe we are the first to quantify its importance in urban rental markets, finding that its scope appears economically significant and policy relevant. We find that a 10% increase in Census tract level ownership concentration correlates to roughly a 1% increase in building rents, and that in Manhattan markups account for 30% of rents.

Second, we explore the link between monopoly pricing and urban policies, specifically zoning constraints. We show the theoretical link between zoning constraints and monopoly markups and quantify the relationship in our estimation, finding modest but appreciable spillover effects.

Lastly, we caution that an important aspect of the residential real estate market beyond the scope of this paper is the decision of landowners to enter and exit the market. We have highlighted the existence of monopoly pricing power and the complex interaction between that and urban policies. However, monopoly profits from renting, and thus urban policies affecting those profits, impact entry and exit decisions. Policies which impact those markups will likely impact the size of the rental market.

References

Affeldt, Pauline, Lapo Filistrucchi, and Tobias J Klein. 2013. "Upward Pricing Pressure in Two-Sided Markets." *The Economic Journal* 123 (572):505–523.

Albouy, David and Gabriel Ehrlich. 2018. "Housing Productivity and the Social Cost of Land-Use Restrictions." *Journal of Urban Economics* 107:101–120.

Albouy, David, Gabriel Ehrlich, and Yingyi Liu. 2016. "Housing Demand, Cost-of-Living Inequality, and the Affordability Crisis." Tech. rep., National Bureau of Economic Research.

Amemiya, Takeshi. 1977. "The Maximum Likelihood and the Nonlinear Three-Stage Least Squares Estimator in the General Nonlinear Simultaneous Equation Model." *Econometrica* 45 (4):955–968.

Armstrong, Timothy B. 2014. "Large market asymptotics for differentiated product demand estimators with economic models of supply." *Manuscript* .

———. 2016. “Large Market Asymptotics for Differentiated Product Demand Estimators with Economic Models of Supply.” *Econometrica* 84 (5):1961–1980.

Arnott, Richard. 1989. “Housing Vacancies, Thin Markets, and Idiosyncratic Tastes.” *The Journal of Real Estate Finance and Economics* 2 (1):5–30.

Arnott, Richard and Masahiro Igarashi. 2000. “Rent Control, Mismatch Costs and Cearch Efficiency.” *Regional Science and Urban Economics* 30 (3):249–288.

Bajari, Patrick and C Lanier Benkard. 2003. “Discrete Choice Models as Structural Models of Demand: Some Economic Implications of Common Approaches.” *Unpublished Manuscript* .

Basu, Kaushik and Patrick M Emerson. 2003. “Efficiency Pricing, Tenancy Rent Control and Monopolistic Landlords.” *Economica* 70 (278):223–232.

Bayer, Patrick, Fernando Ferreira, and Robert McMillan. 2007. “A Unified Framework for Measuring Preferences for Schools and Neighborhoods.” *Journal of Political Economy* 115 (4):588–638.

Bayer, Patrick, Robert McMillan, and Kim Rueben. 2004. “An Equilibrium Model of Sorting in an Urban Housing Market.” Tech. rep., National Bureau of Economic Research.

Berry, Steven. 1994. “Estimating Discrete-Choice Models of Product Differentiation.” *The RAND Journal of Economics* 25 (2):242–262.

Berry, Steven and Philip Haile. 2016. “Identification in Differentiated Products Markets.” *Annual Review of Economics* 8:27–52.

Berry, Steven and Philip A Haile. 2014. “Identification in Differentiated Products Markets Using Market Level Data.” *Econometrica* 82 (5):1749–1797.

Berry, Steven and Panle Jia. 2010. “Tracing the Woes: An Empirical Analysis of the Airline Industry.” *American Economic Journal: Microeconomics* 2 (3):1–43.

Berry, Steven, James Levinsohn, and Ariel Pakes. 1995. “Automobile Prices in Market Equilibrium.” *Econometrica* 63 (4):841–890.

Brueckner, Jan K. 1987. “The Structure of Urban Equilibria: A Unified Treatment of the Muth-Mills Model.” *Handbook of Regional and Urban Economics* 2:821–845.

Brunner, Daniel, Florian Heiss, André Romahn, and Constantin Weiser. 2017. "Reliable Estimation of Random Coefficient Logit Demand Models." Tech. Rep. 267, DICE Discussion Paper.

Caplin, Andrew and Barry Nalebuff. 1991. "Aggregation and Imperfect Competition: On the Existence of Equilibrium." *Econometrica* 59 (1):25–59.

Chamberlain, Gary. 1987. "Asymptotic Efficiency in Estimation with Conditional Moment Restrictions." *Journal of Econometrics* 34 (3):305–334.

Chamberlin, Edward Hastings. 1933. *The Theory of Monopolistic Competition*. Cambridge; Harvard University Press.

Chen, Yong, John M Clapp, and Dogan Tirtiroglu. 2011. "Hedonic Estimation of Housing Demand Elasticity with a Markup Over Marginal Costs." *Journal of Housing Economics* 20 (4):233–248.

Conlon, Christopher and Jeff Gortmaker. 2019. "Best Practices for Differentiated Products Demand Estimation with pyblp." *Unpublished Manuscript* .

———. 2020. "Best Practices for Differentiated Products Demand Estimation with PyBLP." *The RAND Journal of Economics* 51 (4):1108–1161.

Diamond, Rebecca, Tim McQuade, and Franklin Qian. 2019. "The Effects of Rent Control Expansion on Tenants, Landlords, and Inequality: Evidence from San Francisco." *American Economic Review* 109 (9):3365–94.

Dubé, Jean-Pierre, Jeremy T Fox, and Che-Lin Su. 2012. "Improving the Numerical Performance of Static and Dynamic Aggregate Discrete Choice Random Coefficients Demand Estimation." *Econometrica* 80 (5):2231–2267.

Evans, Alan W. 1991. "On Monopoly Rent." *Land Economics* 67 (1):1–14.

Gandhi, Amit and Jean-François Houde. 2018. "Measuring Substitution Patterns in Differentiated Products Industries." *Unpublished Manuscript* .

Glaeser, Edward L. 2007. "The Economics Approach to Cities." Tech. rep., National Bureau of Economic Research.

Grigolon, Laura and Frank Verboven. 2014. "Nested Logit or Random Coefficients Logit? A Comparison of Alternative Discrete Choice Models of Product Differentiation." *Review of Economics and Statistics* 96 (5):916–935.

Gyourko, Joseph and Richard Voith. 2000. "The Price Elasticity of the Demand for Residential Land: Estimation and Implications of Tax Code-Related Subsidies on Urban Form." Tech. rep., Lincoln Institute of Land Policy.

Hansen, Bruce E and Seojeong Lee. 2019. "Inference for Iterated GMM Under Misspecification." *Unpublished Manuscript* .

Jaffe, Sonia and E Glen Weyl. 2013. "The First-Order Approach to Merger Analysis." *American Economic Journal: Microeconomics* 5 (4):188–218.

Knittel, Christopher R and Konstantinos Metaxoglou. 2014. "Estimation of Random-Coefficient Demand Models: Two Empiricists' Perspective." *Review of Economics and Statistics* 96 (1):34–59.

Kuminoff, Nicolai V, V Kerry Smith, and Christopher Timmins. 2013. "The New Economics of Equilibrium Sorting and Policy Evaluation Using Housing Markets." *Journal of Economic Literature* 51 (4):1007–62.

Nevo, Aviv. 2000. "A Practitioner's Guide to Estimation of Random-Coefficients Logit Models of Demand." *Journal of Economics & Management Strategy* 9 (4):513–548.

Nocke, Volker and Nicolas Schutz. 2018a. "An Aggregative Games Approach to Merger Analysis in Multiproduct-Firm Oligopoly." Tech. rep., National Bureau of Economic Research.

———. 2018b. "Multiproduct-Firm Oligopoly: An Aggregative Games Approach." *Econometrica* 86 (2):523–557.

Perloff, Jeffrey M and Steven C Salop. 1985. "Equilibrium with Product Differentiation." *Review of Economic Studies* 52 (1):107–120.

Ricardo, David. 1817. *On the Principles of Political Economy and Taxation*. London; John Murray.

Shaked, Avner and John Sutton. 1983. "Natural Oligopolies." *Econometrica: journal of the Econometric Society* :1469–1483.

Smith, Adam. 1776. *An Inquiry into the Nature and Causes of the Wealth of Nations*. London; William Strahan and Thomas Cadell.

Stone, Jon. 2019. "Berlin Set to Hold Referendum on Banning Big Landlords and Nationalising Private Rented hHusing." *The Independent* [News article].

Online Appendix of
Is the Rent Too High? Landownership and Monopoly Power

C. Luke Watson and Oren Ziv

A Propositions 1 and 2

Recall that $D_a = \frac{e^{F(a,y-r(a),y)/\sigma_\epsilon}}{\sum\limits_{a' \epsilon \mathcal{A}} \{e^{F(a',y-r(a'),y)/\sigma_\epsilon}\}} \cdot M$ from the main text using logit demand. Here, we switch to indexing buildings using j rather than a. To make notation easier, let $\alpha = \frac{\partial F(a,y-r,y)}{\partial r} < 0$ be the (negative) marginal utility of consumption, and set $\sigma_\epsilon = 1$.

A.1 Proposition 1

Binding zoning restrictions, by reducing quantities at a plot k, increase rents at that plot. The rest of Proposition 1 will follow as long as plots, as competing products, are strategic complements in pricing decisions.

Definition A.1. Strategic Complements: If the cross derivative of a given player's own payoff function with respect to her action and that a rival's action is positive, then the actions are strategic complements.

In our Bertrand oligopoly setting, rents are strategic complements if

$$\frac{\partial^2 \pi_j}{\partial r_j \partial r_k} = \frac{\partial\left[\partial D_j / \partial r_j\right]}{\partial r_k} \cdot (r_j - C_j(D_j)) + \frac{\partial D_j}{\partial r_j} \cdot \left(-\frac{\partial C_j}{\partial D_j}\frac{\partial D_j}{\partial r_k}\right) + \frac{\partial D_j}{\partial r_k} \geq 0. \tag{20}$$

Denote the derivative of marginal cost as $\frac{\partial C_j}{\partial D_j} := c_j$. When we apply Logit demand functions, this becomes:

$$\frac{\partial^2 \pi_j}{\partial r_j \partial r_k} = -\alpha^2 D_j D_k (1 - 2D_j)(r_j - C_j) - c_j \alpha D_j (1 - D_j) - \alpha D_j D_k \tag{21}$$

$$= \underbrace{-\alpha D_j D_k}_{>0} \left[\underbrace{\frac{D_j}{(1 - Dj)}}_{>0} + \underbrace{(-c_j \alpha D_j (1 - D_j))}_{>0 \text{ if } c_j > 0} \right]. \tag{22}$$

Note, we use the equilibrium relationship that $(r_j - C_j) = -r_j / \varepsilon_j$.

Thus, generally the strategic nature of pricing decisions is ambiguous. A sufficient condition for strategic complements in the logit case is that $c_j \geq 0 \forall j$. This is true with constant marginal costs or diseconomies of scale for the building. With decreasing marginal costs, the strategic complementary of pricing decisions is ambiguous and may vary between pairs of buildings.

If marginal cost is constant, then the rent increase could only be due to an increase in monopoly markups. With variable marginal cost, this the degree that the markup changes is ambiguous. Decreasing marginal costs would push the landowner to expand quantity supplied and travel further down the demand curve, which may lead to a smaller markup per unit but greater profit (and lower rent). On the other hand, increasing marginal costs attenuate the landowner's desire to expand keeping the landowner in a steeper part of the demand curve but with greater marginal costs eating into the markup.

If long as marginal cost is 'locally constant' in equilibrium (i.e., its change is 'small enough'), then we can say buildings are strategic complements in the logit case. Given strategic complements of price strategies, an increase in zoning constrained building k's rent will increase demand for unzoned building j, and increases the price at j accordingly.

If there is sorting; e.g., preference heterogeneity for building attributes, then the relationship is again theoretically ambiguous even with constant marginal cost. Within our Manhattan data, we explore this empirically in Section 8.

A.2 Proposition 2

A more detailed proof of Proposition 2 follows. First, we prove that when an landlord's parcel ownership concentration increases, the landlord increases the prices at all properties. We apply the framework of Nocke and Schutz (2018b) and Nocke and Schutz (2018a) to calculate the price effect by utilizing the ι-markup of the landlord. The authors use a nested-logit model, but we simplify the result removing the nesting structure.[40]

We wish to show that in the logit case with non-decreasing marginal cost, $\frac{\partial r_j}{\partial s_f} > 0, \ \forall \ j \in f$, which proves the proposition. Below, we show this in the two product for intuition and then in the general case with arbitrary number of products.

A.3 Oligopolist Pricing Equation

First, we show that landowner f chooses a common markup (Nocke and Schutz, 2018a,b). Let each landlord solves the following joint-profit equation:

$$\max_{\{r_j\}_{j \in f}} \sum_{j \in f} r_j D_j - C_j(D_j). \tag{23}$$

[40]These results also remove individual heterogeneity in renter preferences in order to take advantage of the IIA property.

Following the insight from Nocke and Schutz (2018b), the first order for each property satisfies:

$$\left(r_j - \frac{\partial C_j}{\partial D_j}\right) = \frac{-1}{\alpha} + \pi_f = \frac{-1}{\alpha(1 - s_f)}. \tag{24}$$

We can rearrange 24 to solve for rent:

$$r_j = \frac{\partial C_j}{\partial D_j} - \frac{1}{\alpha(1 - s_f)} > 0, \tag{25}$$

where marginal cost is positive to yield an upward sloping supply curve. Denote marginal cost as $\frac{\partial C_j}{\partial D_j} = c_j$. We will assume that its derivative is positive: $\tilde{c}_j := \frac{\partial c_\ell}{\partial D_\ell} \geq 0, \ \forall \ell \in J$.[41]

A.4 Two Product Case

Recall again that under logit demand:

$$\frac{\partial D_j}{\partial r_j} = \alpha D_j(1 - D_j) < 0 \tag{26}$$

$$\frac{\partial D_k}{\partial r_j} = -\alpha D_j D_k > 0 \tag{27}$$

Price Effects:

[41] A micro-foundation is that the residential space production function is concave in inputs which implies that the cost function in convex in quantity; hence, marginal cost is non-decreasing in quantity.

$$r_j = \frac{-1}{\alpha(1-s_f)} + c_j(D_j) \tag{28}$$

$$\implies \frac{\partial r_j}{\partial s_f} = \frac{-1}{\alpha(1-s_f)^2} + \frac{\partial c_j}{\partial D_j}\left(\frac{\partial D_j}{\partial r_j}\frac{\partial r_j}{\partial s_f} + \frac{\partial D_j}{\partial r_j}\frac{\partial r_k}{\partial s_f}\right) \tag{29}$$

by symmetry

$$\frac{\partial r_j}{\partial s_f} = \frac{\frac{-1}{\alpha(1-s_f)^2} + \frac{\partial c_j}{\partial D_j}\frac{\partial D_j}{\partial r_k}\left[\frac{\frac{-1}{\alpha(1-s_f)^2} + \frac{\partial c_k}{\partial D_k}\frac{\partial D_k}{\partial r_j}\frac{\partial r_j}{\partial s_f}}{\left(1-\frac{\partial c_k}{\partial D_k}\frac{\partial D_k}{\partial r_k}\right)}\right]}{\left(1-\frac{\partial c_j}{\partial D_j}\frac{\partial D_j}{\partial r_j}\right)} \tag{30}$$

$$= \frac{-1}{\alpha(1-s_f)^2}\left[\frac{1-\frac{\partial c_k}{\partial D_k}\frac{\partial D_k}{\partial r_k} + \frac{\partial c_j}{\partial D_j}\frac{\partial D_j}{\partial r_k}}{\left(1-\frac{\partial c_k}{\partial D_k}\frac{\partial D_k}{\partial r_k}\right)\left(1-\frac{\partial c_j}{\partial D_j}\frac{\partial D_j}{\partial r_j}\right) - \left(\frac{\partial c_j}{\partial D_j}\frac{\partial D_j}{\partial r_k}\right)\left(\frac{\partial c_k}{\partial D_k}\frac{\partial D_k}{\partial r_j}\right)}\right] \tag{31}$$

imposing Logit

$$= \frac{-1}{\alpha(1-s_f)^2}\left[\frac{1-\frac{\partial c_k}{\partial D_k}\frac{\partial D_k}{\partial r_k} + \frac{\partial c_j}{\partial D_j}\frac{\partial D_j}{\partial r_k}}{1-\frac{\partial c_k}{\partial D_k}\frac{\partial D_k}{\partial r_k} - \frac{\partial c_j}{\partial D_j}\frac{\partial D_j}{\partial r_j} - \frac{\partial c_j}{\partial D_j}\frac{\partial c_k}{\partial D_k}\frac{\partial D_k}{\partial r_j}\alpha(1-s_f)}\right] > 0 \tag{32}$$

A.5 General Product Case

Note that we have the following:

$$[r_i] = [\Gamma(s_f)\cdot 1_f] + [c_i(D_i)] \tag{33}$$

$$\mathsf{D}_{s_f} r = [\Gamma'(s_f)\cdot 1_f] + \mathsf{D}_D c \cdot \mathsf{D}_r D \cdot \mathsf{D}_{s_f} r \tag{34}$$

$$\implies \mathsf{D}_{s_f} r \cdot [\mathbb{I} - \mathsf{D}_D c \cdot \mathsf{D}_r D] = [\Gamma'(s_f)\cdot 1_f] \tag{35}$$

$$\implies \mathsf{D}_{s_f} r = [\mathbb{I} - \mathsf{D}_D c \cdot \mathsf{D}_r D]^{-1} \cdot [\Gamma'(s_f)\cdot 1_f] \tag{36}$$

A.5.1 Definitions and Lemmas

Definition A.2. Strictly (Row) Diagonally Dominant : for every row, i, the element along the diagonal, a_{ii}, is greater in magnitude than the sum of the magnitudes of each non-diagonal element in the row $a_{i,j},\ j \neq i$. That is, $|a_{i,i}| > \sum_{j\neq i} |a_{i,j}|$.

Definition A.3. `Z`-matrix : a matrix whose off-diagonal entries are less than or equal to zero.

Definition A.4. `M`-matrix : a `Z`-matrix where every real eigenvalue of A is positive.

Lemma 1. *If A is a* Z*-matrix that is strictly diagonally dominant, then A is an* M*-matrix by* Gershgorin Circle Theorem.

Lemma 2. *If A is an* M*-matrix with positive diagonals and negative off diagonals, then $B = A^{-1}$ is monotone positive; i.e., $b_{ij} > 0, \ \forall \ i, j$; proof in Fan 1958.*

A.5.2 General Case Proof

We need to show that the lemma holds and that the vector $B \cdot \Gamma'(s)$ is a monotone positive vector. Let $[\mathbb{I} - \mathsf{D}_D c \cdot \mathsf{D}_r D] = A$.
First, see that A is (a) a Z-matrix that is (b) Strictly (Row) Diagonally Dominant :

(a) for each row, using logit demand, we have

$$a_{i,i} = 1 - \tilde{c}_i \alpha D_i (1 - D_i) > 0 \tag{37}$$

$$a_{i,j} = \tilde{c}_i \alpha D_i D_j < 0 \tag{38}$$

(b) plug into definition of (row) diagonally dominant

$$\implies 1 + \tilde{c}_i |\alpha| D_i (1 - D_i) > \sum_{j \in f \setminus i} \tilde{c}_i |\alpha| D_i D_j = \tilde{c}_i |\alpha| D_i \sum_{j \in f \setminus i} D_j \tag{39}$$

$$\implies 1 + \tilde{c}_i |\alpha| D_i > \tilde{c}_i |\alpha| D_i \cdot s_f. \tag{40}$$

Thus A satisfies lemma 2, so B is a monotone positive matrix.
Second, $\Gamma'(s_f) = \frac{\mathsf{d}}{\mathsf{d}s_f} \frac{-1}{\alpha(1-s_f)} = \frac{-1}{\alpha(1-s_f)^2} > 0$.
Thus as $B \cdot \Gamma'(s_f)$ is a series of multiplication and addition of positive numbers, so $\mathsf{D}_{s_f} r$ must be a monotone positive vector.

B Separate Developer and Landlord Decisions

The standard assumption in the urban literature is that a competitive construction sector purchases land to produce urban space that is then put on the rental market (or sold to initial owners). We have modeled the choice environment as landowners producing the urban space they provide to the rental market. In this section, we show that under the assumption of competitive construction and the existence of owners of differentiated land that our model leads to the same allocation. This implies that the standard assumptions imply that urban space is constrained. We show this in the horizontal sorting case.

Consider a developer who as *already* purchased land from a land-owner and must now decide how much urban space to provide to the rental market. The construction firms are price takers in factors and space, but can make a quantity choice. We consider the dual builder's problem of maximizing location conditional profit or minimizing costs subject to a level of demand by choosing labor and capital:

$$\max_{k,h}\{r \cdot q_j(k,h) - ik - wh\} \iff \min_{k,h}\{ik + wh \text{ s.t. } q_j(k,h) = d_j(r)\}$$

Given that these are dual problems, they each yield the same solution. Let's consider the cost minimization problem's solution of a building cost $B_j(r, d_j(r))$. With free entry, $\pi_j = r \cdot d_j(r) - B_j(r, d_j(r)) \geq 0$. This provides the builder's solution if the builder buys the right to develop location $j \in J$. The builder will develop a plan for each $j \in J$ and seeks to purchase land from land-owners.

Now, we must consider how land-owners set the price of land, r_j. Clearly, $r_j = \pi_j$, else another developer would bid up the price. This creates an open bid auction for each location, so the land price must also be bid up to the highest potential location profit, which is the monopoly location profit. Suppose a builder decides to set rent at cost and provide enough space to clear the market, then this builder must bid $\pi^{ce} = 0$. Another builder decides to reduce space and increase rent to clear the market, and so bids $\pi^m > 0$. The land-owner will choose the second bidder.

Here, free entry into the construction sector creates the incentives to engage in monopolistic behavior in the rental market when there is downward sloping demand. If urban space was viewed as homogeneous by renters, then developers would not be able to adjust market rents and space and make profits since all renters would have the same willingness to pay.

C Detailed Construction of Samples

Here, we discuss the exact steps in sample construction. Recall, the samples we use in the paper are as following:

- 2008-2015 NYC: Ownership matched, unconstrained;
- 2010 Manhattan: IV, Estimation, Unconstrained, New Unconstrained.

C.1 2008-2015 NYC

We begin with all buildings in NYC, and then drop buildings based on:

1. missing location information, plots that are under construction, vacant, or are parks;

2. residential area is zero, there are zero residential units, or market values equal zero;
3. plots where the building is not classified as a private rental building (i.e., we drop owner occupied single family residences, condominium and cooperative buildings, 100% publicly owned buildings, any remaining commercially classified buildings, buildings designated as land-marks);
4. missing building characteristic information;
5. building has less than four units.

Next, we link this sample to the MDRC files that link reported building owners to shareholders using the BBL building identifiers. We then test if the reported building owner name matched the MDRC owner name (the owning entity, not shareholders) using a fuzzy string matching algorithm. This results in a match rate of roughly 80% for each year. We drop buildings that do not match.[42] Using this matched group, we then calculate HHI and leave-out HHI measures.

Finally, we arrive at our HHI Estimation sample by dropping buildings that

1. have over 10% of units rent stabilized;
2. are zoning constrained;
3. are mixed-use.

This yields the same that is in Table 2.

In Table A1 we present summary statistics for the HHI data.

C.2 2010 Manhattan

We begin with all buildings in Manhattan, and then drop buildings based on:

1. missing location information, plots that are under construction, vacant, or are parks;
2. residential area is zero, there are zero residential units, or market values equal zero;
3. plots where the building is not classified as a private rental building (i.e., we drop owner occupied single family residences, condominium and cooperative buildings, 100% publicly owned buildings, any remaining commercially classified buildings, buildings designated as land-marks);
4. missing building characteristic information;
5. building has less than four units.

To arrive at the estimation sample, we drop buildings where

[42] We believe matching failures happen primarily for two reasons. First, there does not seem to be oversight of the ownership registrations so misspellings are common. Second, the MDRC is a snap-shot that does not save information across years or transactions, so it is possible that a building owner changes and it is not recorded when we have access to the files.

Table A1: Summary Stats:
2008-2015 NYC Unconstrained Rental Buildings

	Bronx	Brooklyn	Manhattan	Queens
	Tract Level			
$\mathsf{HHI}_{g,t}$	0.24	0.21	0.22	0.33
	Building Level			
Owner Share in Tract	11%	5%	8%	3%
Leave-Out HHI in Tract	0.13	0.07	0.11	0.06
Median Monthly Rent	$1,046	$961	$1,813	$925
Median Rent by Median Income	25%	23%	43%	22%
Median Monthly Land Value per Unit	$205	$250	$2,270	$222
Res.Units per Building	33.5	15.5	25.9	11.4
Years Since Construction	81	83	88	72
Years Since Renovation	46	65	36	69
log(Distance CBD)	2.36	1.41	1.53	1.75
log(Distance Subway)	-1.53	-1.69	-1.95	-1.60
Avg Unit Sqft	1004	954	1,031	901
Buildings	1,792	7,621	2,531	1,773

Note: Building data from PLUTO, NPV, FAR, MDRC files. Census tract HHI defined using shares in equation 8. Owner share in tract is building level average. Leave-out building HHI defined using adjusted shares in equation 9. All dollar values nominal, 2008-2015. Median income in 2010 for NYC is $ 50,711, used for all years. Building data from PLUTO, NPV, and FAR files. Monthly rental income is building income divided by total units divided by 12. Median income in 2010 for NYC is $ 50,711. Monthly land value per unit is [Land Value / (12 x Residential Units)]. Years since construction and renovation equal 2010 minus the construction year and most recent major renovation year. Geodesic distances are in log miles based on building (lat,lon) coordinates. Avg Unit Sqft is total building area divided by total units.

1. there is positive commercial building area;
2. the census tracts has fewer than 3 remaining buildings;

This set of buildings constitutes the estimation sample on which we estimate the model. We drop buildings with commercial area – mixed use buildings – because we cannot be sure that we area measuring average residential rents as we cannot separate commercial and tenant income sources. As noted earlier, this is not the same as treating these buildings as outside goods for the model. Utility parameters are identified under the assumption that the parameters do not depend on whether the building has commercial space.[43]
We arrive at the 2010 Unconstrained Manhattan samples by dropping buildings that

1. have over 10% of units rent stabilized;
2. are zoning constrained;
3. are mixed-use.

Finally, the 2010 New Unconstrained Manhattan / NYC sample subsets this by dropping buildings built before 2000. Summary statistics for the 2010 Manhattan samples are in Table 1.

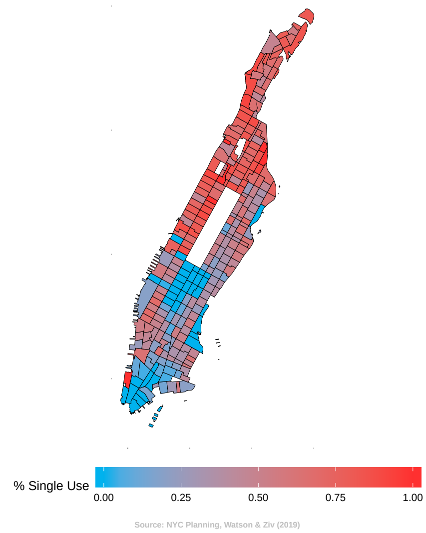
C.3 Spatial Distribution of Single Use, Zoning Constrained, & Rent Control

In Figures A.1 and A.2, we plot the spatial distribution of building use status, zoning constrained status, and rent control status. We define a building as being mixed use if we observe positive commercial space in the building; else, single use. Commercial space includes retail space, office space, or (for a minority of buildings) industrial space. For mixed use buildings, we cannot differentiate commercial versus residential sources of building income.

For figure A.2, a building is considered zoning constrained if the landlord could not legally add another unit at the minimum legally allowed area without affecting existing building units. Within our data we able to observe that whether a building's Floor Area Ration (FAR_j) is below its maximum allowable FAR (MaxFAR_j). A building can be below its MaxFAR but still zoning constrained if (MaxFAR_j) − FAR_j) is less than the minimum allowable unit FAR, meaning a landlord cannot legally add an additional unit. Thus, a building is zoning constrained if (1) (MaxFAR_j) − FAR_j) ≤ 0 or (2) (MaxFAR_j) − FAR_j) $\leq$ (Legal Min Unit FAR). We find that while 80% of rental buildings are zoning constrained

[43]Unreported monte carlo tests show that under the assumptions of the model, parameters remain unbiased. At worst, we believe the model is less efficiently estimated due to smaller samples.

Figure A.1: Distribution of Building Use in Manhattan



Note: Census tract percent of building that are mixed-use, defined as whether there is positive commercial building space. 2010 Manhattan residential buildings with 4+ units. Data from PLUTO, FAR for Manhattan 2010.

only 30% are constrained due to (1).[44] This potentially implies that developers incorporate zoning constraints, which if binding would limit revenues, by building larger units that may attract higher income renters.

Finally, in figure A.2, we plot the spatial distribution of rent controlled buildings. We define rent controlled status by whether a building is on the 2012 NYC Department of Homes and Community Building Registration File. A building is on this list if the building has at least one unit that is rent controlled or rent stabilized. Being rent controlled implies that a landlord is not in complete control of unit pricing, so to some extent the landlord is constrained.

D HHI and Ownership Matching

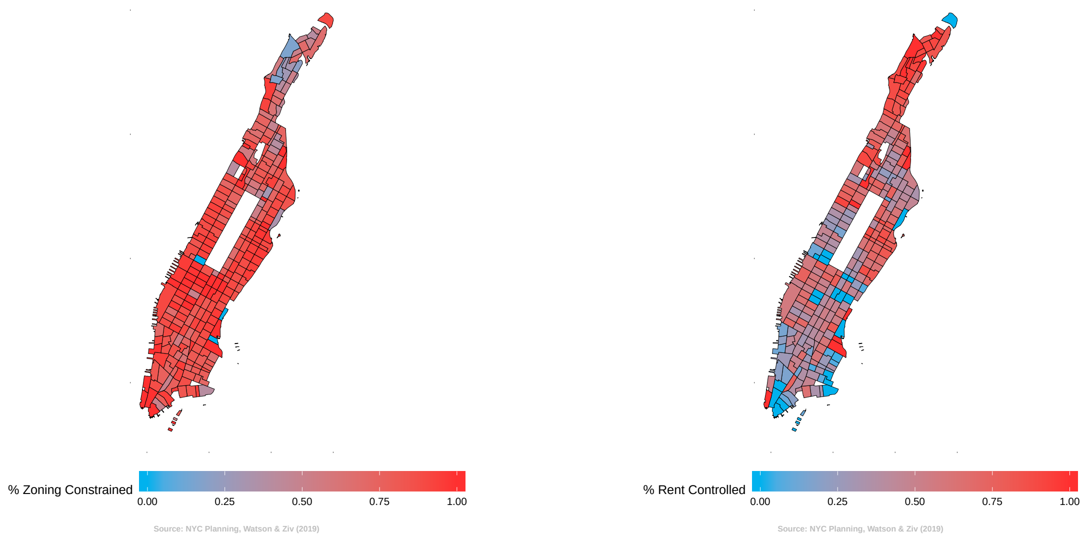
D.1 Ownership Matching

Here we describe how we match buildings to owner groups. This procedure is necessary because a large portion of reported rental building owners are a corporate entity that is

[44]For single-use buildings this is 81.7% and 34.2% and for mixed-use buildings this is 79.2% and 25.8%, respectively.

Figure A.2: Distribution of Zoning Constraints and Rent Stabilization in Manhattan

(a) Zoning Constraints (b) Rent Stabilization



Note: Panel (a) plots by Census tract the percent of buildings that are zoning constrained. Panel (b) plots, by Census tract, the percent of buildings that are rent stabilized. The data is 2010 Manhattan residential buildings with 4+ units. Zoning constrained is defined as building being legally not allowed to add one minimum size residential unit based on floor-area-ratios. A building is rent stabilized if more than 10% of building units are rent stabilized.

itself owned a holding company.[45] Thus the reported ownership structure underestimates the degree of common ownership. The NYC Department of Housing Preservation and Development (HPD) requires that building owners register each building with multiple dwellings (or inhabited by non-family members) and compiles this registration list to create the Multiple Dwelling Registry and Contacts (MDRC). Importantly, the MDRC assigns a unique ID to each building-owner pair and for each owner lists the names of the main shareholders of the corporate owner or partnership. Building owners must re-register annually so the list updates annually. Thus we have a list of buildings with their corporate owner names and shareholder names.[46]

However, we face two data challenges in matching buildings to owners using the MDRC. First, we only have MDRC lists for three years: 2012, 2015, and 2020. Second, the MDRC does not link buildings by common owners. We deal with each in turn.

To create a building owner panel, we append the three MDRC annual files together

[45]We speak loosely with the terms 'corporate entity' and 'holding company'; some building owners are literally a corporation while others are limited liability companies, sole proprietorship, partnerships, or cooperatives.

[46]We arrange the shareholder names based on frequency. For example, if name A is associated with 5 buildings and name B with 4 buildings, then for any set of buildings with both names $\{A, B\}$ we designate name A as the primary name.

and 'back-fill' the ownership from MDRC information for missing years. That is, if we observe a building-owner pair for year 2020, then we assume the owner is the same from 2020, 2019, 2018, and so on.[47] We then merge this with our DOF/PLUTO building year panel of rental buildings. Finally, we use a text matching procedure to ensure that the reported building corporate owner matches the MDRC corporate owner name.[48] Table A2 reports the match rate for the main four boroughs by year used in the rent sample.

Table A2: Match Rate Across Boroughs

	BK	BX	MN	QN
2008	0.79	0.82	0.81	0.80
2009	0.80	0.83	0.83	0.81
2010	0.83	0.86	0.86	0.84
2011	0.83	0.87	0.87	0.84
2012	0.84	0.89	0.87	0.85
2013	0.85	0.88	0.87	0.85
2014	0.84	0.89	0.87	0.84
2015	0.84	0.88	0.87	0.84

Note: 2008-2015 NYC residential buildings with 4+ units. Data from DOF, PLUTO, MDRC files. Match rate between reported owner from PLUTO & FAR and MDRC owner name.

To find all buildings that have common shareholders, we again perform a text matching procedure. We perform this procedure for each tract-year pair in the four main boroughs of NYC for three sets of shareholder names. The first is matching the primary shareholder, the second is matching the primary and secondary shareholders, and the third is matching across all shareholders. Using only the first shareholder name is the most conservative measure of common ownership and is the one with the least expected errors.[49] For any building that does not match to the MDRC, we use the reported ownername (usually a corporate entity) and require an exact string match within the tract-year.[50]

To get a sense of the scale of the issue. For Manhattan rental buildings, we find that the average number of distinct owner groups ('landlords') in a tract-year are 48.6 using the

[47]We find that the 2015 file matches better to years 2016 and 2017 than back-filling the 2020 file, so we extend the 2015 file two years as well as back fill 2014 and 2013.

[48]We use the Stata command `matchit` with a threshold of 0.5.

[49]We again use the Stata command `matchit` but increase the match threshold to 0.55 for primary name matching and to 0.6 for the multi-name matching. As the length of a string increases, the fuzzy text matching procedure is more likely to find false-positive matches.

[50]We use an exact matching because our fuzzy string matching procedure cannot tell the difference between corporate names of the form 555 Street LLC and 554 Street LLC.

reported ownership structure and 34.8 using the MDRC matched ownership structure. For the same set of buildings, we find that within a census tract the average landlord owns 3 buildings when we use the reported ownership structure and 4.3 buildings when we use the MDRC matched ownership structure Table A3 reports these values by year for Manhattan and the other three major boroughs.

Table A3: Difference Between Reported and MDRCC Common Ownership

	Manhattan				Brooklyn, Bronx, Queens			
	Distinct Owners		Avg Bld per Owner		Distinct Owners		Avg Bld per Owner	
	MDRC	Reported	MDRC	Reported	MDRC	Reported	MDRC	Reported
2008	34.2	46.9	4.3	3.0	20.9	24.4	2.5	2.1
2009	34.6	47.8	4.3	3.1	21.1	24.7	2.5	2.1
2010	34.8	48.1	4.2	3.1	21.3	25	2.5	2.1
2011	35.0	48.5	4.3	3.0	21.5	25.2	2.5	2.1
2012	35.3	49.2	4.3	3.0	21.6	25.4	2.5	2.1
2013	35.3	49.4	4.4	3.0	21.8	25.6	2.5	2.1
2014	34.7	49.4	4.3	3.0	21.6	25.7	2.5	2.1
2015	34.8	49.4	4.2	3	21.6	25.7	2.5	2.1

Note: 2008-2015 NYC residential buildings with 4+ units. Data from DOF, PLUTO, MDRC files. Comparison between reported owners in PLUTO & FAR versus MDRC files. Owners matched within tract-years.

D.2 Additional HHI Results

In this section, we probe robustness to our results in Section 5 using two alternative specifications. First, we replace the leave-one-out HHI variable $HHI_{f(j),g,t}$, which calculates for each building, the concentration index at the tract level excluding the building's landowner's own buildings, with the tract-level variable $HHI_{g,t}$, which more simply calculates the total tract-level concentration. Results are largely similar to our main specification, although the point estimates are slightly attenuated.

Second, we explore an alternative specification where price-per-square-foot rather than total rent is the building-level outcome variable. Accordingly, in this specification, total square feet is no longer a control. Results are broadly slimiar to our main specification.

Table A4: The Relationship Between Aggregate Ownership Concentration and Prices

	(1)	(2)	(3)	(4)	(5)	(6)
			ln[Average $r_{j,g,t}$]			
			Panel (A): Manhattan			
$\ln[\text{HHI}_{g,t}]$	-0.012	0.161	0.075	0.009	0.162	0.075
	(0.032)	(0.080)	(0.076)	(0.038)	(0.076)	(0.076)
$\ln[s_{g,t}^{f(j)}]$				-0.028	0.002	-0.013
				(0.026)	(0.025)	(0.027)
Year FEs	Y	Y	Y	Y	Y	Y
Tract FEs	N	Y	N	N	Y	N
Building FEs	N	N	Y	N	N	Y
Observations	2,519	2,504	2,393	2,519	2,504	2,393
R^2	0.29	0.63	0.75	0.29	0.63	0.75
			Panel (B): Bronx, Brooklyn, Manhattan, Queens			
$\ln[\text{HHI}_{g,t}]$	0.053	0.092	0.076	0.047	0.094	0.079
	(0.016)	(0.076)	(0.039)	(0.019)	(0.076)	(0.039)
$\ln[s_{g,t}^{f(j)}]$				0.007	-0.005	-0.038
				(0.014)	(0.013)	(0.014)
Borough-year FEs	Y	N	N	Y	N	N
Tract and year FEs	N	Y	N	N	Y	N
Building and year FEs	N	N	Y	N	N	Y
Observations	13,669	13,592	12,758	13,669	13,592	12,758
R^2	0.4	0.64	0.77	0.40	0.64	0.77

Note: The table replicates the results of Table 2 using tract-level HHI measures $HHI_{g,t}$, instead of the leave-one-out HHI, $HHI_{f(j),g,t}$. Otherwise, controls and specifications match Table 2. Standard errors clustered two ways by Census tract and year.

E Detailed Construction of Average Building Rent

Recovering building average unit rents is a key feature of this analysis that relies on three facts. First, by law, the DOF assesses rental buildings based on their income generation. For single-use, residential rental buildings, this corresponds to the rent paid to landlords. For mixed-use rental buildings, we cannot separate the source of income between commercial and residental tenants. This leads to our sample restriction of single-use buildings in our

Table A5: The Relationship Between Ownership Concentration and Price per Square Foot

	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln[$(Building $r_{j,g,t}$)/(Building Square Feet) $]$					
	Panel (A): Manhattan					
$\ln[\text{HHI}_{f(j),g,t}]$	-0.049	0.210	0.130	-0.012	0.206	0.158
	(0.038)	(0.097)	(0.094)	(0.050)	(0.094)	(0.098)
$\ln[s_{g,t}^{f(j)}]$				-0.046	-0.006	-0.015
				(0.033)	(0.025)	(0.037)
Year FEs	Y	Y	Y	Y	Y	Y
Tract FEs	N	Y	N	N	Y	N
Building FEs	N	N	Y	N	N	Y
Observations	2,517	2,502	2,392	2,517	2,502	2,392
R^2	0.27	0.65	0.74	0.28	0.65	0.75
	Panel (B): Bronx, Brooklyn, Manhattan, Queens					
$\ln[\text{HHI}_{f(j),g,t}]$	0.035	0.163	0.139	0.036	0.164	0.133
	(0.023)	(0.072)	(0.050)	(0.023)	(0.069)	(0.050)
$\ln[s_{g,t}^{f(j)}]$				-0.002	0.001	-0.035
				(0.017)	(0.014)	(0.018)
Borough-year FEs	Y	N	N	Y	N	N
Tract and year FEs	N	Y	N	N	Y	N
Building and year FEs	N	N	Y	N	N	Y
Observations	13,646	13,572	12,738	13,646	13,572	12,738
R^2	0.28	0.59	0.72	0.28	0.59	0.73

Note: The table replicates the results of Table 2 using rent per square foot as the dependent variable and omitting the total square foot variable as a control. Otherwise, controls and specifications match Table 2. Standard errors clustered two ways by Census tract and year.

estimations.

Second, we use the web-scraped NPV data. We believe the NPV data is high quality because it is based on communications with owners who have a financial stake in ensuring the information is correct. However, because we rely on a third party's efforts in web-scraping, we must deal with the fact that the third party did not collect information on all buildings. Primarily, the web-scraped data does not include any building with 4 or 5 units and is randomly missing others.

To remedy this, we rely on the third fact. The DOF uses building income data in its assessment process to derive "market value" which is then used for property taxes. Specifically, the DOF calculates market value using the following formula:

$$\text{MarketValue}_j = \text{GIM}_j \cdot \mathsf{Avg}\left(\text{Annual Rent}\right)_j \cdot \text{units}_j, \tag{41}$$

where the Gross Income Multiplier (GIM) is determined by the DOF based on the building's market value per square foot and its location.

Since we observe market value for all buildings in the FAR dataset, we can use the buildings that overlap the NPV data to backout the the function $\text{GIM}_j = \text{G}(\frac{MV_j}{SQFT_j}, \text{Units} \geq 10, \text{borough}, \text{year})$. We estimate the GIM function via the following:

1. For the matched set, divide market value by income to recover GIM_j;
2. Calculate market value by square feet (mvsqft);
3. By borough and year, calculate the 50-point quantiles of mvsqft;
4. By borough, year, and large building status (units ≥ 10), find the average GIM_j – $\mathsf{Avg}(\text{GIM} \mid \text{B,Y,U>10})$;
5. For the set of buildings that are not in the matched set, calculate $\frac{MV_j}{\mathsf{Avg}(\text{GIM}|\text{B,Y,U>10})} = \hat{Y}_j$.

We use the reported value Y_j for the matched buildings and $\hat{Y}_j$ for the unmatched buildings.

E.1 Additional Information

The income data is ultimately sourced from the Real Property Income and Expense (RPIE) statements that all income generating property owners are required to file annually and face financial penalties for not filing. Nevertheless, not all property owners will file this report. If an owner does not file, the DOF has the right to assign a market value based on its best judgement. In addition, the DOF documentation says that they will adjust report amounts that seem extreme; e.g., a building reporting high costs and no income in an area where other buildings are report incomes above costs. Without access to the RPIE statements, it is not possible to determine which properties have been adjusted.

The DOF Assessment Guidelines show how Income and Market Value relate to each other and how one can be directly inferred using the other. In the table below, we describe the DOF mapping that goes from observed income to market value: $G\colon Y \times SqFt \to M$.

Table A6: Example Mapping of Market Value to Income

y	GIM_{Low}	GIM_{High}	m	Y_j
$[y_1, y_2]$	$\frac{m_1}{y_1}$	$\frac{m_2}{y_2}$	$[m_1, m_2]$	$= MV_j \cdot \frac{y_2}{m_2}$
$[y_2, y_3]$	-	$\frac{m_3}{y_3}$	$[m_2, m_3]$	$= MV_j \cdot \frac{y_3}{m_3}$
$[y_3, y_4]$	-	$\frac{m_4}{y_4}$	$[m_3, m_4]$	$= MV_j \cdot \frac{y_4}{m_4}$

Note: This table provides a simplified example of the Gross Income Multiplier (GIM) method used by the NY DOF that we utilize to infer building income from observed building market value. For 80% of our multi-year sample, we observe both market value and income, which we use to estimate the GIM for the remaining properties, as described in the main text.

E.1.1 Robustness of Calculations

We can check the robustness of our calculations by using an auxilary dataset by the DOF, the Condo/Coop Comparable Rental Income data. By law, condominium buildings must be valued for tax purposes as-if they were rental buildings. To accomplish this, the DOF matches condominiums with rental properties and calculates and expected, market value and income of the condominiums. They publish these comparisons and include the rental building income and market value used in the comparisons. Thus, we are able to check our results for the matched buildings. Our values are nearly identical except for inconsistent rounding behavior on the part of the NYC DOF, typically in the owner's favor.[51]

F BLP Inversion Step

For intuition, if we omit the random coefficients, then the model becomes a standard logit specification using grouped data. Berry (1994) shows that the mean utility can be solved for in closed form as:

$$\ln[s_j] - \ln[s_0] = \delta_j + X_j\beta + \alpha r_j. \tag{42}$$

One can use a linear 2SLS specification to estimate $\{\alpha, \beta\}$.

With random coefficients, the above does not work. However, BLP show that the

[51]For Manhattan, we are able to check against 1,883 rental buildings, and we find 83 buildings where the absolute difference between our assigned GIM and the empirical ratio of market value to income is greater than 0.1; this represents an error rate around 4% of buildings. Again, these errors are due to inconsistent behavior by the NYC DOF.

following is a contraction mapping algorithm guaranteed to converge:

$$\mu_j^{r+1} = \mu_j^r + \left(\ln[s_j] - \ln[D_j(\mu_j^r;\theta)]\right) \ , \forall j. \tag{43}$$

When $\|\mu_j^{r+1} - \mu_j^r\|_\infty \approx 0$ the algorithm has converged.[52] For the nested logit case, Grigolon and Verboven (2014) show that the following modification is also a contraction mapping and necessary:

$$\mu_j^{r+1} = \mu_j^r + \left(\ln[s_j] - (1-\rho)\ln[D_j(\mu_j^r;\theta)]\right) \ , \forall j. \tag{44}$$

Once μ is recovered, then we can use the model's moment conditions to estimate $\{\beta, \alpha, \gamma\}$.

G Instrument Construction

We use "Quadratic Differentiation Instruments," based on Gandhi and Houde (2018), with a spatial radius, as in Bayer, McMillan, and Rueben (2004); Bayer, Ferreira, and McMillan (2007). For the Nested Logit specifications, we create within nest differentiation instruments that exclude rivals in the same Census block-group. These instruments are meant to be *an* approximation to the optimal instruments in the sense of Amemiya (1977) and Chamberlain (1987).[53]

The 'true' optimal instruments are based on the partial derivative of the structural error term:

$$Z^{\mathsf{opt}} = \mathsf{Var}(\delta_j)^{-1} \cdot \mathsf{E}\left[\frac{\partial \delta_j}{\partial \beta} \quad \frac{\partial \delta_j}{\partial \alpha} \quad \frac{\partial \delta_j}{\partial \sigma} \,\middle|\, Z \right]. \tag{45}$$

This has exactly as many moments as parameters, so is exactly identified and no iterative weighting matrix is necessary.

To calculate this object, one must take a stand on the conditional distribution of the structural error, solve the Bertrand pricing problem, back out model-implied structural errors, and then calculate the derivatives. In a major methodological advancement, Conlon and Gortmaker (2019) describe how, given an initial set of estimates, one can calculate this object relatively quickly for most problems. Their `pyblp` software automates most of these steps with various options; however, this is not possible in our problem. Because we do not accurately observe prices for mixed-use buildings, which is roughly half of the

[52] We use a tolerance of 10^{-12}, and we always start the algorithm with the linear specification mean value.

[53] Somewhat more formally they are a finite-order basis-function approximation to the optimal instruments.

choice set, we cannot credibly solve the Bertrand pricing problem.[54] Even conditional on obtaining the true parameter vector, our implied substitution between buildings will be biased up or down based on whether commercial rents are greater or less than residential rents in those buildings, which will bias the calculated 'optimal instrument.'

Nevertheless, Gandhi and Houde (2018) show that the optimal instruments can be approximated, in any dataset, by symmetric functions of the differences in building level covariates without needing to solve the Bertrand pricing problem. Their results formalize the intuition of the more traditional "BLP Instruments" that mark-ups are shifted by utilizing the 'product-space-distance' between products, where more isolated products as more immune to price shocks. However, there are still many choices of potential finite basis functions that can be used.

The authors suggest two 'flavors' for practitioners. First, they propose "Quadratic Differentiation Instruments" (DQ):

$$Z_{hj}^{\mathrm{DQ}} = \sum_{k \in \{K(j)\}} (x_{hk} - x_{hj})^2, \tag{46}$$

where $K(j)$ is a set of rivals for plot j. This is the set that we use in the main text.

Second, they propose "Local Differentiation Instruments":

$$Z_{hj}^{\mathrm{DL}} = \sum_{k \in \{K(j)\}} 1\left[\,|x_{hk} - x_{hj}| < \mathsf{sd}(X_h)\,\right], \tag{47}$$

where $\mathsf{sd}(X_h)$ is the empirical standard deviation of variable X_h. In unreported results, we find that these instruments have less strength relative to the DQ instruments; although, they do still find elastic results. These results are available upon request.

To deal with endogeneity of prices (or any covariate), the authors recommend using a predicted price using plausibly exogenous variation, such as the following additional example:

$$Z_{r,j}^{\mathrm{DQ}} = \sum_{k \in \{K(j)\}} \left(\mathsf{E}[r_k \mid X, W] - \mathsf{E}[r_j \mid X, W]\right)^2, \tag{48}$$

where $\mathsf{E}[r_k \mid X = x_k, W = w_k]$ is from a first stage regression on all exogenous information, (X, W), where W are any variables excluded from the utility function.[55]

[54]In addition, with rent control and zoning constraints, we would need to solve a constrained Bertrand pricing problem, which is not coded in `pyblp`.

[55]Note, Gandhi and Houde (2018) specify W as any already available instrument, which Conlon and Gortmaker (2019) interpret to include $\{Z_{hj}^{\mathrm{DQ}}\}_{h \in H}$ for the building $X's$. Currently, we do not use $\{Z_{hj}^{\mathrm{DQ}}\}_{h \in H}$

G.1 BLP-F Statistic

To assess the validity and *ability* of our instruments in identifying demand parameters, we report the 'first stage' statistics of our instruments, as advised in Armstrong (2016). We report a robust first stage F statistic of the linear regression of building rents on the model controls and instruments and the BLP-F statistic as devised in Armstrong (2014).

The robust F statistic has the virtue that it is robust to heteroskedasticity but cannot discern between the cases when excluded instruments are correlated with rents but "the researcher imposes a model that leads to product characteristics having an asymptotically negligible effect on markups (Armstrong, 2014)." The BLP-F statistic is based on the 'concentration parameter' and is designed to have power in cases when the usual F statistic would falsely reject a null hypothesis of no identification.[56]

The BLP-F statistic is a post-estimation procedure calculated in five steps. First, regress price on all model controls and instruments and then save the residual, $\dot{r}_j$. Second, calculate the sample variance of the residual. Third, regress the model-implied markup, $mu_j = -D_j/[\partial D_j/\partial r_j]$, and instruments on the included model controls, and save the residuals: $\{\dot{mu}_j, \dot{Z}_j\}$. Fourth, regress $\dot{mu}_j$ on $\dot{Z}_j$ and save the predicted values, $\hat{\dot{mu}}_j$. Finally, calculate the BLP-F statistic as the following, where k is the number of instruments:

$$\mathsf{F}^{\mathsf{BLP}} := \frac{\mathsf{Var}(\hat{\dot{mu}}_j)}{\mathsf{Var}(\dot{r}_j)} \cdot \frac{J-k}{k}. \tag{49}$$

Critical values of the BLP-F statistic do not exist. However, as this is based on an standard F statistic, one could rely on 'rules of thumb' in that a statistic should be greater than some number, such as 10 or 25.

H Additional Estimation Details

To aid our estimation, we follow most modern practices in estimating demand parameters. Many of these are based on advice found in Nevo (2000) (*N*), Knittel and Metaxoglou (2014) (*KM*), and Conlon and Gortmaker (2020) (*CG*).

`First`, we scale all $Z = (X, Z^{(x)}, Z^{(r)})$ variables by their empirical standard deviations to put their variances on the same order of magnitude. As in Brunner et al. (2017), we find

as part of W, so that X are building characteristics in the utility function and W is land value from the NYC DOF.

[56] If $y = X\beta + u$, then the concentration parameter is defined as $\mathsf{Var}(X\beta)/\mathsf{Var}(u)$.

this alleviates most model convergence issues.

`Second`, we use an 'overflow safe' method of calculating market shares which gives some protection when a solver inadvertently uses a parameter vector that is far from the true vector, as described in section 3.4 of *CG*.

`Third`, for the inversion step we always use the Berry (1994) logit inversion as the starting value, we use an accelerated fixed point algorithm, called `SQUAREM`, as described in section 3.2 of *CG*, and we use a fixed tolerance of $\|\mu^{s+1} - \mu^{s}\|_{\infty} < 10^{-12}$. *KM* show a loose or variable tolerance can cause catastrophic error propagation from the inversion step to the GMM estimates to the gradient, which can veer the optimization algorithm far off course.

`Fourth`, we use supply the analytical gradients of the GMM objective function using a gradient based solver, as described in *N* and benchmarked by *KM* and *CG*. This not only speeds up computation relative to gradient-free or approximated gradients but is also more reliable.

`Finally`, for technical and theoretical reasons we do *not* include a supply side for the model in estimation. Our main theoretical reasons are that we do not know enough about the marginal cost function for rental buildings nor do we wish to fully model the zoning and rent control constraints for a landlord. Brushing theoretical concerns aside, the analytical derivative of the supply moments effectively requires storing a $J \times J \times J$ three-dimensional matrix (where $J = 9,484$) in computer memory, which is not feasible using even for many super computers. We believe the primary empirical benefit of a supply moment would be to increase precision and ensure elastic demand. However, as the majority of our results do not suffer from either problem – see appendix I – we do not think the supply side is necessary for the model's estimation.

I Additional Estimation Results

Our 2010 Manhattan demand estimation is estimated on a single cross section of data. To probe the robustness of this, we expand the dataset to include the Bronx, Brooklyn, and Queens.

We reinterpret the model as now having four separate markets–the boroughs–within NYC. To do this we also now assume the outside good is composed of small building (1-3 units) rental market. Otherwise, we use the same conceptual sample of single-use, residential buildings to estimate demand. One computational change is that given the size of the new demand estimation problem, we only use a two-step GMM procedure rather than the iterated procedure in the main text.

Below we provide summary statistics for this sample as well as results. We find that the results are almost identical for Manhattan as in the main text. However, we find that the outer-boroughs have lower markup shares of rent.

Summary statistics for the 2010 NYC samples is in Table A7.

Table A7: Summary Stats:
2010 NYC Rental Buildings

	IV	Estimation	Unconstrained	New Unc.
Res.Units per Building	17.9	15.3	10.4	14.1
Households per Building	17.0	14.6	9.9	13.2
Vacancy Rate	5%	5%	5%	6%
Percent Mixed-Use	13%	0%	0%	0%
Percent Rent Stabilized	46%	45%	0%	0%
Percent Zoning Constrained	76%	79%	0%	0%
Median Monthly Rent*	–	$1,028	$1,328	$1,637
Median Rent by Median Income*	–	33%	43%	52%
Median Monthly Land Value per Unit	$4,783	$4,134	$7,659	$4,260
Years Since Construction	84	82	79	3.8
Years Since Renovation	65	67	62	3.8
log(Distance CBD)	1.63	1.71	1.53	1.58
log(Distance Subway)	-1.67	-1.63	-1.61	-1.59
Avg Unit Sqft	813	817	1,033	1,294
Buildings	73,145	53,321	5,215	505

Note: Building data from PLUTO, NPV, FAR, MDRC files. Households allocated based on building units and 2010 Decennial Census and American Community Survey. Median income in 2010 at borough level from 2010 ACS. Vacancy rate is one minus the total households in building divided by total building units. A building is mixed-use if the building has positive commercial area. A building is considered rent stabilized if more than 10% of units are rent stabilized. A building is zoning constrained if the building would not be allowed to create an additional unit based on building floor-area-ratios and minimum unit area requirements. A building is 'new' if it is was built in or after 2000. Geodesic distances are in log miles based on building (lat,lon) coordinates. Monthly land value per unit is [Land Value / (12 x Residential Units)].
(*) – Rent data is only available for single use buildings

J Total Derivative of Monopoly Pricing Rule

The monopoly pricing rule is

$$r_j^\star = mc_j - \frac{D(r_j^\star;\{r_k^\star\}_k)}{m(r_j^\star;\{r_k^\star\}_k))}. \tag{50}$$

Totally differentiating this function, we get

$$\mathsf{d}r_j = \mathsf{d}mc_j - \left[\frac{\frac{\partial D_j}{\partial r_j}\mathsf{d}r_j + \sum_{k\in\mathcal{Z}} \frac{\partial D_j}{\partial r_k}\mathsf{d}r_k}{\frac{\partial D_j}{\partial r_j}} - \frac{\frac{\partial^2 D_j}{\partial r_j^2}\mathsf{d}r_j + \sum_{k\in\mathcal{Z}} \frac{\partial^2 D_j}{\partial r_j \partial r_k}\mathsf{d}r_k}{\left(\frac{\partial D_j}{\partial r_j}\right)^2} D_j \right] \tag{51}$$

$$= \mathsf{d}mc_j - \left(1 - \frac{\frac{\partial^2 D_j}{\partial r_j^2} D_j}{\left(\frac{\partial D_j}{\partial r_j}\right)^2}\right)\mathsf{d}r_j - \sum_{k\in\{\mathcal{Z}\}} \left\{ \left(\frac{\frac{\partial D_j}{\partial r_k}}{\frac{\partial D_j}{\partial r_j}} - \frac{\frac{\partial^2 D_j}{\partial r_j \partial r_k} D_j}{\left(\frac{\partial D_j}{\partial r_j}\right)^2} \right) \mathsf{d}r_k \right\} \tag{52}$$

To arrive at equation 19, we set $\mathsf{d}mc_j = 0$, solve 52 for $\mathsf{d}r_j^{\mathsf{cf}}$, and then manipulate the equation to arrive at an elasticity form. A useful equivalence is the following: $\frac{\partial[\partial D_j/\partial r_j]}{\partial r_k}\frac{r_k}{\partial D_j/\partial r_j} = \frac{\partial \varepsilon_j}{\partial r_k}\frac{r_k}{\varepsilon_j} + \frac{\partial D_j}{\partial r_k}\frac{r_k}{D_j}$.

With preference heterogeneity – i.e., random coefficients – then the expression has no closed form solution, but is easily calculated with our estimated parameters and Monte Carlo integration. For intuition, if there were no individual agent heterogeneity in preferences, then

$$\mathsf{d}r_j = (1 - D_j)\mathsf{d}mc_j + \frac{D_j}{(1 - D_j)} \sum_{k\in\mathcal{Z}} \{D_k \mathsf{d}r_k\} \tag{53}$$

$$= (1 - D_j)\mathsf{d}mc_j + \frac{D_j}{(1 - D_j)} \mathsf{Avg}_D(\mathsf{d}r_k). \tag{54}$$

Without a full model of building costs, we cannot calculate $\mathsf{d}mc_j$, so we cannot calculate the true partial equilibrium change in unconstrained prices. Under the assumption of (locally) constant marginal costs, then our measure *equals* the partial equilibrium change in rental prices. Under the assumption of strictly increasing marginal costs, then $\mathsf{d}mc_j < 0$, so our measure would be the lower bound of the *magnitude* of the rent change. Without additional assumptions, our measure calculates the partial equilibrium change in the monopoly mark-up of unconstrained buildings due to a zoning-shock.