Housing Search and Rental Market Intermediation

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Abstract

Rental brokers as the matchmakers between tenants and landlords contribute 80% of the rental listings in certain markets, but how they smooth the search friction and transmit policy impacts is not well understood. This paper is the first to use a listing-agent matched data set from an online platform to show the heterogeneous impact of the listing capacity of a broker, *i.e.* the agent size, on the rental market outcomes. I document that brokers with greater listing capacity are related to lower rents and shorter listing duration. The dispersion cannot be fully explained by the amenity difference of rentals and points to a sizable agent impact that a broker with greater capacity lists a rental at a lower rent. I develop a search model that features a search-and-matching process in which the capacity constraints of brokers interact with the tenant coordination friction. The capacity constraints differentiate brokers' ability to coordinate tenant search. The smaller rent premium for listings by larger brokers reflects the capacity benefit that larger brokers coordinate tenant search better by reducing the likelihood of facing a binding capacity constraint. An endogenous agent distribution of the listing capacity, which summarizes how frictional the rental market is, arises in the model. I evaluate the counterfactual effects of two rental market policies. First, I show that expanding the brokerage sector will not benefit tenants in the search process. As the mean agent size decreases, the rental market becomes more frictional. Second, I evaluate the impact of shifting the commission liability from tenants to landlords, which is central to the New York rental market reform. As the equilibrium rent increase cannot fully compensate the commission cost on landlords, the policy decreases rental supply and makes searching tenants worse off. I characterize the optimal allocation of the broker's fee and show that brokers with greater listing capacity should list more rentals with the fee paid by landlords.

JEL: R00, R21, R31, L85

Key Words: brokers, rent dispersion, time on market, housing search, New York City

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1 Introduction

The defining feature of the rental market is the search friction. As the match makers between tenants and landlords, real estate brokers arise to solve the search-and-matching problem. While the number of renter-majority cities has doubled over the past decade (RentCafe, 2018), most studies about housing and brokerage focus on the sales markets (Han and Strange, 2015), with limited implication to the rental markets whose intermediation takes a different form. While a growing literature on the housing market micro-structure (Yavaş, 1994; Han and Strange, 2015; Edelstein and Green, 2018) has found a correlation between the housing market outcomes and various intermediation factors, few studies establish the link between these factors and individual brokers, or examine the general equilibrium effect of the brokerage sector.[1]

I document why brokers differ substantially in the listing outcomes and study how the brokerage sector smooths the search friction and transmits policy impacts in the rental housing market. This paper is the first to use a listing-agent matched data set to show the heterogeneous impact of the listing capacity of a broker, *i.e.* the agent size, on the rental market outcomes. Empirically, I show that brokers with greater listing capacity are associated with lower rents and shorter listing duration. Consistent with the micro evidence, I develop a search model to highlight the role of a broker's listing capacity in tenant search. Compared to the canonical search frameworks (Rogerson *et al.*, 2005; Han and Strange, 2015; Wright *et al.*, 2019), the model is augmented with a heterogeneous brokerage sector in which brokers vary by the listing capacity and thus their ability to reduce the search friction. In general equilibrium, the brokerage sector not only pass through but amplify the policy impacts.

Using a unique proprietary data set from an online platform, I study the listing behavior of rental brokers and document new empirical facts about real estate brokerage in Manhattan. Manhattan is the most expensive and the largest renter-occupied market in the US (NYCHVS, 2017; Statista, 2019; Zumper, 2020). The market is highly intermediated, with brokers contributing 80% of the rental listings. The key empirical finding is that brokers differ substantially in the listing outcomes and the listing capacity, with the rents and the listing duration negatively correlated with the agent size. The median rent (listing days) on the right tail of the agent distribution are 19% (56%) lower than that on the left tail. The dispersion across brokers cannot be fully explained by the rental quality difference due to the housing amenities and points to a sizable agent impact that a broker with greater capacity has a smaller rent premium, all else equal. After filtering out the impact of amenities, the residual rent dispersion across brokers is as large as 8.4% of the mean rent, while the residual dispersion of listing duration is 53% of the mean listing time.

What contributes to the agent impact on the rental listing outcomes? I examine a series of factors that may explain the correlation between the residual variables and the agent size. I find evidence that the listing incentive of brokers contributes to the agent impact, by comparing the listings from brokers and from property managers. Brokers are independent contractors whose earnings are based on the commission, while property managers are in salaried positions working for management companies. The difference in the earnings structure makes brokers more incentivized to rent high and match fast. I find the agent impact is much weaker among property managers, suggesting that the listing incentive provided by the commission system is a key factor. I rule out the explanations that large brokers use a deeper rent discount in the listing

[1] The intermediation factors that may affect the housing market outcomes (listing price, listing duration, etc.) include (and is not limited to) the ownership of a property (Rutherford *et al.*, 2005; Levitt and Syverson, 2008), the use of a broker (Hendel *et al.*, 2009), brokerage representation (Miceli, 1991; Han and Hong, 2016), the exclusivity (Rutherford *et al.*, 2004; Bar-Isaac and Gavazza, 2015) and duration of contracts (Anglin and Arnott, 1991), the nature of compensation structure (Munneke and Yavas, 2001), and possible incentive alignment issues (Williams, 1998; Shi and Tapia, 2016). Most studies examine the listing-level variation but do not consider the heterogeneous impact of the listing brokers.

process, or that large brokers have the inventory concern to unload listings faster by setting a lower rent on purpose. I come to similar empirical findings in the agent-level and firm-level analysis, suggesting that the size effect is a robust feature of the brokerage sector.

To understand how the brokerage sector affects policy transmission, I develop a structural model that features a search-and-matching process in which the capacity constraints of heterogeneous brokers interact with the tenant coordination friction. Given the rents posted by brokers, a tenant directs her search to maximize the search value (Peters, 1991; Moen, 1997) but cannot coordinate with others in the search process (Burdett *et al.*, 2001). While a broker's listing supply is constrained by a pre-determined capacity level (*i.e.* agent size), a broker expects a random number of prospective tenants, leading to the possibility of rationing the listing supply in case of excess demand (Peters, 1984). The tenant coordination friction and the capacity impact are two contributing factors to a decreasing rent function in the agent size. The lower rent premium for listings from large brokers reflects the capacity benefit that larger brokers can coordinate tenant search better by decreasing the likelihood of facing a binding capacity constraint, all else equal. In general equilibrium, not all tenants will go for large brokers, because tenant congestion reduces the tenant matching probability with a listing. The equilibrium trades off the capacity benefit and the congestion cost.

The search-and-matching process is embedded in an equilibrium model in which I characterize how landlords supply rental housing and how brokers price rental listings. The model generates the rental quality dispersion due to the landlord selection of brokers to list rentals and attributes the quality-adjusted rent dispersion to the listing pricing choice of brokers who differ in the trade-off between the rent return and the listing duration. I calibrate the search activities by week and discipline the model using the empirical variation of the listing outcomes across brokers. The main quantitative targets of interest include three variables conditioning on the agent size (rental quality, quality-adjusted rent, listing duration). The model generates an endogenous agent distribution of the listing capacity. The agent distribution summarizes how frictional the rental market is, with a smaller mean agent size or tighter listing capacity in aggregate suggesting greater search friction in the rental market.

I use the calibrated model to evaluate the general equilibrium impacts of two rental market policies. First, I examine whether introducing more brokers to the rental market benefits tenants in the search process. Motivated by a decrease in the cost of entry into the brokerage sector, I estimate the impact of an exogenous increase in the number of brokers on the listing outcomes. Earning the commission as a fixed share of the rent in the most expensive rental market may encourage too much entry into the brokerage sector. I point out why modeling broker heterogeneity is crucial to the brokerage sector reform. As expanding the brokerage sector decreases the mean agent size and weakens the coordinating capacity of the brokerage sector, tenants are worse off in the search process, contrary to what a search model without broker heterogeneity predicts. In addition, I find a differential impact of expanding the brokerage sector on the listing outcomes, with small brokers more impacted than large brokers.

Second, I evaluate the impact of shifting the commission liability from tenants to landlords. Listings with the broker's fee paid by tenants (*i.e.* with-fee listing) are prohibited by the Housing Stability and Tenant Protection Act (HSTPA) of 2019, which remains controversial and was legally challenged by the real estate groups.[2] I evaluate the short- and long-run impact of ruling out the with-fee listings on the rental market outcomes. I keep the number of brokers constant in the short run, while in the long-run, I keep the expected agent profit constant to allow for free entry. Shifting the commission liability worth of 10% of annual rent

[2] HSTPA was a major rent reform over the decades in New York and was signed by Governor Andrew Cuomo on June 14, 2019 (`https://www.nysenate.gov/legislation/bills/2019/s6458`). For debates on HSPTA between the tenant and the real estate groups, see (Haag and Ferré-Sadurní, 2020; Wezerek, 2020; Spivack and Ricciulli, 2020; Hu, 2020; Parker, 2020).

to landlords increases the rent by 3.6% (4%) in the short (long) run. The rent increase is not enough to compensate the commission burden, leading to fewer rental supplies by landlords. While tenants save the cost upfront, higher rent and fewer listing supplies will make searching tenants worse off, with the short-term loss worth of 6.6 weeks of the mean market rent before the policy change. In the long run, higher rent induces more brokers to enter the sector and decreases the mean agent size. The short-term impact is amplified due to weaker coordinating capacity of the brokerage sector. The dollar loss of searching tenants in the long run will be as much as 11.5 weeks of the mean market rent before the policy change. I characterize the optimal allocation of the broker's fee and suggest that the optimal fee allocation should vary by the listing capacity. Larger brokers should list more rentals as no-fee than observed in the data.

Related Literature. The paper contributes to a large literature on housing search, with notable examples of Yinger (1981), Wheaton (1990), Krainer (2001), Carrillo (2012), Diaz and Jerez (2013), Piazzesi *et al.* (2015), Albrecht *et al.* (2016), Anenberg (2016). The key contribution is to introduce the capacity constraint of brokers in the search process. In addition, I build on a growing literature, surveyed by Yavaş (1994), Han and Strange (2015) and Edelstein and Green (2018), that studies the role of real estate agents.

This paper is most related to Gilbukh and Goldsmith-Pinkham (2019) who study how the experience of real estate agents in the sales market affects the listing liquidity. Agent experience plays the role to attract more buyer and seller clients for the access to better matching technology, similar to the role of agent size in this paper. The key distinction is that I endogenize the decision of listing pricing. By characterizing the link between the search-and-matching process and the agent size, I show how the rent and the listing liquidity are jointly determined and depend on the listing incentive of brokers. In addition, the empirical findings in the rental market complement their findings on the sales market. While the agent size I define to capture broker heterogeneity differs from the agent experience in their paper, the two measures are correlated to a large extent.[3] Brokers, regardless of rental or sales service provided, share much listing incentive in common, with large/experienced brokers listing lower and matching faster than small/inexperienced brokers.

The micro-foundation for the search technology is crucial to model the listing pricing decision, because it captures the correct marginal effect of the rent choice on the matching probability. I show that using generic matching probabilities that increase in the agent size is not sufficient and can misspecify the correlation between the rent and the agent size.[4] The search-and-matching process here nests the labor search process with jobs from homogeneous firms applied by multiple workers in the labor search framework. I interact the urn-ball coordination friction (Montgomery, 1991; Burdett *et al.*, 2001; Albrecht *et al.*, 2006) with the brokers' capacity constraints in the spirit of Peters (1984). If each broker has one listing only, the capacity constraint is always binding in case of positive demand. If brokers have multiple listings, the capacity constraint is occasionally binding in case of positive demand. I highlight that the interaction of the urn-ball coordination friction and the capacity constraint is crucial to explain the dispersion of the rental market outcomes across brokers.

This paper is one of the few studies on the rental market based on the listing-level evidence. Those studies dating back to Stull (1978) are constrained by the depth or timeliness of the data, increasingly relying on the data sources from private firms (Urban Institute, 2019). Bar-Isaac and Gavazza (2015) is one of the studies that find the relationship between housing atypicality (Haurin, 1988) and the contractual arrangement of

[3] The agent size in this paper counts the number of listings or measures the listing capacity, while the agent experience in Gilbukh and Goldsmith-Pinkham (2019) counts the number of clients.

[4] As shown in Section 5.2, the assumption that the listing matching probability increases in the agent size is insufficient to capture the impact of the agent size. The prediction based on the *ad hoc* matching probability is opposite to what my model predicts and cannot rationalize the negative correlation in the data.

brokers in Manhattan. More atypical units are more likely to be exclusively listed, while rent-stabilized units are more likely to be listed as no-fee. Using a listing-agent matched data set, I add to the literature by studying the agent impact on the listing outcomes and attribute the agent size as a key factor to explain the listing-level correlations.[5]

More broadly, this paper contributes to the literature on the role of real estate agents (Yavaş, 1994; Han and Strange, 2015; Edelstein and Green, 2018) by adopting a structural approach. The analysis highlights two particular roles of brokers. First, brokers play a strategic role in listing pricing to balance the rent/sales return and the listing duration. The price-liquidity relationship has been studied in various sales markets (Stull, 1978; Miller and Sklarz, 1987; Haurin, 1988; Yavaş and Yang, 1995; Forgey *et al.*, 1996; Elder *et al.*, 1999; Krainer, 2001; Anglin *et al.*, 2003; Haurin *et al.*, 2010; Genesove and Han, 2012; Brastow *et al.*, 2012; Diaz and Jerez, 2013; Ngai and Tenreyro, 2014), with no study on the rental market to the best of my knowledge. Second, the brokerage sector plays a coordinating role in rental search and impacts market efficiency. I show the coordinating capacity of the brokerage sector is increasing in the mean agent size, and thus the broker's entry cost. This echoes the existing finding that excess entry due to low entry cost could hurt housing market efficiency (Hsieh and Moretti, 2003; Han and Hong, 2011; Barwick and Pathak, 2015; Barwick *et al.*, 2017; Gilbukh and Goldsmith-Pinkham, 2019).

Last, this paper connects to the literature on real estate commission. The commission rates charged by brokers are quite inflexible in both rental and sales markets (Wachter, 1987; Carroll, 1989), but the allocation of commission liability differs substantially. Sellers in the sales market are responsible for the broker's fee, while the fee could fall on landlords or tenants in the rental market (74% tenants pay the fee in Manhattan). The literature has documented that the fee paid by tenants is considered a screening device of long-term tenants (Ben-Shahar, 2001; Niedermayer and Wang, 2018). I contribute to the literature by finding a new link between the no-fee listing option and the agent size.

The paper is structured as follows. Sections 2-3 provide background information on data and documents empirical facts about rental brokers. Section 4 introduces the search-and-matching process, while Sections 5-6 introduce a search model and characterize the equilibrium properties. I present the method and results of the calibration in Section 7 and conduct policy counterfactuals in Section 8. Section 9 is the conclusion.

2 Data

2.1 Institutional Background

New York City (NYC) is a renter-occupied city, with renters more than twice as many as home owners. NYC has one of the highest rent nationwide, with Manhattan to be the most expensive borough in NYC.[6] Manhattan has a quarter of the housing units of NYC and its homeownership rate is 24.6% as of 2017, one of the lowest nationwide (NYCHVS, 2017).

Different from the rest of the US, the Manhattan rental market hadn't had a unified Multiple Listing Service (MLS) before late 2017 to facilitate rental search as most regions of the US did. A regional MLS

[5] My sample is more representative with better spatial coverage than Bar-Isaac and Gavazza (2015) who use a one-year and smaller sample with no agent information.

[6] According to NYCHVS (2017), the homeownership rate of NYC in 2017 is 32.4%, compared to the US homeownership rate of 63.9% (US Census, 2017). See Zillow Rent Index for cross-city comparison of rent and city rank: https://www.zillow.com/research/data/. As of September 2019, the average rent in Manhattan is $4,336, compared to the US average $1,471. See the market report by the brokerage firm Douglas Elliman: https://www.elliman.com/reports-and-guides/reports/new-york-city/september-2019-manhattan-brooklyn-and-queens-rentals/2-1169 and the report by RentCafe: https://www.rentcafe.com/blog/rental-market/apartment-rent-report/september-2019-national-rent-report/.

is a private database used by real estate agents to disseminate information on rental listings among brokers who may represent tenants/landlords in the rental market. Tenants searching in NYC instead rely more on public online platforms.[7] The rental data comes from StreetEasy, which is the major online listing platform in NYC with 1.2 million unique users and plays a crucial rule in rental search of New Yorkers.[8] Posting vacant rentals on StreetEasy is free of charge to listing agents as of late 2017 and the platform provides tenants with real-time information on rents and rental stocks, free of charge. The information benefit fuels its growing popularity as the dominant platform in Manhattan.[9]

The Manhattan rental market is highly intermediated, with less than 0.5% of the properties directly from the owners. Brokers are the major source of rental listings. With the majority working as independent contractors (NAR, 2019), brokers on StreetEasy post 80% of the rental listings to match landlords with tenants. They earn commission proportional to the rent in a closed deal. Due to the commission-based earnings structure, brokers are more incentivize than listing providers in a salaried position to rent out a unit quickly at the highest possible rent. One feature of StreetEasy listings is tenant access to information of the listing brokers. Besides the listed rent and the housing amenities, a listing posts agent information, including the name, the contact and the affiliated brokerage firm. Tenants can trace all rentals listed by the agent that are currently on the market.[10]

2.2 Data Description

The main data source is a matched listing-agent data set from StreetEasy in Manhattan for the period 2010-2017. I keep the details on data filtering in Appendix B. Rental listings come from various sources (brokerage, management company, owner). I focus on the listing behavior of brokers, as brokerage listings cover about 80% of the rentals. A key feature of StreetEasy listings is exclusiveness, meaning that a unit cannot be double-listed by another source.[11] The exclusive-listing rule protect agents from competing for tenants for broker's fee, and motivates agents to optimize their listing strategies to rent high and match fast. Hence, the feature makes the data set ideal to study the listing behavior of brokers.

I observe the listing history of a rental, including the initial and the last listed rents and dates as well as a list of unit or building amenities. Each rental is matched to a listing broker affiliated with a brokerage firm. As firms are classified into brokerage firms and management companies by StreetEasy, I can identify whether an agent is a broker or a property manager to focus on brokerage listings. The unit amenities include the number of bedrooms, the number of bathrooms, and a series of binary indicators of whether a housing unit is furnished or has certain household appliances (fireplace, dish washer, washer dryer). The building amenities are captured by a series of binary indicators of having certain facilities (elevator, doorman, pet allowed,

[7] NYC Rent Guidelines Board places "Online" and "Brokers" as one of the most common apartment hunting method in the City. See the guide at: https://www1.nyc.gov/site/rentguidelinesboard/resources/finding-an-apartment.page.

[8] StreetEasy was launched in 2006 in Manhattan and was acquired by the Zillow Group in 2013: https://www.mercurynews.com/2013/08/19/zillow-buys-real-estate-website-streeteasy-for-50-million/

[9] To see the growing importance of online listing, Appendix Figure C.3 shows that from 2010 to 2017, "StreetEasy" has more than doubled its popularity measured by Google search interest, outgrowing the popularity of "rent and Manhattan".

[10] See Appendix Figure C.4 for an example of a broker-listed rental and the agent characteristics available to tenants. The second major source of listings (20%) is property managers. Both brokers and property managers are required by the Department of State to obtain a broker's license. Different from brokers, property managers as delegates of landlords are salary-based positions. Note that the responsibilities and earning structure of brokers and property managers may overlap. Property managers can work for landlords to list units and earn commission fee, while brokers may receive similar non-monetary benefit including insurance and marketing support as property managers from the affiliated brokerage firms.

Listings by brokers and by property managers on StreetEasy provide different information to the tenants. A tenant can see agent information for a broker-listed unit, but only firm information for a unit listed by a property manager (see Appendix Figure D.1 for an example of a rental listed by a management company).

[11] See the listing quality policies of StreetEasy for details: https://streeteasy.com/nyc/posting_listings?ticket_url=https%3A%2F%2Fsupport.streeteasy.com%2Fhc%2Fen-us%2Frequests%2Fnew%3Fticket_form_id%3D55449.

concierge, gym, pool, garage, children's playroom, roof deck, garden). I geocode the building addresses using Google's geocoding API to get the precise geospatial coordinates, which I use to classify units into local markets to account for unobserved spatial heterogeneity. I divide Manhattan into 28 neighborhoods defined by the NYC Department of City Planning.[12]

In addition, I take into account two factors relevant to the listing pricing in NYC. The first indicates whether a listing is *no-fee*. Broker's fee is paid either by a landlord (no-fee) or by a tenant (with-fee). A no-fee listing does not necessarily mean a discount to a tenant. As the upfront cost can be rolled into the rent, a no-fee listing is expected to have a higher rent, all else equal. The commission rate as a percentage of the annual rent is non-disclosed in general, with the most common rate ranging from 8.3% (one month's rent) up to 15% of the annual rent.[13] The second factor is related to rent regulation in NYC and indicates whether there is a rent-stabilized unit in a building. Rent stabilized units are affordable rentals whose annual rent increase is regulated by the government, so the rent should be lower than the market rate. I get the rent-stabilized building lists by year from the NYC Rent Guidelines Board.[14] The building indicator is less than ideal, but it provides a reasonable estimate of rent-stabilized units at the aggregate level for each year.

2.3 Descriptive Statistics: Brokerage Listings and Brokers in Manhattan

2.3.1 Brokerage Listings in Manhattan

Table 1 summarizes the characteristics of brokerage listings by year. The number of listings and buildings grows steadily from 2010 to 2013, with the growth slowing down from 2014 to 2017, consistent with the increasing popularity of rental search by StreetEasy (see Appendix Figure C.3). In 2010, 25,267 listings are matched to 4,124 brokers from 631 firms, compared to 77,598 listings matched to 7,062 brokers from 1,506 brokerage firms in 2017. The data shows extensive spatial coverage, with listings from all 12 community districts and 28 neighborhoods. I report the medians of rents and listing days. The last listed rent is less than 3% lower than the initial rent, implying the rent discount is limited. The median listed rents in 2010 dollars are about $2,700, and the median listing time is 25 days.[15] On the heat maps, Figures 1a-1c show the listing distribution in Manhattan, the medians of real rent and listing days by neighborhood respectively. Locations matter to the leasing activities and listing outcomes. The neighborhood correlation of the medians of rent and listing days is 0.20, showing that listings in places with high rent are less liquid on the market.

2.3.2 Brokers in Manhattan

At a point of time, a broker differ in their listing capacity, which I define as the agent size. The agent heterogeneity could come from difference in age or working experience (Gilbukh and Goldsmith-Pinkham,

[12] Our results do not depend on the market division by Neighborhood Tabulation Area, Community District, school district, or police precinct, as their boundaries to a large extent overlap with each other.

[13] The commission fee is further split with the brokerage firm that an agent works for, which could be 50-50 or even 60-40 split, depending on working experience and performance. See StreetEasy's blogpost on *How Commissions Work for NYC Rental Agents*: `https://streeteasy.com/agent-resources/nyc-101/how-commissions-work-nyc-rental-agents/`.

[14] See NYC Rent Guidelines Board (RGB) website for the description of the data: `https://www1.nyc.gov/site/rentguidelinesboard/resources/rent-stabilized-building-lists.page`. I use the Wayback Machine (`https://archive.org`) to retrieve the historical building lists for the early years from the Internet archives of the RGB websites. I merge the list of rent-stabilized buildings with the StreetEasy data using the building identifier (Borough-Block-Lot number) from the Primary Land Use Tax Lot Output (PLUTO) database and the year as the key.

[15] Appendix Figure C.5.5a shows that more than 60% of rentals see no difference between last and initial listed rents; about 20%-40% of rentals see rent discount; almost no rentals see listed rent increase in the listing period. Figure C.5.5b shows that the median rent discount conditional on listed rent change is about 5% on average and is highly seasonal.

The rent and the days on market remain stable across years, but within a year, both indicators exhibit strong seasonality. July (January) is the peak (trough) of the hot (cold) season in a year with higher (lower) rent and fewer (more) listing days. See Appendix Figure C.6 for the monthly trends of selected listing percentiles of the real rent and the listing days on market.

Table 1: Listing Summary Statistics by Year

	Year								
Listings by brokers	2010	2011	2012	2013	2014	2015	2016	2017	Total
No. of Listings	25,267	27,812	34,619	43,999	56,496	62,511	68,235	77,598	56,295
No. of Buildings	7,532	7,974	9,318	10,647	12,383	13,221	13,698	14,202	12,019
No. of Neighborhoods	28	28	28	28	28	29	28	28	28
No. of Community Districts	12	12	12	12	12	12	12	12	12
No. of Brokers	4,124	4,438	5,031	5,871	6,740	7,073	7,222	7,062	6,365
No. of Brokerage Firms	631	730	897	1,099	1,203	1,343	1,424	1,506	1,215
Median Initial Rent (2010 $)	2,708	2,801	2,804	2,794	2,727	2,741	2,712	2,638	2,727
Median Last Rent (2010 $)	2,685	2,757	2,730	2,757	2,670	2,717	2,672	2,594	2,685
Median Days on Market	34	26	27	26	24	22	25	22	25

Note: Initial and last listed rents are adjusted to 2010 dollars. Neighborhoods (excluding the central park) refer to the Neighborhood Tabulation Area defined by the NYC Department of City Planning.

2019). Empirically, I define a stock measure of the agent size as follows.

$$Agent\_Size_{j,y} = \text{Ceil}\left(\frac{1}{52}\sum_{w\in\{1,\dots,52\}}\sum_i \mathbb{I}\{(y,w)\in \text{Weekly-Date}(Init\_Date_{ij}, Last\_Date_{ij})\}\right) \tag{1}$$

For broker j in year y, the sum $\sum_i \mathbb{I}\{\cdot\}$ counts the number of listings per week whose dates on market overlap with a weekly date (y,w). The agent size is the weekly mean of the listing counts that smooths out the seasonal impact. The function Ceil$(\cdot)$ rounds up the mean to the nearest integer, putting brokers into a discrete set of types. The agent size measure is robust to alternative definitions and reflects the inflow of fresh listings instead of the inventory of unmatched listings.[16]

Table 2: Agent Summary Statistics by Year

	Year								
Brokers	2010	2011	2012	2013	2014	2015	2016	2017	Total
Agent Size	2.6	2.5	2.6	2.8	3.1	3.1	3.1	3.3	2.9
Listing Volume (Monthly)	0.5	0.5	0.6	0.6	0.7	0.7	0.8	0.9	0.7
No. of Listings/Agent	6.1	6.3	6.9	7.5	8.4	8.8	9.4	11.0	8.3
No. of Buildings/Agent	3.8	3.7	3.9	4.0	4.2	4.3	4.4	4.7	4.2
No. of Neighborhoods/Agent	2.3	2.3	2.4	2.4	2.5	2.5	2.5	2.6	2.4
No. of Community Districts/Agent	2.0	2.0	2.0	2.0	2.1	2.1	2.1	2.2	2.1

Note: The sample is rental brokers in Manhattan and agent means are reported. Neighborhoods refer to the Neighborhood Tabulation Areas defined by the NYC Department of City Planning.

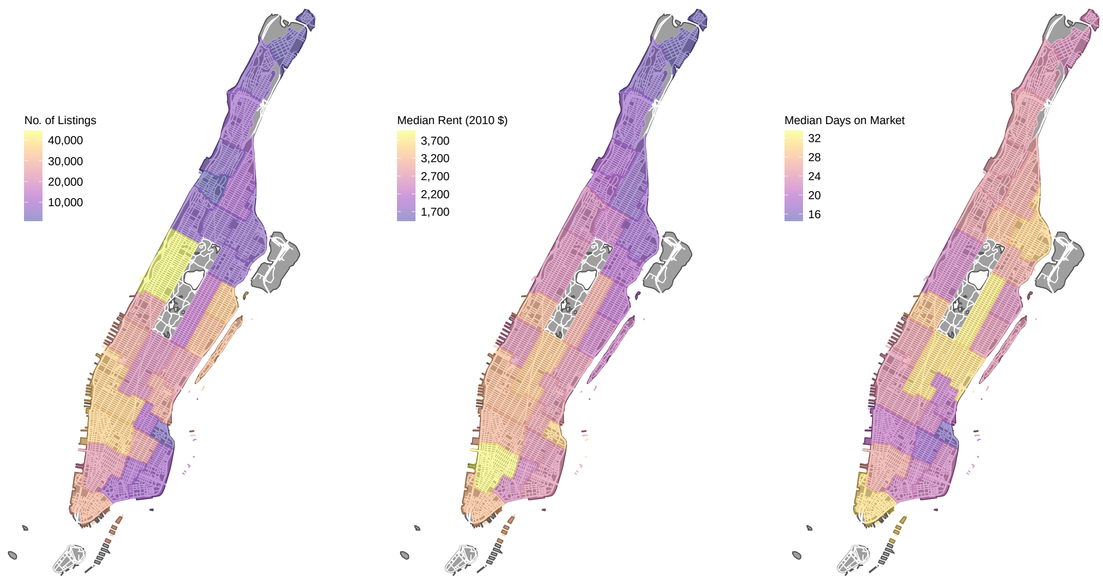
In Table 2, I summarize the agent characteristics by year. On average, a broker lists 8.3 rentals in a year which come from 4.2 buildings in 2.4 neighborhoods. A broker has 2.9 rentals on average at a point of time and initiates 0.7 listings on average every month. One reason why these numbers look small is that many brokers are part-time and some work not only in the rental market but also in the sales market. While the

[16] The agent size measure is robust to alternative definitions. Using a weekly median or adjusting the observation bandwidth does not make much difference in measurement. The weekly bandwidth is smaller than the median listing days and smooths the workday effect. I find that the majority of listing incidence is either fully exclusive or inclusive in a given week.

A large agent size reflects a large inflow of fresh listings instead of a large inventory of unmatched listings. To see the point, I consider a volume measure of the agent size, which is found to be highly correlated with the stock measure (0.82).

$$Monthly\_Volume_{j,y} = \text{Ceil}\left(\frac{1}{12}\sum_{m\in\{1,\dots,12\}}\sum_i \mathbb{I}\{(y,m) = \text{Monthly-Date}(Init\_Date_{ij})\}\right)$$

The monthly volume shows the number of listings that a broker j in year y initiates per month on average. I will provide evidence that a larger agent size is related to shorter listing duration, meaning that a larger agent size does not reflect a larger inventory of unmatched listings.



a No. of Listings **b** Median Rent (2010 $) **c** Median Days on Market

Figure 1: Heat maps of the number of listings, rent, and days on market by neighborhood in Manhattan. The sample is rental listings (2010-2017) by brokers in Manhattan. Rent refers to the last listed rent (2010 $). Neighborhoods are defined by the NYC Department of City Planning.

agent size measure focuses only on the rentals, the concern of unobserved sales listing is minor in the rental listing analysis. Rental and sales markets require very different real estate knowledge to intermediate, with rental deals closing much faster and generating more steady earnings and client stream than sales.

3 Stylized Facts

Before going to the model, I document 3 facts about the rent, the listing duration, and the agent size in the Manhattan rental market. Motivated by the evidence, I introduce a search-and-matching process in Section 4 embedded in a search model with heterogeneous brokers in Section 5.

3.1 Stylized Fact: Rent and Listing Duration

Fact 1: the rent and the listing days are negatively correlated with the agent size.

In Table 3, I report the medians of rent and listing days by the listing year and the percentile group of the agent distribution. The median rent in the top percentile (> 99th) of the agent distribution is $2,513 in 2010 USD, or 19% lower than the median rent in the bottom percentile (≤ 25th). The median listing time in the top percentile is 18 days, or 56% less than the time in the bottom percentile. In Figure 2a and 2b, I show that the rent and the listing days distributions are more left-skewed for brokers in the top than in the bottom percentile of the agent distribution.

I decompose the rent (listing duration) into a housing and an agent component. The housing component consists of a location-date fixed effect (FE_{nt}) and a set of unit or building amenities ($\mathbf{X}_{int}$). The agent

Table 3: Rents and Days on Market by Year and Percentile of Agent Distribution

	Brokers: Median Rent (2010 $)								
Agent Size Percentile	2010	2011	2012	2013	2014	2015	2016	2017	Total
min - p25	3,070	3,096	3,137	3,073	3,120	3,198	3,068	3,005	3,096
p25 - p50	2,997	3,096	3,093	3,082	3,030	3,105	3,022	2,911	3,037
p50 - p75	2,811	2,874	2,909	2,973	2,866	2,924	2,790	2,766	2,853
p75 - p90	2,702	2,783	2,665	2,760	2,565	2,672	2,712	2,583	2,662
p90 - p95	2,456	2,585	2,628	2,573	2,562	2,561	2,530	2,514	2,553
p95 - p99	2,403	2,491	2,591	2,589	2,575	2,554	2,550	2,544	2,554
p99 - max	2,395	2,407	2,208	2,532	2,581	2,610	2,536	2,456	2,513
	Brokers: Median Days on Market								
Agent Size Percentile	2010	2011	2012	2013	2014	2015	2016	2017	Total
min - p25	48	40	40	40	40	40	42	38	41
p25 - p50	43	36	39	39	38	37	39	35	38
p50 - p75	41	32	36	35	35	30	34	29	34
p75 - p90	32	27	27	27	25	23	26	23	25
p90 - p95	29	21	21	21	21	18	21	21	21
p95 - p99	21	17	20	19	17	17	20	19	19
p99 - max	28	16	17	17	16	16	19	18	18

Note: The sample is the rental listings (2010-2017) by brokers in Manhattan. Rent refers to the last listed rent (2010 $). The decreasing step of the percentiles balances the number of listings in the groups at the right tail where listings are more concentrated.

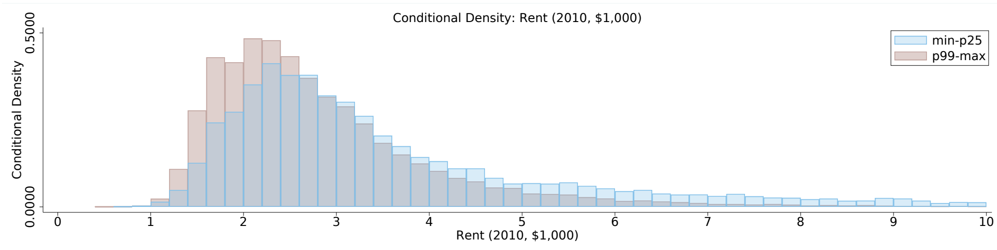
component filters out the housing impact and captures the broker characteristics, including the agent size ($Agent\_Size_{jt}$) and the no-fee option (No_Fee_{ijnt}) that indicates whether a listing is no-fee. In Appendix Table C.1, I report the summary statistics of the listing characteristics and apply the following model to decompose the listing outcomes.

$$\log(Y_{ijnt}) = \underbrace{FE_{nt} + \mathbf{X}_{int} \cdot \mathbf{B}}_{\text{Housing: location-date, amenities}} + \underbrace{\sum_l \mathbb{I}\{Agent\_Size_{jt} = l\}\gamma_l + No\_Fee_{ijnt} + e^Y_{ijnt}}_{\text{Agent}} \tag{2}$$

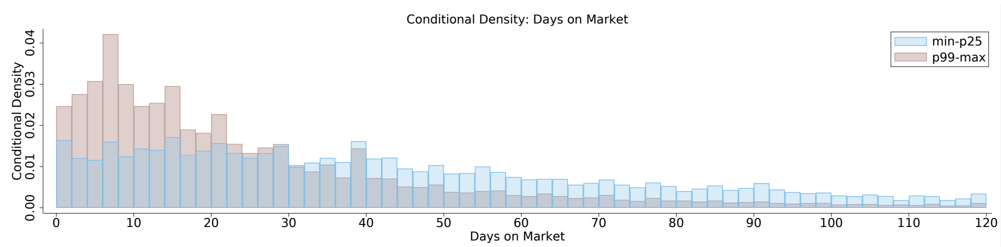
The outcome variable Y_{ijnt} is either the real rent or the listing days. Each observation represent a listing i from broker j in the neighborhood n and on the quarterly date t. In the log rent model, I estimate a hedonic price model by assuming a Gaussian error, while in the log time equation, I estimate an accelerated failure time model by assuming a Weibull exponentiated error.

Fact 2: adjusted for the housing amenities, the residual rent and the residual listing duration are negatively correlated with the agent size.

To understand how brokers affect the listing outcomes, I compare in Table 4 the explained variations of the rent (Col. 1-4) and the listing duration (Col. 5-8) in four cases, depending on whether the housing amenities or the observed agent attributes are included in equation (2). Col. 1 (Col. 5) controls the location-date fixed effect only, while Col. 2 (Col. 6) additionally includes the agent attributes. R^2 increases by 4 pp in both the rent and listing days equations, showing that agent attributes have the predictive power on the listing outcomes. Col. 3 (Col. 7) builds on Col. 1 (Col. 5) to include the housing amenities. R^2 increases by 60 pp (7 pp), showing that most variation of rent is attributed to the housing amenities. Col. 4 (Col. 8) builds on Col. 3 (Col. 7) to include the agent attributes. The increase in R^2 from 75% to 76% (12% to 14%)



a Conditional Density of Real Rent



b Conditional Density of Days on Market

Figure 2: Conditional density distribution of rent and days on market for the top and bottom percentiles of the agent distribution. The sample is the listings (2010-2017) by brokers in Manhattan.

is due to the unique contribution of the agent characteristics that is orthogonal to the housing amenities.[17]

I residualize the log rent (listing days) by filtering out the variation due to the amenities and the location-date fixed effect and aggregate the residuals by the discrete agent size level. Figures 3a and 3b show the residual log rent and residual log listing days are negatively correlated with the agent size, suggesting a sizable and direct impact of brokers on the listing outcomes.[18] The gap of the residual rent between the bottom and top percentiles (≤ 25th and > 99th) of the agent distribution is as large as 8.4% of the mean rent, while the gap of the residual listing days is 53% of the mean listing time. Table 5 shows that 88% (94%) of the residual variation of the log rent (log listing time) is explained by the log agent size. Conditioning on the housing amenities, one unit increase in the agent size is related to a 0.5% decrease in the listed rent and a 2.9% decrease in the listing time.

Fact 3: the mean rental quality is negatively correlated with agent size.

I define the rental quality as the predicted rent in Model 3 of Table 4 whose log form is a linear combination of the housing amenities weighted by the estimated hedonic prices. To see the housing impact on the listing outcomes, I show in Figures 3c and 3d the negative relationship of the predicted rent and the predicted listing days with the agent size. The evidence suggests that listings do not meet brokers at random and there is selection of brokers that contributes to Fact 1.

To explore the source of the selection, I report in Appendix Table C.3 the average housing attributes by the agent size group and show that the distribution of unit or building amenities depends on the agent size.

[17] As the Weibull parameters are greater than 1 in Col. 5-8, the hazard rates are increasing. In Appendix Figure C.7, I show the listing hazard of Col. 8 at the selected percentiles of the agent distribution.

[18] While there are concerns that the residual variation may come from the unobserved amenities, the issue is limited. I find the coefficients on the dummies γ_l on the discrete agent size level in Models 4 and 8 of Table 4 are negatively correlated with the agent size. The range of γ_l in the log rent (listing days) equation is similar to that of the residual variation in Figure 3a (3b). As the agent size is correlated with the no-fee status, I focus on the residual variation of the listing outcomes to summarize the total agent impact. In Section 8.2, I further separate the no-fee impact from the total agent impact.

Table 4: Reduced-Form Models of Rent and Days on Market (DOM)

	(1) Log Rent	(2) Log Rent	(3) Log Rent	(4) Log Rent	(5) Log DOM	(6) Log DOM	(7) Log DOM	(8) Log DOM
Agent Size Dummies		(Omitted)		(Omitted)		(Omitted)		(Omitted)
Is No-fee Listing		0.070***		0.011***		-0.007		-0.019**
		(0.006)		(0.003)		(0.009)		(0.008)
Adjusted R^2	0.15	0.19	0.75	0.76	0.05	0.09	0.12	0.14
Housing Amenities			✓	✓			✓	✓
Agent Characteristics		✓		✓		✓		✓
Location-Date FE	✓	✓	✓	✓	✓	✓	✓	✓
Survival Distribution					Weibull (1.01)	Weibull (1.05)	Weibull (1.05)	Weibull (1.07)
N	396,537	396,537	396,537	396,537	396,537	396,537	396,537	396,537

Note: clustered-robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010. Errors are clustered by the neighborhood and the quarterly date. The sample is the rental listings (2010-2017) by brokers in Manhattan. The dummies of discrete agent size levels are used to allow the non-parametric impact of the agent size on the listing outcomes. The location-date fixed effect allows the models to condition on the neighborhood and the quarterly date. The rent refers to the last listed rent (2010 $). Accelerated failure time models using the Weibull survival distribution are estimated, with the parameter reported in the parenthesis. See Appendix Table C.2 for the complete table.

Table 5: Residuals of Rent and Days on Market (DOM)

	(1) Residual Log Rent	(2) Residual Log DOM	(3) Residual Log Rent	(4) Residual Log DOM
Agent Size	-0.005***	-0.029***		
	(0.001)	(0.003)		
Log Agent Size			-0.033***	-0.186***
			(0.003)	(0.016)
Constant	0.036***	0.234***	0.058***	0.339***
	(0.009)	(0.027)	(0.007)	(0.031)
Adjusted R^2	0.656	0.869	0.875	0.939
N	20	20	20	20

Note: robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010. The residuals of log rent and log listing days take out the variation due to the housing amenities and the location-date fixed effect (Models 3 and 7 in Table 4). Observations are weighted by the number of listings. The range of the agent size (1-20) covers more than 99% of the brokers in the sample.

While the number of bedrooms is similar across brokers, rentals listed by large brokers have fewer bathrooms and fewer amenities in the unit (wash dryer, fireplace, is furnished) or in the building (doorman, elevator, garage, concierge, gym, pool). Another difference lies in the rent-stabilized status of a building. While 71% of the listings by brokers in the top percentile of the agent distribution indicate a rent-stabilized unit in a building, the share in the bottom percentile decreases to 38%.

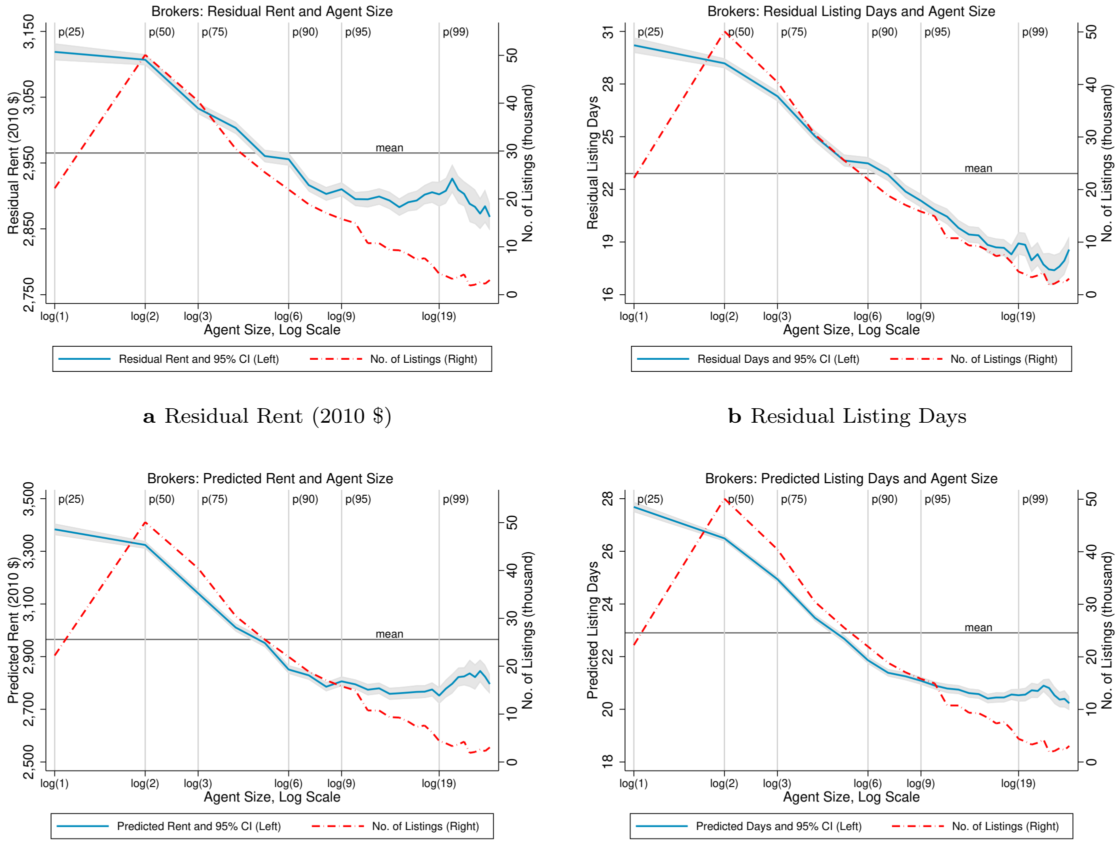
I don't find evidence that atypical rentals (Haurin, 1988) which differ from an average rental in housing attributes are disproportionally listed by a particular agent group. I construct an atypicality index to measure the distance of housing attributes between a rental and an average rental in the same location within a range of time and find no statistical difference in the atypicality distributions across the agent groups.[19]

[19] In the sales market, atypical houses are found to be less liquid, reflected by longer listing time and lower prices (Haurin, 1988; Glower, Haurin and Hendershott, 1998; Han and Strange, 2016). I follow the definition by Han and Strange (2016) to define the atypicality index of a listing i as follows.

$$Atypicality_{int} = \sum_k |exp(\hat{\beta}^0_{nt} + \hat{\beta}^k_{nt} h^k_{int}) - exp(\hat{\beta}^0_{nt} + \hat{\beta}^k_{nt} \bar{h}^k_{int})| / exp(\widehat{log\ rent}), \text{ with } \bar{h}^k_{int} = \sum_{i'} h^k_{i'n't'} \mathbb{I}\{n' = n, t' = t\}$$

where k is the index of a housing attribute, $\bar{h}^k_{int}$ is the average attribute given location n and quarterly date t, $\hat{\beta}^k_{nt}$ is the estimated coefficient of attribute k from a linear log rent equation and $\hat{\beta}^0_{nt}$ is the intercept of the log rent equation. To get the coefficient estimates, I estimate a log rent model by community district and quarterly date, with the set of housing attributes listed in Appendix Table C.1 as the control variables. $\widehat{log\ rent}$ is the estimated log rent that normalizes the index.

The average atypicality indices across agent groups lie in a narrow range between 0.33 and 0.34, with the index distribution (Appendix Figure C.8) not statistically different across groups by the Kolmogorov-Smirnov test.



a Residual Rent (2010 $) **b** Residual Listing Days

c Predicted Rent (2010 $) **d** Predicted Listing Days

Figure 3: Rent, listing days, and agent size. The percentiles of the agent distribution are reported, with the bottom 90% of rentals covered. The predicted and residual rents (listing days) are centered at the mean predicted by Model 3 (Model 7) in Table 4, with the residuals adjusted for the housing amenities and the location-date fixed effect. For the control variables, see Appendix Table C.1. Rent refers to the last listed rent (2010 $). The sample is rental listings (2010-2017) by brokers in Manhattan.

3.2 What Contributes to the Agent Impact on the Listing Outcomes?

To understand the source of the agent impact in the stylized facts, I examine what are (not) the factors contributing to the correlation between the agent size and the listing outcomes.

3.2.1 Does Listing Incentive matter? Brokers vs Property Managers

I examine whether the listing incentive contributes to the agent impact. The listings by the brokers from the brokerage firms are compared to the listings by the property managers from the management companies. The difference between the two agent groups lies in the earnings structure. A broker works as an independent contractor, while a property manager holds a salaried position.[20] Brokers are more incentivized than property managers to optimize listing strategies, thus expected to show a stronger agent impact on the

[20] The property managers list about 20% rentals. Listings by brokers and property managers usually do not overlap, with more than 95% of listings in a building either listed by brokers or listed by property managers. As a salary worker, management listings do not post agent information (Appendix Figure D.1). The distribution of management listings are not as left-skewed as that of brokerage listings (Appendix Figure D.2).

listing outcomes. I find a negative relationship between the residual rent and the agent size for units listed by the bottom 90% of managers, but no significant variation of the residual listing days for units listed by the bottom 95% managers (Appendix Figures D.3 and D.4). The correlation of the residual rent (residual listing days) and the agent size is much stronger for the brokers than for the property managers.[21] The evidence points out that the listing incentive provided by the commission system contributes to the agent impact observed in the stylized facts. Moreover, it provides empirical support to the modelling assumption about the rent-liquidity trade-off in the broker's objective in Section 5.

3.2.2 Rent Discount and Inventory Concern

I examine whether the rent discount which I define as the difference between the initial and last listed rents contributes to the agent impact on the listing outcomes. Lower rent can result from a deeper discount on rent in the listing process. Instead of using the last listed rent, I use the initial asking rent and the initial listing date to account for the time fixed effect. The listing share with at least one rent update is lower than 40%. Conditional on a rent discount, the average rent discount is about -5%, showing limited opportunities to wait for a lower rent in Manhattan (Appendix Figure C.5). Using the initial rent, I find similar regression results about the agent impacts on the listing outcomes, suggesting that the rent discount cannot account for the agent impact. Appendix Figure C.11 shows that the residuals of log rent and log listing days are decreasing in the agent size, similar to what Figure 3 shows.

I examine whether the agent impact on the listing outcomes is attributed to the inventory concern about listings. A brokers of a larger agent size may want to reduce the number of listings in the inventory faster by setting a lower rent. To check the robustness of the empirical results, I use the monthly listing volume (defined in Fn.16), which is a flow value measuring how fast listings arrive. I show that brokers with larger listing stock are associated with larger monthly volume (Appendix Figure C.12), with a listing-level correlation of 0.82. As the monthly volume increases, the residual rent and the residual listing days decrease (Appendix Figure C.13), similar to what Figure 3 shows. The result points out that the inventory concern about listings does not contribute to the agent impact on the listing outcomes.

3.2.3 Agent Impact and Aggregation Method: Firm- vs Agent-Level Evidence

I examine whether the agent impact is affected by the method to aggregate the listing outcomes. I identify the affiliated firm of a broker and define the firm size as the sum of the listing stock of agents. As agents are about 6 times as many as firms, I make the comparison based on the relative scales, *i.e.* the percentiles of the agent/firm distribution. As the firm size increases, the rent and the listing days are found decreasing. In Appendix Figure C.14, I compare the agent-based and firm-based residuals of rent and listing days at the selected percentiles of the agent/firm distributions. Conditioning on the housing amenities, large firms tend to list a rental at a lower rent and see fewer listing days. The negative correlation of the residual rent (residual listing days) and the firm size is quantitatively similar to what I find using the agent size. The agent impact does not depend on how I aggregate the listing outcomes.

[21] The correlation of the residual log rent (listing days) and the log agent size is -0.80 and -0.27 (-0.90 and -0.60) for brokers and property managers respectively. Listings are aggregated by the source (brokerage firm, management company) and the agent size, with the correlations weighted by the listing count. I leave the analysis of the management listings in Appendix D.

4 Search-and-Matching Process

I describe and characterize a search-and-matching process which is the key element of the main model in Section 5. I consider a search technology with which tenants search for rentals through intermediaries. Brokers (or agents interchangeably) differ in the number of listings l capable to supply, *i.e.* the agent size. I use l to index the submarket that groups the brokers with the same listing capacity. The set of submarkets is finite, $\mathbb{L} = \{1, 2, \ldots, \mathcal{L}\}$. Tenants can choose which brokers to go for. While brokers in the same submarket are *ex ante* identical in the rental supply, the number of prospective tenants may differ across brokers *ex post*. Listings available to a broker are randomly assigned to the incoming tenants. Let the number of brokers and tenants in submarket l be $a(l)$ and $b(l)$ respectively. Denote the market tightness measures—the tenant-agent ratio $\theta(l)$ and the tenant-listing ratio $\eta(l)$—as follows.

$$\theta(l) = \frac{b(l)}{a(l)}, \ \eta(l) = \frac{\theta(l)}{l} \tag{3}$$

In a round of search, a tenant can choose one listing at most for a chance of a tenant-listing match. The agent size l of a broker j is observable to a tenant i, but the number of competing tenants at the broker j (other than i) is *ex ante* unobservable to all, thus a random variable. In the case of local excess demand in which tenants outnumber the listings posted by a broker, a broker rations the listing supply. The inability of tenants to coordinate rental search is common knowledge.

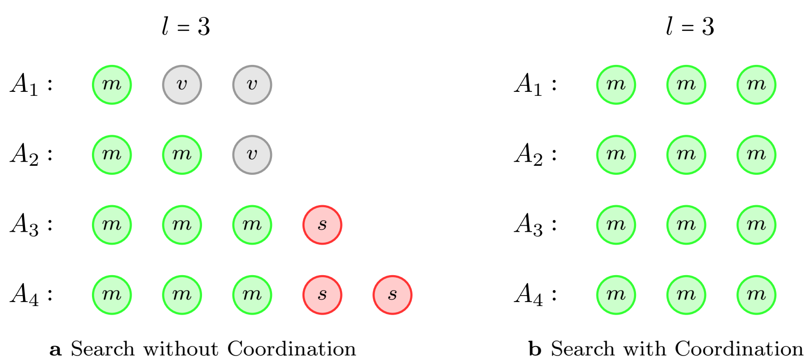
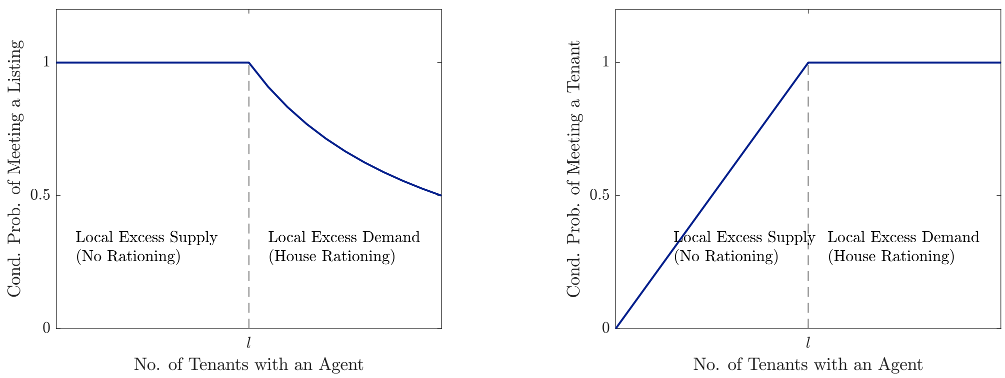


Figure 4: An example of a matching problem with 12 tenants, 4 brokers (A) holding 3 listings each ($l = 3$). A green circle denotes a tenant-listing match (m); a gray circle means a vacant rental (v); a red circle denotes an unmatched searching tenant (s). Panel 4a shows one matching outcome without coordination among tenants, while Panel 4b shows the outcome of search with coordination.

Figure 4 shows an example of the matching problem with 12 tenants and 4 brokers posting 3 listings each. Without search coordination, local excess supply and local excess demand may co-exist at the broker level. With search coordination, local conditions do not matter and all tenants can be matched to vacancies. Figure 5 shows the *ex post* tenant probability of meeting a listing and the *ex post* listing probability of meeting a tenant as functions of the number of tenants. If the local demand is smaller than the listing capacity, there is local excess supply, with all tenants matched with probability 1. If the local demand is greater than the listing capacity, there is local excess demand, with l listings randomly assigned to l tenants and the rest tenants being unmatched.



a Tenant: Probability of Meeting a Listing **b** Listing: Probability of Meeting a Tenant

Figure 5: Matching probabilities at a broker with capacity l as functions of the number of tenants.

4.1 Tenant Matching Probability

Given the tenant-agent ratio $\theta = b_l/a_l$ in a large market ($a_l, b_l \to \infty$), denote the *ex ante* tenant matching probability with a listing in submarket l as $\pi_b(l,\theta)$.

$$\pi_b(l,\theta) = \sum_{x=0}^{b_l-1} \binom{b_l-1}{x} \left(\frac{1}{a_l}\right)^x \left(1-\frac{1}{a_l}\right)^{b_l-1-x} \min\left\{1, \frac{l}{x+1}\right\} \to \sum_{x=0}^{\infty} \frac{e^{-\theta}\theta^x}{x!} \min\left\{1, \frac{l}{x+1}\right\} \tag{4}$$

For a tenant i who goes to a broker j of capacity l, if there are x out of a total $b_l - 1$ number of competing tenants at the broker j, the tenant matching probability in a large market is approximated by a Poisson distribution with the arrival rate captured by the tenant-agent ratio θ in submarket l.[22]

4.2 Local Housing Demand

The listed rent is a take-it-or-leave-it offer to the tenants.[23] As tenants cannot coordinate their search, the number of tenants y visiting a broker j of capacity l is a random variable. A broker will randomly assign the available listings to the tenants. If a tenant does not receive a listing offer from a broker (in the case of excess demand), she restarts the search process in the next round. If a tenant receives a listing offer, the tenant has the option to reject the offer and wait for a new match in the next round, based on a random draw of the private value $v \sim F(v)$. The value is *i.i.d.* across tenants and rental units and captures the match quality realized after an on-site visit. I rule out the possibility that a rejected offer can be recalled by a tenant in the same round. If the tenant acceptance follows a cutoff rule determined by a reserve value v_R, the tenant acceptance probability is $1 - F(v_R)$. For an broker of size l, I define the local demand as the

[22] An alternative form of $\pi_b(l,\theta)$ with infinite summation is $\pi_b(l,\theta) = \frac{l}{\theta}(1-e^{-\theta}) - \sum_{x=0}^{\max\{l-2,0\}}(\frac{l}{x+1}-1)\frac{exp(-\theta)\theta^x}{x!}$, $l \geq 1$. In recursive form, $\pi_b(l+1,\theta) = \frac{l+1}{l}\pi_b(l,\theta) - \frac{1}{l}\sum_{x=0}^{l-1}\frac{exp(-\theta)\theta^x}{x!}$, with $\pi_b(1,\theta) = \frac{1}{\theta}(1-e^{-\theta})$ and $l \geq 1$. The tenant matching probability $\pi_b(l,\theta)$ in the special case of $l = 1$ coincides with the urn-ball matching probability that Burdett *et al.* (2001) derive in a large labor market where an unemployed worker can submit only 1 job application.

[23] This rules out the bargaining which I believe is plausible in the Manhattan market. In Appendix Figure C.5, I show that more than 60% of listings doesn't experience any rent change during the listing time. Conditional on the rent change, the rent discount is about -5%.

expected number N of tenants who accept the tenant-listing matches.

$$N(l,\hat{\theta}) = \sum_{y=0}^{b_l} \binom{b_l}{y} \left(\frac{1-F(v_R)}{a_l}\right)^y \left(1-\frac{1-F(v_R)}{a_l}\right)^{b_l-y} \min\{y,l\} \to \sum_{y=0}^{\infty} \frac{e^{-\hat{\theta}}\hat{\theta}^y}{y!} \min\{y,l\} \tag{5}$$

If there are y out of a total b_l number of tenants at a broker of size l, the expected number of tenants in a large market is approximated by a Poisson distribution. Its arrival rate is the effective tenant-agent ratio $\hat{\theta}$, denoted by a hat symbol and defined as the tenant-agent ratio θ in submarket l multiplied by the acceptance probability $1-F(v_R)$. The ratio measures how likely a listing is matched to a tenant who will accept the match. The probability $1-F(v_R)$ enters equation (5) non-linearly, because there are infinitely many tenants searching in a submarket—instead of only one tenant—who make independent choices based on the realized private values.[24]

4.3 Properties of the Search-and-Matching Process

The search-and-matching technology is constant return to scales, leading to a similar identity that bridges the demand- and supply-side matching probabilities in the standard search models (Rogerson *et al.*, 2005; Wright *et al.*, 2019). By equations (4) and (5), the local demand $N(l,\theta)$ and the tenant matching probability $\pi_b(l,\theta)$ are linked as follows.

$$\eta\pi_b(l,\theta) = \frac{N(l,\theta)}{l} \equiv \pi_a(l,\theta) \tag{6}$$

The left side is the tenant matching probability $\pi_b(l,\theta)$ multiplied by the tenant-listing ratio η, while the right side is the ratio of the local demand to the agent size, *i.e.* the listing matching probability with a tenant $\pi_a(l,\theta)$. The ratio of $\pi_a(l,\theta)$ to $\pi_b(l,\theta)$, which is equal to the tenant-listing ratio, is comparable to the market tightness measure in the standard labor search framework. I derive the properties of $\pi_b(l,\theta)$, $N(l,\theta)$ and $\pi_a(l,\theta)$ in the following sets of lemmas.

Lemma 1. *Given θ, $N(l,\theta)$ and $\pi_b(l,\theta)$ are increasing and concave in l. $\pi_a(l,\theta)$ is decreasing in l.*

Proof. See Appendix A.1. □

Lemma 1 says that tenants going to large brokers expect a higher matching probability and larger brokers expect more tenants to visit.[25] For the analysis later, denote the elasticity of local demand $N(l,\theta)$ (or of $\pi_a(l,\theta)$) with respect to θ to be $\varepsilon(l,\theta)$. I summarize the property of $\varepsilon(l,\theta)$ in the following lemma.

Lemma 2. *$\varepsilon(l,\theta)$ is decreasing in θ and increasing in l, with $0 \le \varepsilon(l,\theta) \le 1$, $\varepsilon(l,0) = 1$ and $\varepsilon(l,\infty) = 0$.*

Proof. See Appendix A.2. □

The elasticity measures the percentage impact of local demand (listing matching probability) in response to the increase of tenants per broker. Lemma 2 says that due to competition among brokers, 1% increase in the tenant-agent ratio is factored into less than 1% growth of the local demand. The elasticity is decreasing in θ, related to the diminishing response of local demand to market tightness in the next lemma.

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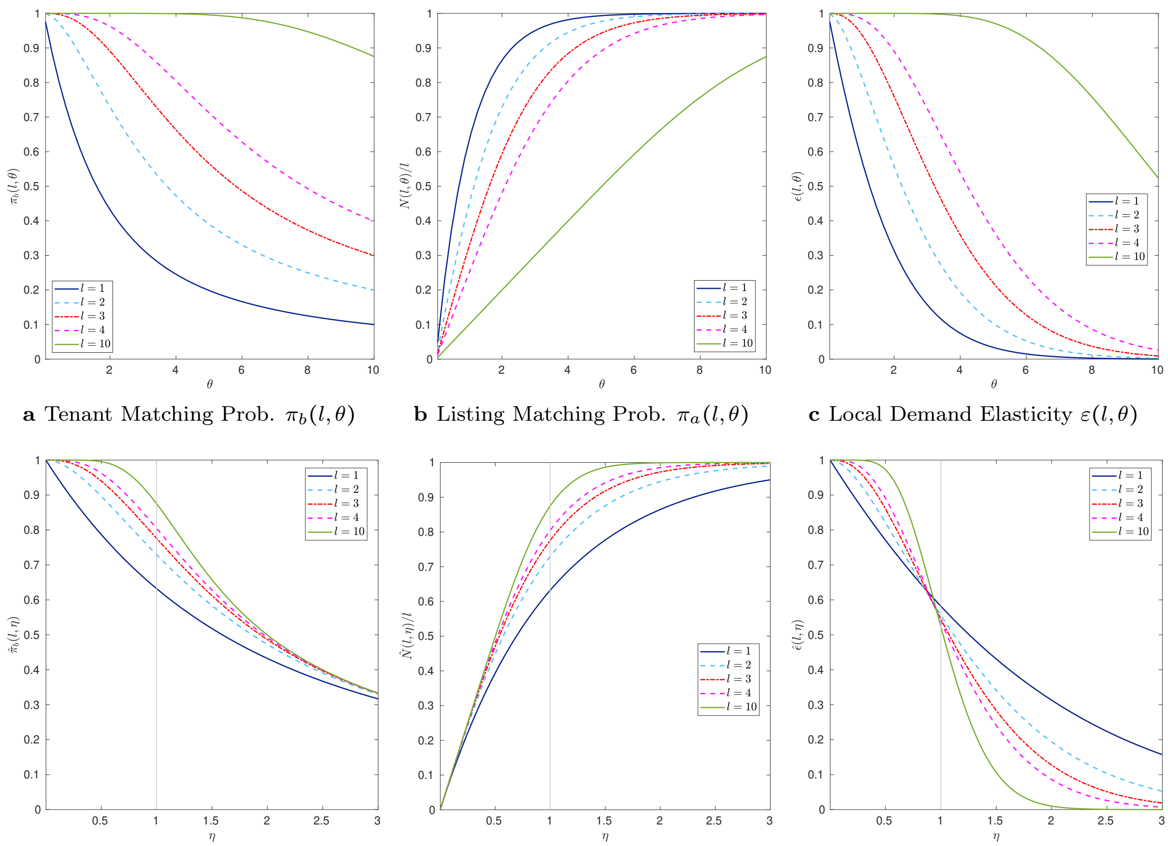
[24] An alternative form of $N(l,\hat{\theta})$ with finite summation is $N(l,\hat{\theta}) = l - \sum_{y=0}^{l-1}(l-y)\frac{exp(-\hat{\theta})\hat{\theta}^y}{y!}$. In recursive form, I can rewrite N as $N(l+1,\hat{\theta}) = N(l,\hat{\theta}) + 1 - \sum_{y=0}^{l}\frac{exp(-\hat{\theta})\hat{\theta}^y}{y!}$, with $N(0,\hat{\theta}) = 0$ and $l \ge 0$. Because tenants cannot coordinate their search, the local demand in submarket l won't exceed the listing capacity, $N(l,\hat{\theta}) < l$.

[25] The reason why $\pi_a(l,\theta)$ decreases in l is that the comparative statics is conducted with a fixed $\theta = \eta l$ which is a function of the tenant-listing ratio and the agent size. When I take the total impact of the agent size into account, I show numerically later that $\pi_a(l,\eta l)$ is increasing in l.

Lemma 3. *$N(l,\theta)$ and $\pi_a(l,\theta)$ are increasing and concave in θ. $\pi_b(l,\theta)$ is decreasing in θ.*

Proof. See Appendix A.3. □

Lemma 3 shows the conflict of interest between brokers and tenants. On one hand, an broker prefers the tenant-agent ratio to be higher, as it improves the listing matching probability and increases profit. On other hand, a tenant prefers the tenant-agent ratio to be lower, as less competition among tenants improves the tenant matching probability. In equilibrium, the tenant-agent ratio balances these two forces.



a Tenant Matching Prob. $\pi_b(l,\theta)$ **b** Listing Matching Prob. $\pi_a(l,\theta)$ **c** Local Demand Elasticity $\varepsilon(l,\theta)$

d Tenant Matching Prob. $\hat{\pi}_b(l,\eta)$ **e** Listing Matching Prob. $\hat{\pi}_a(l,\eta)$ **f** Demand Elasticity $\hat{\varepsilon}(l,\eta)$

Figure 6: Comparative statics of the tenant matching probability π_b, the listing matching probability π_a and the demand elasticity ε in the space of (l,θ) or (l,η) at selected levels of listing capacity.

In Figure 6, I first show the comparative statics of $(\pi_b,\pi_a,\varepsilon)$ in the (l,θ) space for selected agent sizes. As l and $\theta=\eta l$ impose two opposite effects, the total impact of l is not straightforward.[26] I then show $(\pi_b,\pi_a,\varepsilon)$ in the (l,η) space numerically.[27] The monotone properties that hold in the (l,θ) space (Lemmas 1-3) may no longer hold globally in the (l,η) space. For η not too large, the tenant matching probability π_b is increasing in l, as tenants who search without coordination are less likely to encounter local excess demand at large brokers. As $\pi_a=\eta\pi_b$ by equation (6), the listing matching probability π_a is increasing in l. Last, the demand elasticity ε in the neighborhood of $\eta=1$ is not monotonic in l. As the agent size increases, two forces—capacity and congestion—competes with each other. When the tightness η is small, the capacity

[26] As l increases, $\pi(l,\theta)$ and $\varepsilon(l,\theta)$ are increasing in the first argument and $\pi_a(l,\theta)$ is decreasing in the first argument. The second argument $\theta=\eta l$ will proportionally increase in l, leading to a decrease in $\pi(l,\theta)$ and $\varepsilon(l,\theta)$ and an increase in $\pi_a(l,\theta)$.

[27] I plot $\hat{\pi}_b(l,\eta)=\pi_b(l,\eta l)$, $\hat{\pi}_a(l,\eta)=\pi_a(l,\eta l)$ and $\hat{\varepsilon}(l,\eta)=\varepsilon(l,\eta l)$ in the (l,η) space.

benefit of large brokers is dominant, leading the demand elasticity to increase in l through the first argument of $\varepsilon(l, \eta l)$. When η is large, the congestion cost at large brokers is dominant, leading the demand elasticity to decrease in l through the second argument of $\varepsilon(l, \eta l)$.

5 Model

I consider a search model with tenants, landlords, and brokers (or agents interchangeably). A tenant directs search for a rental residence, while a broker with multiple listings from landlords look for tenants. Time is discrete. A period that denotes the lease term is a year, while a round in rental search is a week. The agent size of a broker is observable, which allows the choices to be contingent on the agent size. I focus on the steady state equilibrium in the analysis. I introduce the tenant preference, the broker's problem and the landlord problem in Sections 5.1, 5.2 and 5.3 respectively and report the optimality conditions in Section 5.4. The determinants of the agent distribution are summarized in Section 5.5. I introduce the equilibrium concept in Section 5.6.

5.1 Tenant's Problem

A tenant has two states, searching or matched. In the searching state, she can contact one broker at most for a chance of meeting with a listing. It doesn't matter whether a tenant searches by listing or agent, because she is *ex ante* indifferent in equilibrium. When a tenant receives a listing offer, she observes her private value

$$\tilde{v} = vq, \;\; v \sim F(v) \tag{7}$$

with which a tenant decides whether to accept the offer. The house value is increasing in the rental quality q, which is exogenous in the model. The taste shock v captures that an on-site visit reveals more information about rental quality and it is $i.i.d.$ across tenants and units. Search is costly. If a tenant searches for a rental of quality q, she pays a sunk cost qc_b for each round of search. This reflects the cost of time and short-term residence (hotel, Airbnb etc.).[28]

The annual flow value of a matched tenant is $z(v, q, R) = vq - R$, which consists of the private value vq net of the annual rent R. The rent R in equilibrium depends on the agent size l and the rental quality q, but not the shock v. Denote $V_b(z, q)$ and $U_b(q)$ to be the value of a matched tenant and of a searching tenant for a rental of quality q respectively. Once a tenant is matched, she enjoys a constant flow z each period until a separation shock hits and the tenant goes back to the searching state. The value $V_b(z, q)$ is expressed recursively as follows.

$$V_b(z, q) = z + \beta[\delta V_b(z, q) + (1 - \delta) U_b(q)] \tag{8}$$

where $\beta < 1$ is the discounted factor between two leasing terms and δ is the continuation probability.

A broker charges a constant share $\tau > 0$ of the annual rent R as the cost of service, which is paid only when there is a deal. To facilitate the discussion later on the listing option as no-fee or with-fee, I assume $\tau_b \in [0, \tau]$ is commission rate paid by a tenant, with the remainder $\tau_L = \tau - \tau_b$ paid by a landlord. The tenant

[28] The assumption that the search cost is proportional to the housing quality captures that tenants for higher-tier rentals tend to have higher cost of time and to choose more expensive temporary residence. The product form vq allows me later to separate the housing from the agent impacts in the analysis.

search value in submarket l has the following form.

$$U_b(l,\theta_l,q) = \underbrace{-qc_b}_{\text{Search Cost}} + \pi_b(l,\theta_l) E \max\{\underbrace{-\tau_b R + V_b(z(v,q,R),q)}_{\text{Accept a Match}}, \underbrace{\beta_s U_b(q)}_{\text{Reject a Match}}\} + [1-\pi_b(l,\theta_l)] \underbrace{\beta_s U_b(q)}_{\text{No Match}} \quad (9)$$

where $\beta_s < 1$ is the discount factor between two search rounds and $U_b(q) = \max_l U_b(l,\theta(l),q)$ is the maximum search value. A tenant takes as given the endogenous tenant matching probability $\pi_b(l,\theta_l)$ that depends on the tenant-agent ratio θ_l. With probability $\pi_b(l,\theta_l)$, a searching tenant receives a listing and has two options: (1) to accept a match and pay the broker's fee, or (2) to reject and wait until next round for a better match. With probability $1-\pi_b(l,\theta_l)$, no match arrives. Because the option term $V_b(z(v,q,R),q) - \beta_s U_b(q)$ is increasing in v, the tenant acceptance rule is reduced to a threshold. I define the reserve value in submarket l as $\tilde{v}_R(\cdot)$ at which accepting and rejecting a match is indifferent.

$$-\tau_b R(l,q) + V_b(z(\tilde{v}_R(\cdot),q,R(l,q)),q) = \beta_s U_b(q) \quad (10)$$

The type of rentals q demanded by a tenant is exogenously determined (by age, family size etc.), thus not a choice variable in the model. I assume perfect mobility of tenants, which requires that the search value be equalized across brokers.

$$U_b(l,\theta(l),q) = U_b(q) \quad (11)$$

I show in Section 5.4 that the equilibrium tenant-agent ratio $\theta(l)$ does not depend on q.

5.2 Broker's Problem

Landlords delegate the rent choice to brokers. The assumption is motivated by the fact that brokers are more market-informed than landlords. Define the quality-adjusted rent $R_a = R/q$ as the ratio of the listed rent R and the rental quality q. Its log form is additive, consistent with the empirical rent decomposition in Section 3.

To capture the broker's listing incentive to price high and match fast, the objective of a broker of capacity l maximizes the expected listing value of a rental of quality q by choosing R_a. The broker earns τ share of the rent R as the commission in a closed deal. The rent choice balances the rent-liquidity trade-off (Yinger, 1981) between the rent return R and the listing matching probability $\pi_a(l,\hat{\theta}_l)$ that is decreasing in rent.[29] The agent listing value of a quality-q rental by signing a one-year lease is

$$\underbrace{\sum_{y=0}^{l} \frac{e^{-\hat{\theta}}\hat{\theta}^y}{y!} \cdot \frac{y}{l} \cdot R_a q}_{\text{Local Excess Supply}} + \underbrace{\sum_{y=l+1}^{\infty} \frac{e^{-\hat{\theta}}\hat{\theta}^y}{y!} \cdot 1 \cdot R_a q}_{\text{Local Excess Demand}} = \pi_a(l,\hat{\theta}) \cdot R_a q$$

where $\hat{\theta} = \theta[1 - F(\tilde{v}_R(\cdot))]$ is the effective tenant-agent ratio to measure the arrival rate of a tenant who will accept a match. Given the acceptance rule $\tilde{v}_R(R_a,q)$, a broker of capacity l solves

$$\hat{\Pi}_a(l,\theta_l,q) = \max_{R_a,\tilde{l}\le l} \underbrace{\pi_a(\tilde{l},\hat{\theta}(\theta_l,\tilde{v}_R(R_a,q)))}_{\text{Listing Matching Prob.}} \cdot \underbrace{R_a q}_{\text{Rent}}, \text{ with } \hat{\theta}(\theta_l,v_R) = \theta_l[1-F(v_R)] \quad (12)$$

The equilibrium quality-adjusted rent R_a depends on the agent size l, which captures the agent impact

[29] As will be shown in Section 5.4, the tenant acceptance rule is increasing in rent. Together with Lemma 3, I can show that the local housing demand is decreasing in rent.

on the listed rent. A broker has the option to set the rationing threshold $\tilde{l}$, given the constraint of listing capacity l. I guess and verify in Section 6 that $\hat{\Pi}_a(l, \theta(l), q)$ is increasing in l, so a broker will not hoard listings. A broker may post multiple listings of different rental quality, which requires tracking the quality distribution by the broker. I show in Section 5.4 that R_a and v_R do not depend on q. With the listing value linear in q, it is thus sufficient to track the mean rental quality $q(l)$ of a broker.

Remark. The optimal rent can be interpreted as a Markov solution that treats inventory and newly arrived listings identically and avoids tracking the whole inventory history of listings as the individual agent state. It thus suffices to make a single choice of R_a. The setting in which brokers post multiple listings nests the special case of the owner listing where a broker is restricted to serve one landlord only.

The micro-foundation for the search technology is crucial to the modeling of listing pricing decision, because it captures the correct marginal effect of the rent choice on the listing matching probability in the context. Assuming a matching probability that increases in the agent size is insufficient, leading to the misspecification of the marginal effect and the quality-adjusted rent as a function of the agent size.[30] □

5.3 Landlord's Problem

A landlord with a house of quality q meets a broker at random in each round of search and decides whether to accept a take-it-or-leave-it offer from the broker to rent out the house. I consider two types of landlords, sophisticated and naive. A sophisticated landlord is selective on the listing brokers, while a naive landlord accepts any broker she meets. Introducing the naive type allows me to calibrate the model better and the model properties in Section 6 does not depend on the assumption.

The objective of a sophisticated landlord is to choose an acceptance rule $\chi_L(l, q) \in \{0, 1\}$. The outside option of not renting out a house ($\chi_L = 0$) is to stay off the market and to receive $c_{v0} + c_{v1}q$ which captures the owner occupancy value or the rental vacancy cost. c_{v0} and c_{v1} are parameters to be calibrated. If a landlord chooses the renting option ($\chi_L = 1$), the occupancy value is forgone, whether a tenant is found or not. If a tenant is not found, a landlord gets zero. If a tenant is found, a landlord receives the rent payment. Then, the matched pair is replaced by a new pair of landlord and tenant. The landlord listing value with an l-size broker is

$$\hat{\Pi}_L(l, \theta_l, q) = [1 - (1 - \beta\delta)\tau_L]\hat{\Pi}_a(l, \theta_l, q) \tag{13}$$

If a landlord chooses the renting option, a listing is posted in the next search round. When a tenant is found, a landlord pays $\tau_L \in [0, \tau]$ share of the annual rent as the commission to the broker. As a matched tenant may renew the lease with probability δ, the effective fee in the first term of the lease is $(1 - \beta\delta)\tau_L$. The acceptance rule to maximize the value of a sophisticated landlord is

$$\chi_L(l, q) \in \arg\max_{\chi_L \in \{0,1\}} \chi_L \underbrace{\hat{\Pi}_L(l, \theta(l), q)}_{\text{Renting Option}} + (1 - \chi_L) \underbrace{(c_{v0} + c_{v1}q)}_{\text{Owning Option}} \tag{LL}$$

[30] To show that a generic matching probability that increases in the agent size is *not* sufficient for the modeling purpose, I apply the listing matching probability from Gilbukh and Goldsmith-Pinkham (2019) to the rental market setting as an example, $\pi_a^{alt}(l, \hat{\eta}) = 1 - exp(-\nu(l)\hat{\eta})$. $\hat{\eta}$ is the effective tenant-listing ratio. $\nu(l)$ is increasing to capture the positive impact of the agent size l on the matching probability. By solving the listing pricing problem with the replaced listing matching probability, I can show that the optimal quality-adjusted rent is increasing in $\nu(l)\hat{\eta}$. At the equilibrium tightness $\hat{\eta}(l)$, it is increasing in the agent size l. The correlation of the quality-adjusted rent and the agent size based on the *ad hoc* matching probability is opposite to what my model predicts and cannot rationalize the negative correlation in the data. The issue is that the elasticity of the matching probability with respect to $\hat{\eta}$ (or equivalently the demand elasticity) is assumed to be globally decreasing in l and $\hat{\eta}$, but I show in Section 4 that the listing matching probability I derive with micro-foundation invalidates the *ad hoc* assumption. As listing pricing in Gilbukh and Goldsmith-Pinkham (2019) is exogenous, their assumption on the matching probability does not affect the analysis on liquidity.

The landlord choice of brokers trades off the renting and the owning values. I normalize to zero the owner's operating costs (maintenance, taxes, insurance) that do not affect the landlord choice.

Remark. The agent size of a broker at the meeting round may differ from the agent size at the listing round. The agent size of a broker in the listing round is a random variable. In problem (LL), the uncertainty faced by landlords can be resolved by the Law of Large Numbers. Under the invariant agent distribution, a full contingency plan can be set up such that any landlord who accepts a broker of an arbitrary agent size l in the meeting round can be served in the listing round by a broker of the same agent size l. □

5.4 Optimality

For brevity, I suppress index l and focus on an arbitrary submarket. Rewrite the tenant values as follows.

$$\begin{aligned}(1-\beta\delta)V_b(z,q) &= z+\beta(1-\delta)U_b(q),\ \ z=qv-R \\ (1-\beta_s)U_b(l,\theta_l,q) &= -qc_b+\pi_b(l,\theta_l)E\max\{-\tau_b R+V_b(z,q)-\beta_s U_b(q),0\}\end{aligned} \tag{14}$$

Because the tenant values are proportional to q, I can separate the housing and the agent impacts on the listed rent. I show that v_R and $R_a = R/q$ are independent of q.

5.4.1 Reservation Equation

The equation about the reserve value (10) is simplified to the following form.

$$qv_R = \hat{\tau}_b R+\hat{\beta}_s\delta(1-\beta_s)U_b(q),\ \text{ where } \hat{\tau}_b = 1+(1-\beta\delta)\tau_b,\ \hat{\beta}_s=\beta+\frac{\beta_s-\beta}{\delta(1-\beta_s)} \tag{15}$$

Using integration by parts and (15), I obtain the *reservation equation* that uniquely solves a reserve value v_R, given (l,θ_l,R_a).

$$\underbrace{v_R-\hat{\tau}_b R_a}_{\text{Accept a Match}} = \underbrace{-\hat{\beta}_s\delta c_b+\frac{\hat{\beta}_s\delta}{1-\beta\delta}\pi_b(l,\theta_l)\int_{v_R}^{\infty}[1-F(v)]dv}_{\text{Option Value: Reject and Wait for a Future Match}} \tag{RE}$$

This is the indifference condition of a marginal tenant ($v=v_R$). Note that (RE) is independent of quality q. The left side is the net flow payoff of accepting a match, while the right side is the flow payoff of rejecting a current match, *i.e.*, the option value of receiving a new match net of the search cost in the next round. As the left side is increasing in v_R and the right side is decreasing in v_R, there is a unique $\tilde{v}_R(l,\theta_l,R_a)$ to solve the equation. Given (l,θ_l), $\tilde{v}_R(l,\theta_l,R_a)$ is increasing and convex in R_a.

5.4.2 Price Setting Equation

The first order condition of a broker's maximization problem (12) leads to the *price setting equation* in which the optimal rent balances the rent return and the listing duration.[31]

$$\hat{\tau}_b R_a = \underbrace{\frac{\overbrace{r(v_R)}^{\text{Surplus to Extract}}}{\varepsilon(l,\theta_l[1-F(v_R)])}}_{\text{Demand Elasticity}}\underbrace{\left(1+\frac{\hat{\beta}_s\delta}{1-\beta\delta}\pi_b(l,\theta_l)[1-F(v_R)]\right)}_{\text{Tenant Response to Rent}} \text{ with } \varepsilon(l,\theta)=\frac{\partial N(l,\theta)}{\partial\theta}\frac{\theta}{N} \tag{PS}$$

[31] I show in Section 4 that π_a in equation (12) is decreasing in R_a and that the first order condition is sufficient.

where $r(v) = [1-F(v)]/f(v)$ is the inverse hazard rate of v. Note that (PS) is independent of q and has three components. First, the inverse hazard rate measures how much surplus a broker can extract from a tenant *ex ante*. Second, the elasticity measures how sensitive a broker's demand is to the market condition. As there are many brokers instead of one who coordinate tenant search, a 1% increase in the tenant-agent ratio is associated with less than 1% increase of a broker's demand ($\varepsilon < 1$, Lemma 2), leading to a rent markup. The last term captures the tenant response to rent. As the response of the reserve value to 1 unit increase in $\hat{\tau}_b R_a$ is less than 1%, a broker optimally increases rent above $r(v_R)$. I show in Section 7 that if $v \sim exp(\lambda_v)$, the quality-adjusted rent dispersion across brokers is purely attributed to the demand elasticity, while the other two components are constant in equilibrium.

5.4.3 Landlord Choice of Brokers

In problem (LL), a landlord chooses to rent out, if and only if the renting value outweighs the owning value, $\chi_L(l,q) = \mathbb{I}\{\hat{\Pi}_L(l,\theta(l),q) \geq c_{v0} + c_{v1}q\}$. Given the landlord choice, the feasible rental set of an l-size broker is defined as

$$\mathcal{Q}(l) = \{q : l \in \mathcal{L}(q)\} \tag{16}$$

where $\mathcal{L}(q) = \{l : \chi_L(l,q) = 1\}$ is the set of brokers selected by a landlord with a rental of quality q.

5.5 Agent Distribution

To derive an endogenous agent distribution, I characterize how the agent size transits across two consecutive rounds of search. If a broker of size l has no incoming listings ($l' = 0$), she is replaced by a new broker with the initial size drawn from an exogenous distribution $Pr^N(l)$ that will be estimated from the data. If a broker of size l receives $l' \geq 1$ listings, she continues to operate the business with the agent size transition denoted by $Pr^R(l'|l)$. With random meeting of landlords and brokers in a large market, I can approximate $Pr^R(l'|l)$ by a Poisson distribution and express the agent size transition $Pr(l'|l)$ as follows.[32]

$$\begin{aligned} Pr(l'|l) &= Pr^R(l'|l) + Pr^R(l'=0|l) \cdot Pr^N(l'), \text{ for } l, l' \geq 1 \\ \text{where } Pr^R(l'|l) &= \frac{e^{-\gamma(l)}\gamma(l)^{l'}}{(l')!}, \ \gamma(l) = \Gamma[\phi Pr(q \in \mathcal{Q}(l)) + 1 - \phi] \end{aligned} \tag{17}$$

The listing-agent ratio $\gamma(l)$ is the aggregate landlord-agent ratio Γ multiplied by the weighted mean of the agent probability of listing a rental $\phi Pr(q \in \mathcal{Q}(l)) + 1 - \phi$. ϕ is the share of the sophisticated landlords. I show in Section 6 that $\gamma(l)$ is increasing, so a large broker is expected to be large in the future search. In calibration, I generalize the transition probability $Pr^R(l'|l)$ to the negative binomial distribution which introduces a stopping parameter $r > 0$ and nests the Poisson distribution in (17) as a special case ($r = \infty$).[33] The extension relaxes the constraint on the Poisson distribution that the mean and the variance are identical, allowing me to explain the excess dispersion in the empirical agent distribution. The agent distribution in

[32] Denote N_L and A to be the number of landlords and brokers, with $\Gamma = N_L/A$. For an l-size broker, the probability of being selected by a landlord is $1/A$. The agent listing probability is p_l. l' rentals out of N_L will be listed by the broker. Put together,

$$Pr^R(l'|l) = \binom{N_L}{l'}\left(\frac{p_l}{A}\right)^{l'}\left(1 - \frac{p_l}{A}\right)^{N_L L - l'} \to \frac{e^{-\gamma(l)}\gamma(l)^{l'}}{(l')!}, \ p_l = \phi Pr(q \in \mathcal{Q}(l)) + (1-\phi)$$

[33] The stopping parameter r in the negative binomial distribution ($NBin$) can be micro-founded and interpreted as the spare agent capacity not filled with listings. Denote the negative binominal distribution as $NBin(r, p_l)$ where r and p_l stands for the spare capacity and the listing arrival probability respectively. I can show that if p_l is a specific function $\gamma(l)$, $NBin$ is

the next round $a(l')$ is updated as follows.

$$a(l') = \sum_{l \geq 1} Pr(l'|l)a(l), \text{ for } l' \geq 1$$

As the agent distribution by the listing capacity and the rental quality $a(l,q) = Pr(q|l,\mathcal{Q})a(l)$ can be decomposed into the marginal distribution $a(l)$ and the conditional distribution $Pr(q|l,\mathcal{Q})$, it is sufficient to characterize the agent distribution of the listing capacity $a(l)$ and the landlord choice of brokers $\chi_L(l,q)$ (or the feasible rental set $\mathcal{Q}(l)$ equivalently).[34]

The number of brokers is endogenous, depending on the outside option of being a broker. When I calibrate the steady state equilibrium, the number of brokers is not separately identified from the aggregate landlord-agent ratio Γ. When conducting policy analysis, I consider the response of the brokerage sector by keeping the expected broker profit $\tau E_l[\hat{\Pi}_a(l,\theta(l),q(l))l]$ constant as the free entry condition to pin down the size of the brokerage sector after a policy change.

5.6 Directed Search Equilibrium

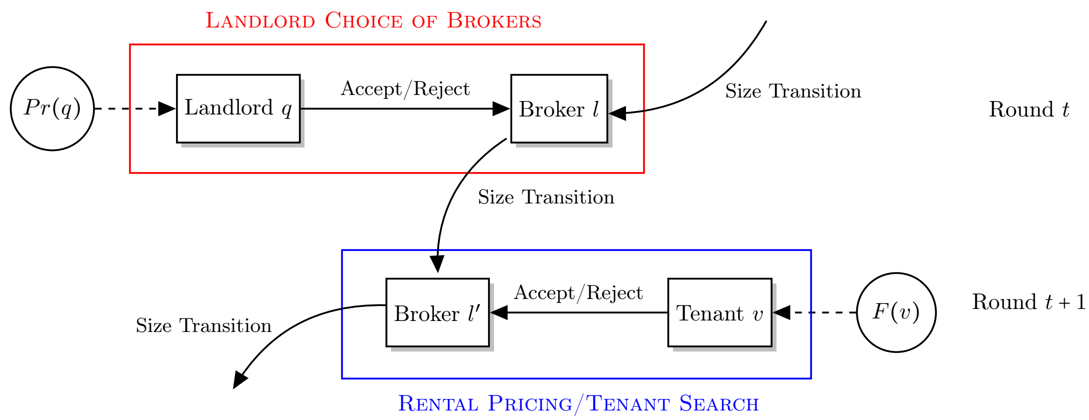


Figure 7: Illustration of the model from a rental's view. Endogenous choices and exogenous processes are represented by solid and dashed black lines respectively. Landlords, brokers and tenants are indexed by the rental quality q, the agent size l, and the taste shock v respectively.

In Figure 7, I illustrate from a rental's view how landlords and tenants are matched by brokers. On the supply side, a broker in a round of search expects random arrival of landlords. A landlord chooses whether to accept a broker's offer to rent out a house, based on the broker's listing capacity that is pre-determined. If the renting option is chosen, the listing will be posted in the next round of search. On the demand side,

degenerate to Poisson in the limiting case.

$$Pr^R(l'|l) = \binom{r+l'-1}{l'}(1-p_l)^r p_l^{l'}, \text{ with } p_l = \frac{\gamma(l)}{r+\gamma(l)}$$

$$mean(l'|l) = \frac{rp_l}{1-p_l} = \gamma(l), \; var(l'|l) = \frac{rp_l}{(1-p_l)^2} = \gamma(l)[1+r^{-1}\gamma(l)] \xrightarrow{r\to\infty} \gamma(l)$$

The transition matrix in (17) is the same except that $Pr^R(l'|l)$ is adapted to $l'|l \sim NBin\left(r, \frac{\gamma(l)}{r+\gamma(l)}\right)$. The extension can deal with finiteness of the data, while the Poisson benchmark provides basic intuition through the limiting case.

[34] Specifically, the conditional distribution $Pr(q|l,\mathcal{Q})$ is derived by Bayes rule.

$$Pr(q|l,\mathcal{Q}) = \frac{Pr(q|l,\mathcal{Q})Pr(q)}{\sum_q Pr(q|l,\mathcal{Q})Pr(q)} = \frac{\chi_L(l,q)Pr(q)}{\sum_q \chi_L(l,q)Pr(q)} = \begin{cases} \frac{Pr(q)}{\sum_{q\in\mathcal{Q}(l)} Pr(q)} & \text{if } q \in \mathcal{Q}(l) \\ 0 & \text{otherwise} \end{cases}$$

brokers of different listing capacity expect random arrival of tenants. When there is a match, the matched landlords and tenants go off the market and are replaced by new pairs to be matched in the future. If no match is found, landlords and tenants start over the process. From a rental's view, the assumption of listing in the next round makes it clear how a broker's supply and demand are determined by breaking up the simultaneous determination of the supply and the demand. While the agent size of a broker may change in the meeting round (t) and in the listing round ($t+1$) under the assumption, in the steady state equilibrium, the uncertainty can be resolved in the landlord problem by setting up a full contingency plan.

To define the equilibrium, I focus on the tenant-listing ratio η instead of the tenant-agent ratio $\theta(l,\eta) = \eta l$ for comparison across the submarkets $l \in \mathbb{L} = \{1, 2, \ldots, \mathcal{L}\}$. I define the equilibrium objects in the (l,η) space and denote them with a hat symbol $\wedge$. The equilibrium is defined as follows.

Definition 5.1. Directed Search Equilibrium. Given the aggregate landlord-agent ratio Γ, the aggregate tenant-landlord ratio Θ, the rental quality distribution $Pr(q)$ and the initial size distribution $Pr^N(l)$, a directed search equilibrium consists of

(a) the quality-adjusted rent $\hat{R}_a(l,\eta)$, the reserve value $\hat{v}_R(l,\eta)$, the choice on brokers $\chi_L(l,q)$

(b) the quality-adjusted search value $\hat{u}_b(l,\eta)$, the tenant-listing ratio $\eta(l)$

(c) the listing-agent ratio $\gamma(l)$, the agent size transition $Pr(l'|l)$, the agent distribution $a(l)$

such that

(1) Given (l,η), equations (RE) and (PS) jointly solve for $\hat{R}_a(l,\eta)$ and $\hat{v}_R(l,\eta)$.

(2) $\chi_{LL}(l,q)$ solves the landlord problem (LL).

(3) Given $\eta(l)$, tenants are indifferent.

$$\hat{u}_b(l_1,\eta(l_1)) = \hat{u}_b(l_2,\eta(l_2)), \text{ with } \hat{u}_b(l,\eta) = \frac{\hat{v}_R(l,\eta) - \hat{\tau}_b \hat{R}_a(l,\eta)}{\hat{\beta}_s \delta(1-\beta_s)}, \ \forall l_1, l_2 \in \mathbb{L} \tag{18}$$

(4) Market clearing of tenants

$$\textstyle\sum_l \eta(l)a(l)l = B \sum_l a(l)l, \text{ with } B = \frac{\Theta}{E_l \gamma(l)/\Gamma} \tag{19}$$

(5) $a(l)$ is consistent with $Pr(l'|l)$ and $\gamma(l)$ at the steady state.

$$a(l') = \textstyle\sum_l Pr(l'|l)a(l) \tag{20}$$

Condition 1 says that reserve value and rent are optimal. Condition 2 indicates landlord choice on brokers is optimal. Conditions 3 and 4 that make up $\mathcal{L}$ equations of $\eta(l)$ are indifference and market clearing conditions. As the unconditional probability of a landlord who accepts to list a rental is $\gamma(l)/\Gamma$, the tenant-listing ratio B is greater than the tenant-landlord ratio Θ. Condition 5 defines the agent distribution at the steady state.

6 Equilibrium Characterization

After discussing the uniqueness of the equilibrium in Section 6.1, I focus on the rental demand in Section 6.2 and examine the quality-adjusted rent gradient. In Section 6.3, I switch to the rental supply and discuss how the landlord choice of brokers is related to the dispersion of rental quality.

6.1 Unique Equilibrium and Tenant-Agent Ratio

Following the auction literature (Krishna, 2009), I assume that $F(v)$ has a weakly increasing hazard rate. In addition, I impose a restriction on the second derivative of the hazard function.

Assumption 1. The hazard rate $h(v)$ of $v \sim F(v)$ is weakly increasing and weakly concave.

I maintain the assumption for the rest of the paper.[35] Equations (RE) and (PS) form two equations of (R_a, v_R). While equation (RE) shows that R_a is increasing in v_R, equation (PS) under Assumption 1 implies that R_a is decreasing in v_R.[36] Hence, there is a unique pair of (R_a, v_R) to solve the equation system. Together with the equilibrium objects in Section 5.6, there is a unique equilibrium that describes the rental market. In addition, the following lemma guarantees that the vector of the tenant-listing ratio $\{\eta(l)\}$ is a stable solution to the system of $\mathcal{L}$ equations made up by equations (18) and (19).

Lemma 4. *The quality-adjusted search value $\hat{u}_b(l, \eta)$ is decreasing in η.*

Proof. See Appendix A.4. □

The lemma says that the search value is decreasing in the tenant-listing ratio due to more competition among tenants. Take the case of two submarkets with $l_1 < l_2$ as an example to see why $\{\eta(l)\}$ is stable. Start with a disequilibrium $\hat{u}_b(l_1, \eta_1) < \hat{u}_b(l_2, \eta_2)$. Tenants in submarket l_1 will find it profitable to go to submarket l_2. Then, η_2 increases and η_1 decreases. As $\hat{u}_b(l, \eta)$ is decreasing in η, $\hat{u}_b(l_1, \eta_1)$ increases and $\hat{u}_b(l_2, \eta_2)$ decreases. The equilibrium is reached when there is no profitable deviation, *i.e.* $\hat{u}_b(l_1, \eta_1) = \hat{u}_b(l_2, \eta_2)$.[37] In the following proposition, I show how tenants are distributed across the submarkets.

Proposition 6.1. *The tenant-agent ratio $\theta(l)$ and the effective tenant-agent ratio $\hat{\theta}(l)$ are increasing in l.*

Proof. See Appendix A.5. □

Proposition 6.1 says that large agents attracts more incoming tenants per agent than small agents and expect more tenants to accept the listings. The proposition does not directly imply an increasing tenant-listing ratio $\eta(l) = \theta(l)/l$, which depends on how fast $\theta(l)$ increases relative to l. I prove in next section that if certain conditions hold, $\eta(l)$ is locally increasing. The proof relies on building a random search equilibrium as the reference point of the directed search equilibrium.

[35] Many distributions satisfy the assumption, including the exponential distributions, and the Gamma or the Weibull distributions with the shape parameter greater than 1.

[36] Using Assumption 1, Lemmas 2 and 3, I can show that the first derivative of the agent problem is decreasing in R_a, indicating that the problem is concave and the first order necessary condition is also sufficient.

[37] For the general case with a finite number of submarkets, an iterative method is used to sequentially approach the equilibrium tenant-listing ratios in a similar way as in the case of two submarkets.

6.2 Quality-Adjusted Rent Dispersion and Agent Size: a Random Search Perspective

I discuss when the tenant-listing ratio is locally increasing and characterize how the quality-adjusted rent depends on the agent size. First, I characterize the market tightness in a random search equilibrium that is outcome-equivalent to a constrained direct search equilibrium.[38] The *randomness* in random search refers to equal tenant matching probabilities. Matching with a listing is thus independent of the agent size. The no arbitrage condition of equal search values remains, so tenants have no incentive to deviate. Denote $\eta^{RS}(l)$ as the tenant-listing ratio implied in random search (RS) that solves

$$\hat{\pi}_b(l_1, \eta^{RS}(l_1)) = \hat{\pi}_b(l_2, \eta^{RS}(l_2)),\ \forall l_1, l_2 \in \mathbb{L},\ \sum_{l \in \mathbb{L}} \eta^{RS}(l) a(l) l = B \sum_l a(l) l$$

where B and $a(l)$ are evaluated at the equilibrium values. With equations (RE) and (15), the no arbitrage condition implies that R_a and $\tilde{v}_R$ in random search are constant across submarkets. The random search equilibrium is outcome-equivalent to a constrained directed search equilibrium where R_a is restricted to be constant across submarkets.[39] I want to show that once the constraint is relaxed, large and small brokers differ in their incentive to deviate from the constant level of rent. To see the point, I introduce the probability of local excess supply (ES) conditioning on a successful match

$$Pr^{ES}(l, R_a) = \frac{Pr(y < l | l, R_a)}{\hat{\pi}_b(l, \hat{\eta}^{RS}(l))},\ \text{where } Pr(y < l | l, R_a) = \sum_{y=0}^{l-1} \frac{exp(-\hat{\theta})\hat{\theta}^y}{y!},\ \hat{\theta} = \hat{\eta}^{RS}(l) l \qquad (21)$$

where $\hat{\eta}^{RS}(l)$ is the effective number of tenants per listing. The denominator $\hat{\pi}_b(l, \hat{\eta}^{RS}(l))$ is the average probability of a tenant meeting an acceptable listing, while the numerator $Pr(y < l | l, R_a)$ is the probability of a sub-event that the meeting with an acceptable listing happens when there is local excess supply.[40] If $Pr^{ES}(l_1, R_a) < Pr^{ES}(l_2, R_a)$ for $l_1 < l_2$ holds, tenants who go for the brokers with larger listing capacity are less likely of being rationed. Large brokers are thus better to coordinate tenant search. The differential in the coordinating capacity is the key to show that the quality-adjusted rent is decreasing in the agent size, which rationalizes Fact 2 about the agent impact in Section 3. For $l_1 < l_2$, let $S_R(l_1, l_2)$ be an interval containing the optimal rent $\hat{R}_a(l_i, \eta(l_i))$, $i = 1, 2$. Under the following conditions, I show that the tenant-listing ratio $\eta(l)$ is locally increasing and the quality-adjusted rent is decreasing.

Proposition 6.2. *For $l_1, l_2 \in \mathbb{L}$ and $l_1 < l_2$, if (1) $\hat{\pi}_b(l, \eta)$ increases in l, and (2) $Pr^{ES}(l_1, R_a) < Pr^{ES}(l_2, R_a)$ for $R_a \in S_R(l_1, l_2)$, then in the directed search equilibrium,*

(a) large brokers expect more tenants per listing: $\eta(l_1) < \eta(l_2)$

(b) large brokers prefer lower quality-adjusted rents: $\hat{R}_a(l_1, \eta(l_1)) > \hat{R}_a(l_2, \eta(l_2))$

Proof. See Appendix A.6. □

[38] There are two reasons to characterize a random search equilibrium as the baseline. First, I can always find a random search version of a directed search model, with the random search counterpart with an exogenous matching probabilities. Second, a random search equilibrium serves as a baseline to separately characterize v_R and R_a in a sequential way, instead of solving them simultaneously from equations (RE) and (PS).

[39] Note that the constant rent restriction in the directed search equilibrium together with the no arbitrage condition of equal search value leads to a constant reserve value and a constant tenant matching probability by (RE) and (15). There are $\mathcal{L} - 1$ degrees of freedom, so the level of R_a is undetermined.

[40] The listing matching probability with an accepting tenant is $\hat{\pi}_a(l, \hat{\eta}^{RS}(l))$, implying the *average* probability of a tenant meeting an acceptable listing is $\hat{\pi}_b(l, \hat{\eta}^{RS}(l)) = \hat{\pi}_a(l, \hat{\eta}^{RS}(l))/\hat{\eta}^{RS}(l)$ by (6). The average probability $\hat{\pi}_b(l, \hat{\eta}^{RS}(l))$ is *not* equal to what a tenant perceives to be the probability $\hat{\pi}_b(l, \eta^{RS}(l))[1 - F(\tilde{v}_R)]$ of meeting an acceptable listing. The difference arises, because a tenant has the option to reject. In a large market, a broker infers the average number of accepting tenants from $\hat{\eta}^{RS}(l)$, so the acceptance probability $1 - F(\tilde{v}_R)$ kicks in non-linearly in the probability. A tenant does not make inference from the market perspective, but regards the listing meeting and the tenant taste shock as independent events.

Condition 1 says that given the market tightness, tenants going for large brokers have a higher tenant matching probability. As shown in Figure 6, the condition holds in general. Condition 2 says that in random search, tenants going for large brokers are coordinated better, which is reflected by a higher conditional probability of local excess supply.[41] I maintain these two conditions in the rest of the paper.

To understand why Condition 2 is needed for the decreasing quality-adjusted rent, I show in the proof of Proposition 6.2 that the conditional probability $Pr^{ES}(l, R_a)$ is equal to $\hat{\varepsilon}(l, \hat{\eta}^{RS})$. The ability to coordinate tenant search is thus associated with the demand elasticity which is inversely related to the rent choice by equation (PS). The demand elasticity $\hat{\varepsilon}(l, \hat{\eta})$ is not globally increasing in l (Figure 6). Besides the coordinating capacity, tenant congestion is another factor contributing to the dispersion of quality-adjusted rent. In Figure 6, the demand elasticity $\hat{\varepsilon}(l, \hat{\eta})$ is decreasing in the effective tightness $\hat{\eta}$, meaning that the quality-adjusted rent should be higher in more congested submarkets.

In equilibrium, whether large brokers are better to coordinate tenant search depends on the effective tenant-listing ratio $\hat{\eta}$, or tenant congestion. When $\hat{\eta}$ is low, large brokers may coordinate tenant search better than small brokers (as $\hat{\varepsilon}(l, \hat{\eta})$ is increasing in l). This is the case I show to be consistent with the data. In the other case where $\hat{\eta}$ is high, small brokers may coordinate tenant search better, leading to a locally increasing rent gradient.

To summarize, there is a trade-off between the capacity benefit and the congestion cost; tenant congestion at larger brokers will decrease the capacity benefit more. The reason why the quality-adjusted rent decreases in the agent size is that the capacity benefit remains large and the tenant congestion is limited for large brokers. I summarize the implications of Proposition 6.2 in the following corollary.

Corollary 6.3. *In the directed search equilibrium, the larger the agent size ($l_1 < l_2$),*

(a) the lower the reserve value: $\hat{v}_R(l_1, \eta(l_1)) > \hat{v}_R(l_2, \eta(l_2))$

(b) the smaller the tenant matching probability: $\hat{\pi}_b(l_1, \eta(l_1)) > \hat{\pi}_b(l_2, \eta(l_2))$

(c) the higher the effective tenant-listing ratio: $\hat{\eta}(l_1) < \hat{\eta}(l_2)$

(d) the larger the listing matching probability: $\hat{\pi}_a(l_1, \hat{\eta}(l_1)) < \hat{\pi}_a(l_2, \hat{\eta}(l_2))$

(e) the greater the landlord listing value: $\hat{\Pi}_L(l_1, \theta(l_1), q) < \hat{\Pi}_L(l_2, \theta(l_2), q)$

Proof. See Appendix A.7. □

Because the quality-adjusted rent is decreasing in the agent size, a tenant optimally lowers the reserve value when choosing a large broker. As the directed search equilibrium relaxes the constraint of the equal tenant matching probabilities in random search, more tenants will go for large brokers in response to the decreasing rent gradient across submarkets. With more tenants in direct search going for large brokers, the competition among tenants tightens and the tenant matching probability thus decreases.

From a broker's view, the number of accepting tenants per listing is increasing in the agent size, because the tenant-listing ratio is higher and the rejection threshold is lower for large brokers. As brokers benefit from tighter competition among tenants (Lemma 3), the listing matching probability is increasing in the agent size and a broker will list up to the capacity. As a result, the expected listing time is decreasing in the agent size, consistent with Fact 2 about the negative correlation between the residual listing duration and

[41] Condition 1 is stronger than Lemma 3 in which $\pi_b(l, \theta)$ globally increases in l (with a fixed θ). When η is not too large, Condition 1 holds (See Figure 6). In Appendix Figure C.15, I show graphically the response of $Pr^{ES}(l; R_a)$ to R_a and its sensitivity to B. In calibration, Condition 2 holds.

the agent size. Last, I show that a rental listed by a larger broker yields a higher landlord listing value, as a broker with greater listing capacity can coordinate tenant search better and have a listing go off the market faster. While the agent distribution summarizes how frictional the rental market is, the difference of the landlord listing values across brokers measures how much the search friction can be reduced by expanding the listing capacity.

6.3 Rental Quality Dispersion and Agent Size: Landlord Choice of Brokers

I explain how the landlord choice on brokers is related to the rental quality dispersion, leading to a prediction consistent with Fact 3 in Section 3.1. As the landlord listing value $\hat{\Pi}_L(l, \theta(l), q)$ is increasing in l (Corollary 6.3), I simplify the set of acceptable brokers $\mathcal{L}(q)$ to a threshold function $\hat{L}(q)$ in the landlord problem (LL) and characterize $\hat{L}(q)$ in the following lemma.

Lemma 5. *Brokers with $l \geq \hat{L}(q)$ are accepted. If $c_{v0} > 0$ and c_{v1} is sufficiently small, $\hat{L}(q)$ is decreasing.*

Proof. See Appendix A.8. □

The condition $c_{v0} > 0$ is necessary to generate the rental quality dispersion. If $c_{v0} = 0$, there is no quality dispersion across submarkets. The condition on c_{v1} disciplines the sign of the correlation between the rental quality and the agent size.[42] The inequality $l \geq \hat{L}(q)$ shows that a landlord are selective on small brokers who may produce a lower listing value than the outside option. With the threshold $\hat{L}(q)$ decreasing in q, small brokers are accepted if q is sufficiently large. From a broker's view, the set of feasible rentals $\mathcal{Q}(l)$ is reduced to a threshold function $\hat{Q}(l)$. Landlords with $q \geq \hat{Q}(l)$ will accept an agent of size l. The landlord choice on brokers leads to a decreasing threshold $\hat{Q}(l)$. Using the rental quality distribution conditional on meeting a sophisticated landlord $Pr^S(q|l, \hat{Q})$, I derive the following proposition.

$$Pr^S(q|l, \hat{Q}) = \begin{cases} \frac{Pr(q)}{\sum_q Pr(q) \cdot \mathbb{I}\{q \geq \hat{Q}(l)\}} & \text{if } q \geq \hat{Q}(l) \\ 0 & \text{otherwise} \end{cases} \tag{22}$$

Proposition 6.4. *The mean rental quality $q(l) = \phi E(q|l, \hat{Q}) + (1 - \phi)E(q)$ is decreasing in the agent size l.*

Proof. See Appendix A.9. □

As $Pr^S(q|l_2, \hat{Q})$ first-order stochastic dominates $Pr^S(q|l_1, \hat{Q})$ for $l_1 < l_2$, the negative correlation between mean rental quality and agent size arises. Besides the coordinating role of large brokers in tenant search, I emphasize in Proposition 6.4 that large brokers enable the rentals in the low-quality tiers to participate in the rental market. The presence of large brokers is crucial to thicken the rental market by admitting more diverse rental supply, especially the affordable-tier rentals, to the market.

7 Calibration

7.1 Computing Algorithm

I externally calibrate the set of parameters $\mathcal{C}^{exog} = \{\mathcal{L}, \beta, \delta, \tau_b, \tau_L, c_b\}$ and the distributions $Pr^N(l)$, $F(v)$, $Pr(\ln q)$ that are pinned down independent of the computing algorithm. The set of internally calibrated pa-

[42] When c_{v1} is small, I show in the next proposition that the correlation between the rental quality and the agent size is negative. If c_{v1} is large and $c_{v0} + c_{v1}q$ as a function of q increases faster than $\hat{\Pi}_L(l, \theta(l), q)$, units in high-quality tiers will opt out of the rental market, leading to an increasing $\hat{L}(q)$ and a positive correlation between the rental quality and the agent size.

rameters $\mathcal{C}^{endo} = \{\beta_s, c_{v0}, c_{v1}, \Gamma, \phi, \Theta, r\}$ are chosen to minimize the model-data distance of certain moments. The model is scalable and identified up to a multiple of the agent distribution, so I normalize $\sum_l a(l) = 1$. I elaborate how to identify the parameters in the section.

Given the parameters, I solve the equilibrium at the steady state. The computing algorithm consists of an outer loop to iterate over the agent distribution $a(l)$ and an inner loop to solve for the vector of tightness $\{\eta(l)\}$. I start with an initial guess of the agent distribution $a(l)$ and the agent listing probability $\gamma(l)/\Gamma$. The probability is needed to construct an initial tenant-listing ratio B for the inner loop. I then use equations (RE) and (PS) to solve for the quality-adjusted rent $\hat{R}_a(l,\eta)$ and the reserve value $\hat{v}_R(l,\eta)$ and to derive the quality-adjusted search value $\hat{u}_b(l,\eta)$ by submarket. Using the indifference condition (18) to equate the search values across submarkets and the market clearing condition of tenants (19), I solve for $\eta(l), l \in \{1,\ldots,\mathcal{L}\}$ from the $\mathcal{L}$ number of equations. The uniqueness of the solution is due to Assumption 1, while the stability is guaranteed by Lemma 4. With $\eta(l)$, I derive the listing value $\hat{\Pi}_L(l,\theta(l),q)$ and the landlord choice on brokers $\chi(l,q)$ which pins down the listing-agent ratio $\gamma(l)$ and the agent size transition matrix $Pr(l'|l)$. To move to the next iteration, I update the agent distribution $a(l)$ using $Pr(l'|l)$ and equation (20), and the agent listing probability $\gamma(l)/\Gamma$. The algorithm stops when the change of $a(l)$ and $\gamma(l)/\Gamma$ in consecutive iterations are sufficiently close.

7.2 Calibrated Parameters and Distributions

I list the parameters to be calibrated in Table 6. The maximum agent size is set to $\mathcal{L} = 20$ which can cover more than 99% of the agents in the data. Increasing $\mathcal{L}$ further does not quantitatively improve the estimation, because the probability mass at the right tail converges to zero as $\mathcal{L}$ increases. The rental cash flow is discounted at $\beta = 0.98$ annually. Besides the preset parameters, I discuss how to calibrate the rest of parameters from the data.

Table 6: Calibrated Parameters

Parameter	Value	Internal	Description	Target/Source
Tenant				
λ_v	1	N	Parameter of $F(v)$	$v \sim exp(\lambda_v)$ with unbiased belief $E(v) = 1$
δ	0.78	N	Lease renewal rate	Turnover rate 22% (NYCHVS, 2017)
β	0.98	N	Discount factor, matched (year)	Preset parameter
β_s	0.919	Y	Discount factor, searching (week)	Dispersion of quality-adjusted rent
c_b	0.043	N	Tenant search cost	Weekly cost of short-term residence
Θ	0.872	Y	Aggregate tenant-landlord ratio	Mean of listing days on market
Agent and Landlord				
$\mathcal{L}$	20	N	Maximum agent size	> 99% of agent coverage
τ	0.10	N	Commission rate (total)	Industry norm, 8%-15%
τ_L	0.026	N	Commission rate (landlord)	Share of no-fee listings
c_{v0}	10,252	Y	Outside option of renting (level)	Mean of the mean quality distribution
c_{v1}	0.032	Y	Outside option of renting (slope)	Variance of the mean quality distribution
ϕ	0.186	Y	Share of sophisticated landlords	Gap of mean quality, listed vs all units
Γ	3.608	Y	Aggregate landlord-agent ratio	Mean of the agent distribution
r	3.899	Y	Stopping parameter in $NBin(r,\cdot)$	Variance of the agent distribution

Note: The search rounds are calibrated in weekly frequency and the lease terms are in annual frequency. The Column *Internal* indicates that parameters are not set explicitly in a closed form, but is instead chosen implicitly to match certain moments.

7.2.1 Externally Calibrated Parameters and Distributions

Commission paid by landlords τ_L and by tenants τ_b. As discussed in Fn.13, the total commission rate $\tau = \tau_{LL} + \tau_b$ of a broker ranges from 8.3% for an average rental to 15% for a luxury rental. The commission rate is non-disclosed, so I target $\tau = 10\%$ as a compromise. I set $\tau_L = 26\%\tau$ to match the fact that the share of no-fee listings is 26% (Table C.1). In the extension in Section 8.2.3, I endogenize the choice on τ_L and τ_b and discuss how the optimal allocation of broker's fee should vary across brokers.

Search cost c_b. I calibrate the total cost $c_b q$ per round of search to the weekly cost of short-term residence and excludes the broker's fee. The daily average rate of an average hotel room in Manhattan is \$280 in 2016.[43] The mean of the rental quality $q = \$3,804 \cdot 12\ months$ targets the average annual rent listed by brokers on StreetEasy in 2016. Putting together, the search cost is $c_b = \$280 \cdot 7\ days/(\$3,804 \cdot 12\ months) = 0.043$, meaning that the weekly search cost is 4.3% of the annual rent.

Lease renewal rate δ. I calibrate δ to match the mean turnover rate $1 - \delta$. Using the question on the move-in year in the New York City Housing Vacancy Survey in 2017, I calculate the residence years and focus on the renter households who resided for less than 20 years and signed a standard lease in NYC (1-year or 2-year contract). The criteria is to screen out the renter households in the rent-controlled units who are less able and thus less likely to move. With the control of renter and housing characteristics, I estimate a log-normal survival model of residence years to accommodate non-linear turnover hazard.[44] The turnover hazard in Appendix Figure C.16 has a hump shape in the length of lease, with the peak near 3.5 years of residence. I choose $1 - \delta = 0.22$, which is the hazard rate at the mean years of residence.

Initial size distribution $Pr^N(l)$. I estimate the distribution using the sub-group of brokers who list at least 1 unit in a year but are not present in the previous year in the data set. The distribution is more left-skewed than the empirical agent distribution.

Tenant value distribution $F(v)$. Given rental quality q, the distribution $F(v)$ is associated with the dispersion of idiosyncratic value $\tilde{v} = vq$ to capture the realized value after on-site visit. I assume $v \sim exp(\lambda_v)$ with $\lambda_v = 1$, so that tenants have unbiased expected value on the rental quality, $E(\tilde{v}) = q$.

Rental quality distribution $Pr(\ln q)$. To estimate $Pr(\ln q)$, I first estimate a hedonic rent model with the housing amenities and the location-date fixed effect (Model 3, Table 4) that captures the rent variation unrelated to the agent impact. Rental quality is defined as the predicted annual rent, *i.e.* a linear combination of unit features weighted by the estimated hedonic prices. The issue of using the distribution of the predicted rent as the rental quality is that the observed distribution is subject to the selection but $Pr(\ln q)$ is not. In the model, the selection bias results from the landlord choices on brokers. I overcome the selection issue in the data by defining $Pr(\ln q) \approx Pr(\ln q | l \geq 15)$ based on the sub-sample with $l \geq 15$, as the model predicts limited selection of brokers at the right tail of the agent distribution. This leads to an estimated distribution $Pr(\ln q)$ whose mean is lower than the mean of the unconditional distribution of the predicted log rent.[45]

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[43] See p.52 of the NYC Hotel Market Analysis Report by the NYC Department of City Planning, https://www1.nyc.gov/assets/planning/download/pdf/plans-studies/m1-hotel-text/nyc-hotel-market-analysis.pdf?r=a. Alternatively, home-sharing through Airbnb in Manhattan results in limited saving (7.3%) on the daily cost. See the news coverage from Hotel News Now on the NYC hotel market analysis by Smith Travel Research, http://www.hotelnewsnow.com/Articles/27295/STR-Airbnb-qualified-competitor-to-NYC-hotels.

[44] The control variables in the survival model includes the log household income, the log household size, the log householder age, immigration status of the householder, indicator of lease type (1- or 2-year), the housing type (single-family, condominium, cooperative), the borough of the housing unit.

[45] In Appendix Figure C.17, I show the estimated dostribution $Pr(\ln q)$ which I discretize into 100 equal-sized intervals.

7.2.2 Internally Calibrated Parameters

Discount factor of searching tenants β_s. The parameter measures the value discount between two rounds of search. As β_s increases, the option value of the marginal tenant ($v = v_R$) increases, thus affecting the reserve value and the demand elasticity. Increasing the option value adds more weight to future search and reduces the heterogeneous impact of today's matching technology across agents, leading to a more concentrated distribution of the demand elasticity. Using (PS) and (RE), I show that the log dispersion of the quality-adjusted rent across submarkets and the log dispersion of the demand elasticity are equal in equilibrium, so I identify β_s through the quality-adjusted rent dispersion.[46]

$$Var_l[\ln \hat{R}_a(l, \eta(l))] = Var_l[\ln \hat{\varepsilon}(l, \hat{\eta}(l))]$$

Outside option of renting c_{v0} and c_{v1}, share of sophisticated landlords ϕ. Denote the cumulative mass function of rental quality as $F_q(q)$. Upon meeting a landlord, the agent listing probability is $\gamma(l)/\Gamma = 1 - \phi F_q([\hat{\Pi}_L(l, \theta(l), 1) - c_{v1}]^{-1} c_{v0})$, which is negatively correlated with the mean rental quality $q(l)$. Hence, the parameters c_{v0} and c_{v1} can be identified through the steepness and the level of the mean rental quality across submarkets. As ϕ measures the extent of landlord selection on brokers, I can identify ϕ through the distance of rental quality between the listed units and all units, $\partial q(l)/\partial \phi = E(q|l, \hat{Q}) - E(q)$. I can separately identify ϕ, c_{v0} and c_{v1} due to non-linearity of the mean rental quality $q(l)$.

Aggregate landlord-agent ratio Γ, stopping parameter r. As Γ is proportional to the average agent size $\gamma(l)$, Γ can be identified by matching the model mean of the agent size with the empirical mean. As the variance is larger than the mean of the empirical agent distribution, I use the stopping parameter r in the negative binomial distribution to control the excess dispersion (see Fn.33). The smaller r is, the larger the ratio of the variance to the mean.

Aggregate tenant-landlord ratio Θ. The parameter controls the average number of tenants per landlord and is positively correlated with the tenant-listing ratio B. The difference between Θ and B comes from the fact that not all landlords will choose to list rentals on the market. The ratio B determines how long a listing will be on the market. The larger B is, the shorter the listing time. I thus identify Θ through the mean listing days in the data.

7.2.3 Criterion Function

To calibrate the parameters $\mathcal{C}^{endo} = \{\beta_s, c_{v0}, c_{v1}, \Gamma, \phi, \Theta, r\}$, I numerically solve the following problem to minimize the model-data distance.

$$\mathcal{C}^{endo} = \arg\min{}_{\mathcal{C}} \; \mathbf{e}(\mathbf{X}^M, \mathbf{X}^D|\mathcal{C})^T \cdot \mathbf{e}(\mathbf{X}^M, \mathbf{X}^D|\mathcal{C}), \text{ with } e_j(\mathbf{X}^M, \mathbf{X}^D|\mathcal{C}) = \frac{m_j(\mathbf{X}^M|\mathcal{C})}{m_j(\mathbf{X}^D)} - 1$$

where $\mathbf{e}(\mathbf{X}^M, \mathbf{X}^D, \mathcal{C})$ is a vector of error functions that depend on the model data $\mathbf{X}^M$, the observed data $\mathbf{X}^D$ and the internally calibrated parameters $\mathcal{C}$. An error function is defined as the percentage deviation of the model moment $m_j(\mathbf{X}^M|\mathcal{C})$ from the observed moment $m_j(\mathbf{X}^D)$. I target three distributions and one

[46] Given the parameters, I derive the relationship by first rewriting (RE) using the quality-adjusted search value u_b.

$$\hat{\pi}_b(l, \eta(l)) exp(-\hat{v}_R(l, \eta(l))) = (1 - \beta\delta)[(1 - \beta_s)\hat{u}_b(l, \eta(l)) + c_b]$$

where I use the assumption $v \sim exp(\lambda_v = 1)$. As the search values are equal across submarkets in the equilibrium, the left side is thus constant across l. Next, I evaluate (PS) at the equilibrium and take log on both side. The term in the parenthesis on the right of (PS) is linear in the expression above, which is constant across l. The equation of equal variance thus follows.

moment. The distributions are the quality-adjusted rent, the mean rental quality and the mean listing days across submarkets. Besides, I target the mean agent size but keep the agent distribution untargeted. For the three targeted distributions, I aim to minimize the distance at each discrete level of the agent size. With $\mathcal{L} = 20$ submarkets in calibration, the three distributions share equal weights and are associated with 20 error functions each. The same weight attached to a distribution is assigned to the error function of the mean agent size. The distribution of the quality-adjusted rent disciplines β_s; the distribution of the mean rental quality disciplines c_{v0}, c_{v1} and ϕ; the distribution of listing days identifies Θ; the mean agent size disciplines Γ. All three distributions contribute to identifying r, as it is related to the tail fatness of the agent distribution.

The data counterpart of the quality-adjusted rent R_a is defined as the residual of the hedonic rent model (Col 3 in Table 4), while the data counterpart of the mean rental quality $E_l(\ln q|l, \hat{Q})$ is estimated from the mean predicted rent conditioning on the agent size from the hedonic rent model. I define in the model the predicted listing days on market as the expected listing time $[1 + (1 - \pi_{a,l})/E_l(\pi_{a,l})] \cdot 7\ days$. This is the mean of a geometric distribution conditional on the agent size, with the success probability to be the listing matching probability $\pi_{a,l}$ and the unconditional mean $E_l(\pi_{a,l}) = \sum_l \pi_{a,l} a_l = 0.28$. Deriving time on market from a geometric distribution is not only based on the model assumption, but also supported by the empirical evidence of constant hazard rate of staying on the market (see Fn.17). As one round of search stands for a week, I multiply the expected time by 7 to convert it into the number of days. In the data, I derive the predicted listing days by first estimating an accelerated failure time model (Col 7 in Table 4) and then averaging the predicted listing days. The expected listing time depends on the agent size but not the rental quality in the model, which is consistent with the fact that housing amenities explain limited variation of the log days on market (see Table 4).

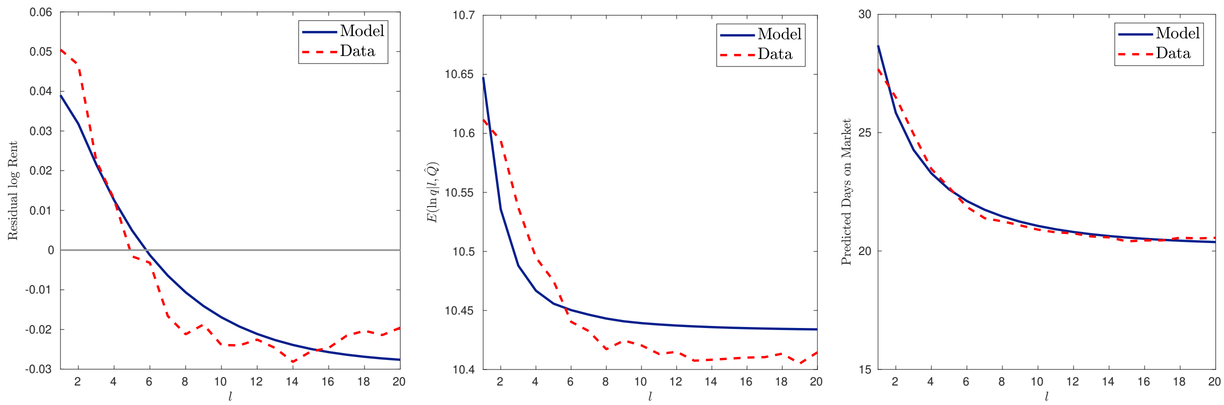
Minimizing the criterion function yields the discount factor in the search $\beta_s = 0.92$, the aggregate landlord-listing ratio $\Gamma = 3.61$, and the share of sophisticated landlords $\phi = 0.19$. The parameters about the outside option of renting ($c_{v0} = 10,252, c_{v1} = 0.032$) imply that the monthly value of not renting out an average unit is worth $[c_{v0} + c_{v1} E_l q(l)]/12 = \$954$ in 2010 dollar. The aggregate tenant-landlord ratio is $\Theta = 0.872$. The stopping parameter of the negative binominal distribution is $r = 3.9$.

7.3 Model Fit and Quantitative Predictions

Targeted and untargeted distributions. In Figure 8, I make model-data comparison of the mean rental quality, the quality-adjusted rent and the mean listing days by agent size. The model matches the distributional patterns quantitatively. To show the model validity, I show in Figures 9a and 9b two untargeted series as functions of the agent size: the agent distribution and the residual listing days on market.

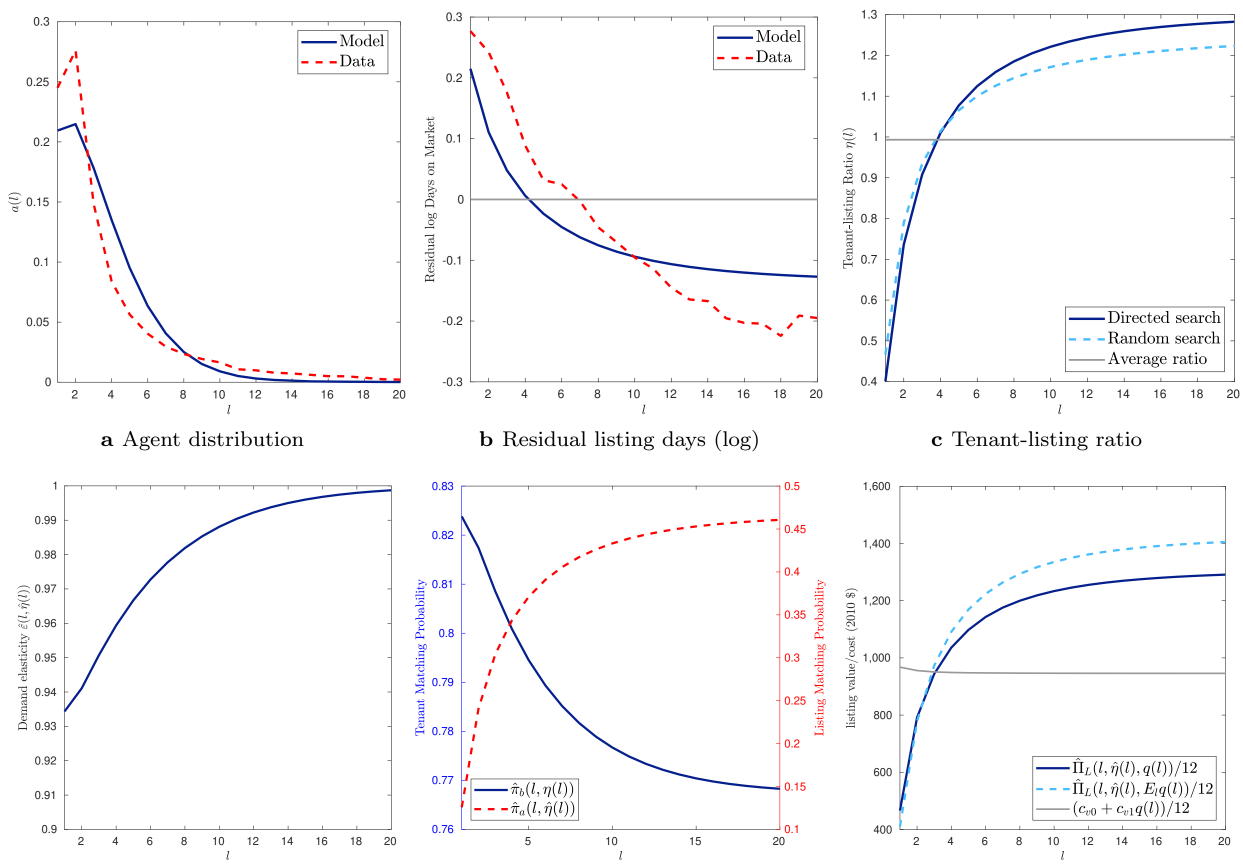
The calibrated agent distribution matches the data counterpart closely. At the left tail, it can explain why small brokers dominate the market. At the top of the agent distribution, the model is consistent with the excess dispersion of the fat tail for the largest brokers. As the source of listing time dispersion in the model is attributed to the broker heterogeneity, the log deviation of the expected listing time from the mean corresponds to the residual log days on market in the data. The model series can generate 35 pp. difference in residual listing days between the smallest and largest agent group, compared with 50 pp. difference in the data.

Quantitative predictions. I show in Figures 9c-9f four model series (tenant-listing ratio, demand elasticity, listing matching probability, weekly listing value of landlords) whose empirical counterparts are not directly observable with the constraint of the data. The tenant-listing ratio which is increasing and



a Quality-adjusted rent (log) **b** Rental quality (log) **c** Predicted listing days

Figure 8: Targeted distributions in calibration.



a Agent distribution **b** Residual listing days (log) **c** Tenant-listing ratio

d Demand elasticity **e** Matching probability **f** Listing value (monthly)

Figure 9: Untargeted Distributions in calibration.

concave in the agent size goes up from 0.40 for $l = 1$ to 1.28 for $l = 20$, with the mean to be $B = 0.993$. As expected, the tenant-listing ratio implied by the case of random search is less disperse and ranges from 0.47 to 1.22. The demand elasticity as an increasing function of the agent size shows that the local demand of the smallest agents (0.934) is 6.5% less elastic than that of the largest agents (0.999). As the tenant-listing ratio is increasing in the agent size, the tenant matching probability ($\pi_{b,l}$) is decreasing, with the mean equal to 0.81. When the acceptance rule of tenants is taken into account, the tenant probability of finding a unit ($\pi_{b,l}[1-F(v_{R,l})]$) is 0.276, which is constant across submarkets under the exponential distribution of the taste shock. When translating the probability into search time ($(\pi_{b,l}[1-F(v_{R,l})])^{-1} \cdot 7\ days$), a tenant on average spends 25.4 days on the market. I convert the landlord listing value into the monthly value, $\hat{\Pi}_L(l, \theta(l), q(l))/12$. The monthly listing value of the largest agents ($1,291 in 2010 USD) is 2.8 times larger than that of the smallest agents ($466). These values take into account the difference of the mean rental quality across agents. To see the pure agent impact, I fix the rental quality at the unconditional mean. The weekly listing value of the largest agents ($1,405) is 3.4 times larger than that of the smallest agents ($410).

8 Policy Counterfactuals

8.1 Role of Intermediation: Does a Larger Brokerage Sector Benefit Tenant Search?

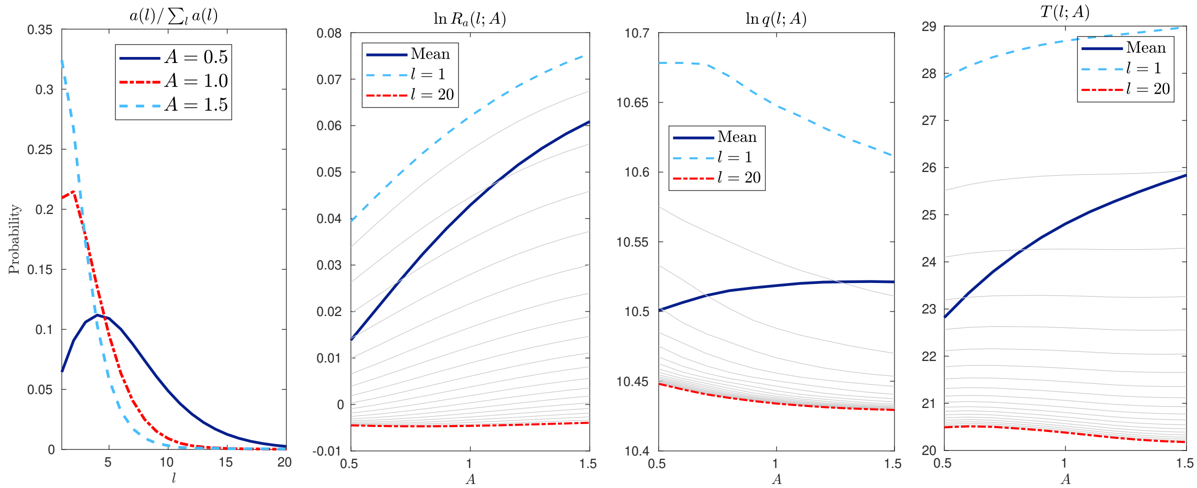
I consider an experiment that increases the total number of brokers in the calibration from 50% to 150% of the benchmark level. This exercise effectively decreases the aggregate landlord-agent ratio Γ from 200% to 66% of the benchmark level and keeps the rest parameters constant, including the aggregate tenant-landlord ratio Θ. The shock to the brokerage sector has no direct impact on the total number of landlords or tenants. I show how the intermediation channel affects the rental market outcomes.

A positive shock to the total number of brokers can be motivated by lowering the entry cost or increasing the commission of brokers. Brokerage licensure in the New York State requires taking 120-hour course work and passing examination.[47] With the low entry cost, being a broker in NYC is very well paid, as the broker's fee is a fixed fraction of the annual rent (no less than 1-month rent) and NYC is among the most expensive rental markets in the US (Zumper, 2020). As of 2019, there are about 25,000 licensed rental or sales brokers in NYC (Haag and Ferré-Sadurní, 2020) whose median earning ($94,020) is 80% higher than the median earning for all occupations ($51,850) (New York State Department of Labor, 2019).

I find that introducing more brokers to the rental market makes tenants worse off in the search process and decreases the mean profit of brokers. The prediction under the assumption of heterogeneous brokers is opposite to what a search model without broker heterogeneity predicts. With homogeneous brokers, expanding the brokerage sectors can make tenants better off, because the tenant-agent ratio decreases and the rental supply effectively increases. What is ignored under the assumption of homogeneous brokers is the role of search quality and the endogenous determinant of the agent distribution.

In Table 7, I summarize the impact of a 50% increase or decrease ($A = 1.5$ or $A = 0.5$) in the number of brokers from the benchmark level ($A = 1.0$). I focus on three equilibrium objects (the means of the quality-adjusted rent, the rental quality, and the listing days). With no change in the ratio of the rental demand to the rental supply, increasing the total number of brokers decreases the mean agent size and makes the agent distribution more left-skewed (Figure 10a). The rental market thus becomes more frictional. The mean market rent $E_l \ln R(l) = E_l \ln q(l) + E_l \ln R_a(l)$ increases through two channels, (1) increasing the quality-adjusted rent $R_a(l)$ (Figure 10b), and (2) increasing the rental quality $q(l)$ due to fewer supply of low-tier rentals (Figure 10c). Introducing 50% more brokers to the rental market increases the mean market rent by 2.1%, which is decomposed into a 1.8% increase due to higher quality-adjusted rent and the remaining 0.3%

[47] Qualification for licensure in the New York state requires 120-hour course work (75-hour salesperson course and 45-hour broker course), passing the broker exam, and 2-year working experience under licensed brokers. The details on the application requirement can be found at the New York Department of State: https://www.dos.ny.gov/forms/licensing/0036-f-a.pdf.



a Agent Distribution **b** Quality-adjusted rent **c** Rental quality **d** Listing days on market

Figure 10: Impact of increasing the number of brokers. I consider 50% deviation in the number of brokers ($A = 1.5$ or $A = 0.5$) from the baseline ($A = 1.0$). The average market rent $\ln E_l R(l; A) = \ln E_l R_a(l; A) + \ln E_l q(l; A)$ is decomposed into the quality-adjusted rent $\ln E_l R_a(l; A)$ and the rental quality $\ln E_l q(l; A)$. In Panels 10b-10d, the weighted mean is in dark blue, while the objects at min and max agent sizes are highlighted in light blue and red respectively, with the intermediate agent sizes shown in gray.

Table 7: Experiment: Impact of Increasing/Decreasing the Number of Brokers

	p_{25}	p_{50}	p_{75}	p_{90}	p_{95}	p_{99}
$\Delta \ln R_a(l)$						
$A_{0.5} - A_{1.0}$	-0.029	-0.035	-0.026	-0.018	-0.015	-0.008
$A_{1.5} - A_{1.0}$	0.021	0.023	0.028	0.021	0.018	0.007
$\Delta \ln q(l)$						
$A_{0.5} - A_{1.0}$	-0.002	-0.013	0.003	0.007	0.008	0.011
$A_{1.5} - A_{1.0}$	0.076	0.023	0.014	0.000	-0.003	-0.006
$\Delta \ln T(l)$						
$A_{0.5} - A_{1.0}$	-0.070	-0.093	-0.059	-0.039	-0.033	-0.017
$A_{1.5} - A_{1.0}$	0.115	0.066	0.072	0.037	0.027	0.000
	$\Delta \ln E_l R_a(l)$		$\Delta \ln E_l q(l)$		$\Delta \ln E_l T(l)$	
$A_{0.5} - A_{1.0}$	-0.029		-0.019		-0.084	
$A_{1.5} - A_{1.0}$	0.018		0.003		0.041	
	$\Delta \ln u_b$		$\Delta \ln B$		$\Delta \ln E_l \Pi_a(l)$	
$A_{0.5} - A_{1.0}$	0.095		-0.008		0.609	
$A_{1.5} - A_{1.0}$	-0.057		0.005		-0.269	

Note: I consider a 50% increase or decrease in the number of brokers ($A = 1.5$ or $A = 0.5$) from the baseline ($A = 1.0$), keeping the aggregate landlord-tenant ratio constant. Comparison in log deviation ($\Delta \ln(\cdot)$) from the baseline is made at selected percentiles ($p_{25}, \ldots, p_{99}$) of two agent distributions. *Definition*: quality-adjusted rent $R_a(l) = \hat{R}_a(l, \eta(l))$; rental quality $q(l) = \phi E(q|l, \hat{Q}) + (1 - \phi)E(q)$; listing days on market $T(l) = [1 - \hat{\pi}_a(l, \hat{\eta}(l)) + E_l \hat{\pi}_a(l, \hat{\eta}(l))]/E_l \hat{\pi}_a(l, \hat{\eta}(l)) \cdot 7$; tenant-listing ratio $\eta(l)$; tenant search value $u_b = \hat{u}_b(l, \eta(l))$ which is constant in equilibrium; aggregate tenant-listing ratio B; expected agent profit $E_l \Pi_a(l) = E_l[\tilde{\Pi}_a(l, \theta(l), q(l))l]$.

increase due to higher rental quality. Most of the rent increase is attributed to an increasing share of small brokers on the left tail of the agent distribution through the quality-adjusted rent. With 50% more brokers, the listing time on market will increase by 4.1%; the tenant search value will decrease by 5.7%; the mean profit of brokers will decrease by 26.9%.

Increasing the number of brokers exhibits diminishing impact on rent. The rent impact of decreasing A by 50% is stronger in absolute value than the rent impact of increasing A by 50%. With the size of the brokerage sector cut in half, the mean market rent will decrease by 4.8%, with a 2.9% decrease due to an increasing share of large brokers and lower quality-adjusted rent and the remaining 1.9% decrease due to lower mean rental quality. The listing time on market will decrease by 8.4% and the tenant search value will increase by 9.5%.

To examine how broker heterogeneity contributes to the rent change, I report the percentage deviation from the benchmark at selected percentiles of the agent distributions $(p_{25}, \ldots, p_{99})$. Using the relative ranking of brokers allows us to compare across distributions that evolve with the total number of brokers. I find the rent change, due to the rental quality or the quality-adjusted rent, mainly comes from small brokers. The change in the number of agents have limited impact on the large brokers.

In Figures 10b and 10c where I plot the rental quality and quality-adjusted rent against the number of brokers for each discrete level of the agent size, I come to a similar finding that small brokers play a predominant role in lifting up the mean rent. As the number of brokers increases, the quality-adjusted rent of the small brokers increases faster than that of the large brokers, thus increasing the weighted mean in aggregate. While the rental quality for all agent sizes is decreasing in the number of brokers, the weighted mean across brokers is increasing. This is due to the fact that more weight is attached to small brokers whose rental quality is higher than that of large brokers. In Figure 10d, I show the impact on the listing duration. Introducing more brokers to the market increases the listing days on the left tail of the agent distribution but moderately decreases the listing days on the right tail. Overall, the weighted mean of listing days increases.

8.2 The Impact of New York Rent Reform on Commission Liability

8.2.1 Background

In June 2019, the New York state legislature passed the Housing Stability And Tenant Protections Act. The enactment marks a major pro-tenant rent reform to deal with rent affordability crisis in the past decades.[48] In February 2020, a guidance was issued to ban a landlord's agent from collecting the broker's fee from a prospective tenant and restricts the application fee to fewer than $20, but a judge temporarily blocked the changes after real estate groups sued the New York State.[49]

The controversy lies in whether the new law can achieve tenant protection and how brokers and landlords will respond to the policy change. Tenants see the new law addressing the issue of unaffordably high rent, while brokers claim that it provides limited benefit to tenants (Haag and Ferré-Sadurní, 2020; Wezerek, 2020). The broker's fee paid upfront by landlords could be rolled into the monthly rent. The new law could hurt the profitability of landlords (Hu, 2020; Parker, 2020), leading to a decrease in the rental supply.[50] Without

[48] For the details on the legislation, see the news reports from Curbed New York (Ricciulli, 2020; Spivack and Ricciulli, 2020). As Governor Andrew Cuomo said, "*At the beginning of this legislative session, I called for the most sweeping, aggressive tenant protections in state history,... I'm confident the measure passed today is the strongest possible set of reforms that the Legislature was able to pass and are a major step forward for tenants across New York.*" (Plitt, 2019).

[49] The guidance says that "*no landlord, lessor, sub-lessor or grantor may demand any payment, fee, or charge for the processing, review or acceptance of an application, or demand any other payment, fee or charge before or at the beginning of the tenancy, except background checks and credit checks...*". Brokers can still collect a fee, but it's up to the landlord to pay it. A tenant is only responsible if they hire the broker themselves to find an apartment. The complete guidance from the Department of the State is available at: `https://www.dos.ny.gov/licensing/pdfs/DOS-Guidance-Tenant-Protection-Act-Rev.1.31.20.pdf`. The news on the guidance block comes from Curbed New York (Spivack and Ricciulli, 2020).

[50] There is mixed evidence on the effect of reallocating the fee liability. Berger and Schmidt (2019) explore the rental law change, finding that shifting commission from tenants to landlords does not increase rent in two German cities. After the issuance of HSTPA guidance, a listing platform in NYC finds that the rent for 5% of rentals increased in that week until the

the help of a structural model, it is not clear whether tenants should pay no fee upfront and whether the shift of the commission system is reasonable. As discussed in the New York Times articles (Belkin, 1983; Carmody, 1984), the tension between tenants and brokers on the broker's fee has been present for more than four decades, with the commission rate in 1980s similar to today's level.[51] Among the most expensive US rental markets (Zumper, 2020), cities other than NYC and Boston have the landlords pay the broker's fee in most of the cases, but it is common to charge tenants in the form of the application fee (Carlson, 2016; Sun and Kallergis, 2020).[52]

8.2.2 *Experiment: Impact of Shifting Commission Liability from Tenants to Landlords*

In Table 4, I present the evidence that the no-fee status impacts listing outcomes. The mean market rent is 7% higher for the no-fee listings than for the with-fee listings (Col. 2). Even when the rent has considered the effects of the the housing amenities and the agent size (Col. 4), the no-fee status remains a significant factor to the market rent. When a rental is listed as no-fee, the upfront cost of tenancy can be reduced by as much as 25% by spreading out the housing cost over the lease term.[53] Compared to the with-fee listings, the no-fee listings attract more tenant demand and expect shorter listing time due to lower upfront payment. Conditioning on the housing amenities and the agent size, the no-fee listing time is 1.9% shorter on average than the with-fee listing time (Col. 8).

Table 8: Experiment: Shift of Commission Liability

	no brokerage response						with brokerage response					
	p_{25}	p_{50}	p_{75}	p_{90}	p_{95}	p_{99}	p_{25}	p_{50}	p_{75}	p_{90}	p_{95}	p_{99}
$\Delta \ln R_a(l)$												
$\tau_{L,1} - \tau_{L,0}$	0.025	0.025	0.025	0.024	0.024	0.024	0.027	0.027	0.034	0.031	0.025	0.024
$\Delta \ln q(l)$												
$\tau_{L,1} - \tau_{L,0}$	0.011	0.013	0.010	0.008	0.009	0.008	0.008	0.010	0.021	0.011	0.008	0.007
$\Delta \ln T(l)$												
$\tau_{L,1} - \tau_{L,0}$	-0.013	-0.013	-0.013	-0.013	-0.013	-0.013	-0.012	-0.013	0.016	0.003	-0.014	-0.014
	$\Delta \ln E_l R_a(l)$		$\Delta \ln E_l q(l)$		$\Delta \ln E_l T(l)$		$\Delta \ln E_l R_a(l)$		$\Delta \ln E_l q(l)$		$\Delta \ln E_l T(l)$	
$\tau_{L,1} - \tau_{L,0}$	0.025		0.011		-0.012		0.028		0.012		-0.006	
	$\Delta \ln u_b$		$\Delta \ln B$		$\Delta \ln E_l \Pi_a(l) l$		$\Delta \ln u_b$		$\Delta \ln B$		$\Delta \ln E_l \Pi_a(l)$	
$\tau_{L,1} - \tau_{L,0}$	-0.009		0.013		0.036		-0.017		0.013		0.000	

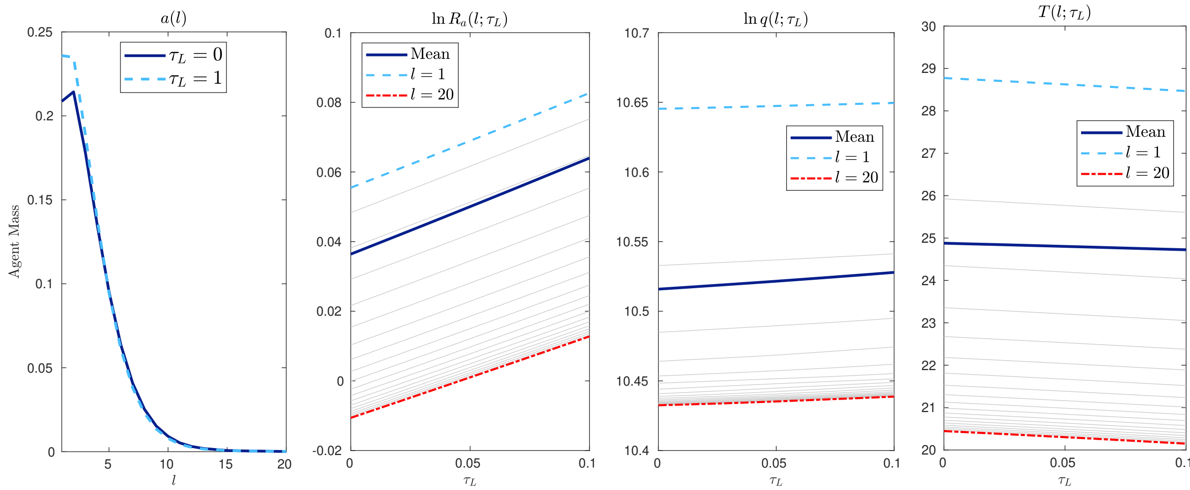
Note: I consider the shift of the commission liability from the tenants ($\tau_{L,0}$) to the landlords ($\tau_{L,1}$). Comparison in log deviation ($\Delta \ln(\cdot)$) from the tenant-paid baseline is made at selected percentiles ($p_{25}, \ldots, p_{99}$) of two agent distributions. Two scenarios are considered, (1) *no brokerage response* keeps the total number of brokers constant, and (2) *with brokerage response* keeps the expected agent profit constant. *Definition*: quality-adjusted rent $R_a(l) = \hat{R}_a(l, \eta(l))$; rental quality $q(l) = \phi E(q|l, \hat{Q}) + (1 - \phi)E(q)$; listing days on market $T(l) = [1 - \hat{\pi}_a(l, \hat{\eta}(l)) + E_l \hat{\pi}_a(l, \hat{\eta}(l))] / E_l \hat{\pi}_a(l, \hat{\eta}(l)) \cdot 7$; tenant-listing ratio $\eta(l)$; tenant search value $u_b = \hat{u}_b(l, \eta(l))$ which is constant across submarkets in equilibrium; aggregate tenant-listing ratio B; expected agent profit $E_l \Pi_a(l) = \tau \cdot E_l[\tilde{\Pi}_a(l, \theta(l), q(l)) l]$.

ban on broker's fee was halted (Wezerek, 2020).

[51] Carmody (1984) finds that the commission rate in the 1980s is even higher than today's level (8.3%-15%), "*Real-estate brokers have always charged fees, but now they are charging as much as 15 to 20% of the first year's rent. Increasingly, brokers are also charging 10 to 15% of the second year's rent on two-year rentals.*" Belkin (1983) finds that the broker's fee for a tenant to urgently find an apartment in one day is 20% of the annual rent.

[52] An article on New York Times (Ferré-Sadurní, 2019) finds that the application fee in NYC could be as much as $500 in 2019. The blogpost by RentPrep shows that as of 2013, 39 out of 50 states have no limit on the non-refundable application fee, https://www.rentprep.com/tenant-screening-news/the-landlord-guide-to-charging-rental-application-fees/.

[53] For example, if a with-fee unit is listed at $3,000/month, the upfront payment includes the first/last-month rent ($\$3,000 \cdot 2$ *months*), security deposit ($3,000) and broker's fee ($> \$3,000$). The minimum total payment is $12,000 before move-in.



a Number of Agents **b** Quality-adjusted rent **c** Rental quality **d** Listing days on market

Figure 11: Impact of shifts of commission liability from tenants ($\tau_L = 0$) to landlords ($\tau_L = \tau = 10\%$). The average market rent $\ln E_l R(l; \tau_L) = \ln E_l R_a(l; \tau_L) + \ln E_l q(l; \tau_L)$ is decomposed into the quality-adjusted rent $\ln E_l R_a(l; \tau_L)$ and the rental quality $\ln E_l q(l; \tau_L)$. The number of brokers at $\tau_L = 0$ is normalized to 1. In Panels 11b-11d, the weighted mean is in dark blue, while the objects at min and max agent sizes are highlighted in light blue and red respectively, with the intermediate agent sizes shown in gray.

I consider an experiment of shifting the commission liability from tenants to landlords which replaces with-fee listings ($\tau_L = 0, \tau_b = \tau$) by no-fee listings ($\tau_L = \tau, \tau_b = 0$). The tenant groups cheer for the reduction of the rental cost, while the real estate groups argue that the upfront cost could be rolled into the monthly rent, which ends up with limited tenant benefit. Using the calibrated model, I examine the policy impact of re-allocating the broker's fee from tenants to landlords.

In Table 8, I report the impact of shifting the commission liability to landlords on three equilibrium objects (the means of the quality-adjusted rent, the rental quality, and the listing days) in two cases. The first case keeps the total number of agents constant (*no brokerage response*), which captures the short-term effect in the rental market with no entry or exit response of brokers. The second case keeps the expected agent profit constant (*with brokerage response*) and endogenizes the total number of brokers in the rental market through the aggregate landlord-agent ratio Θ. This captures the long-term effect of ruling out the with-fee listings.

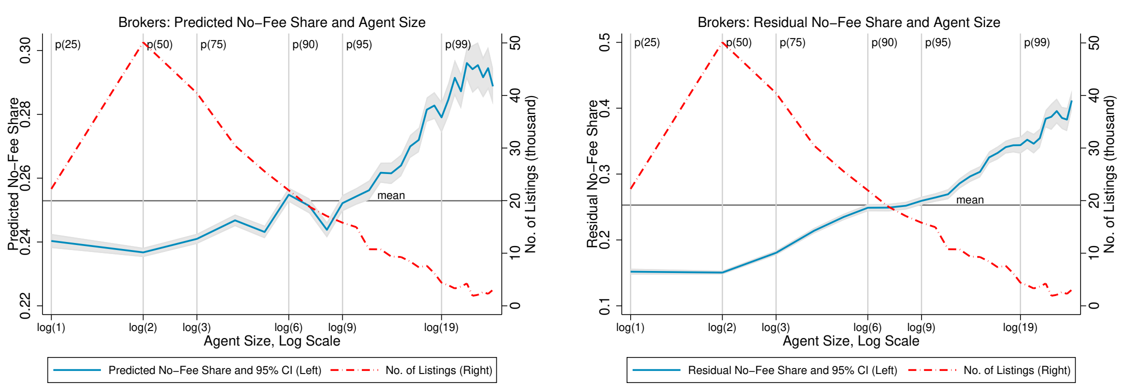
I find that shifting the commission liability to landlords makes tenants worse off and the response of the brokerage sector intensifies the short-term impact. When landlords pay the broker's fee (10% of the annual rent), the market rent in the short run will increase by 3.6%, with a 2.5% increase due to the quality-adjusted rent and the remaining 1.1% increase due to the rental quality. On one hand, the upfront cost is partially passed on to the rent, which is in favor of tenants. On the other hand, as the rent increase cannot fully compensate the broker's fee, fewer landlords choose the renting option, thus decreasing the rental supply. The tenant-listing ratio increases by 1.3%, putting tenants at a disadvantage but benefiting landlords by reducing the listing time by 1.2%. Overall, the tenant search value decreases by 0.9% in the short run. In terms of dollar loss, it is equivalent to 6.6 weeks of the mean market rent.

With a fixed commission rate and a higher listed rent, the expected agent profit is 3.6% higher in the short term, inducing 4.8% more agents to enter the rental market in the long run. I make the constant expected profit assumption to impose the minimum structure on the entry/exit decision of brokers that I lack data on. The mean market rent in the long run will increase by 4.0%, with a 2.8% increase due to the quality-adjusted rent and the remaining 1.2% increase due to the rental quality. The tenant search value decreases by 1.7%, equivalent to 11.5 weeks of the mean market rent in dollar loss. I compare the number of agents in the short- and long-run in Figure 11a. With more brokers in the long run, the agent distribution sees an increasing share of small brokers but not for the large brokers on the right tail. The marginal effects of increasing the landlord portion of broker's fee τ_L on the quality-adjusted rent, the rental quality, and the listing days are quite linear and similar for brokers of different agent sizes (Figures 11b-11d).

8.2.3 Endogenous Allocation of Broker's Fee: a Bargaining Solution

While HSTPA of 2019 rules out the with-fee listings, I discuss how the no-fee listing status is determined in the rental market. I extend the benchmark model to endogenize the fee allocation between landlords and tenants $\tau = \tau_L(l,q) + \tau_b(l,q)$ by relaxing the assumption that the fee is constant across the distribution of agent size and rental quality. I first provide evidence that before HSTPA, there is wide dispersion of the no-fee share across agents. Appendix Table C.3 shows the positive correlation between the no-fee listing share and the agent size, with the share gap between the top and the bottom percentile (> 99th and ≤ 25th) of the agent distribution being as large as 25 pp (= 39% − 14%). The correlation could be attributed to the difference of rental amenities through the landlord selection of brokers. Another possibility is that the correlation is related to the agent impact that large brokers are more likely to list rentals as no-fee, all else equal. To understand the the relationship between the no-fee status and the agent size, I run the following probability model (with details in Appendix Table C.4).

$$\mathbb{I}(No\_Fee_{ijnt} = 1) = FE_{nt} + \mathbf{X}_{int} \cdot \mathbf{B} + e_{ijnt}$$



a Predicted No-Fee Listing Share

b Residual No-Fee Listing Share

Figure 12: No-fee listing share and agent size. No-fee indicates whether the broker's fee is paid by a landlord. The percentiles of the agent distribution by size are reported, with the bottom 90% of rentals covered. The predicted and the residual no-fee shares are centered at the mean predicted by Model 3 in Appendix Table C.4, with the residual adjusted for the housing amenities and the location-date fixed effect. The sample is rental listings (2010-2017) by brokers in Manhattan.

By filtering out the variation due to the housing amenities ($\mathbf{X}_{int}$) and the location-date fixed effect (FE_{nt}), Figure 12 aggregates the predicted and the residual no-fee shares by the agent size and shows that they are positively correlated. The correlation suggests that whether to list a rental as no-fee depends both

Table 9: Residuals of No-Fee Status

	(1) Residual No-Fee	(2) Residual No-Fee
Agent Size	0.012***	
	(0.001)	
Log Agent Size		0.071***
		(0.009)
Constant	-0.102***	-0.138***
	(0.010)	(0.017)
Adjusted R^2	0.880	0.854
N	20	20

Note: robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010. The residual of the no-fee status takes out the variation due to the housing amenities and the location-date fixed effect and (See Model 3 in Appendix Table C.4). Observations are weighted by the number of listings. The range of the agent size (1-20) covers more than 99% of the brokers in the sample.

on the rental quality and directly on the agent size.[54] Conditioning on the housing amenities, including the agent size in the probability model increases the explained variation of the no-fee status from 14% to 20% (Appendix Table C.4). Table 9 shows that more than 85% variation of the residual no-fee share is explained by the agent size. Conditioning on the housing amenities, one unit increase in the agent size is related to a 1.2 pp increase in the no-fee listing share.

In the extended model with endogenous fee allocation, I separate the effect of the no-fee status from the agent impact which attributes the rent differentials across agents to the differential ability to coordinate tenant search. As the no-fee status is decided jointly with the rent, the decision on whether to list a rental as no-fee involves landlords and brokers but not tenants. I show landlords and brokers differ in their preference on the fee allocation and introduce a Nash bargaining problem to solve the conflict. Assume each pair of the broker-landlord negotiation is independent,[55] with the bargaining payoffs of a landlord (BP_L) and of a broker (BP_a) to be

$$\begin{aligned} BP_L(l,q,\tau_L) &= [(1-\beta\delta)^{-1} - \tau_L]R_a(l;\tau_L)\pi_a(l)q - (1-\beta\delta)^{-1}(c_{v0}+c_{v1}q) \\ BP_a(l,q,\tau_L) &= \tau R_a(l;\tau_L)\pi_a(l)q, \text{ with } R_a(l;\tau_L) = [1+(1-\beta\delta)(\tau-\tau_L)]^{-1}\kappa(l) \end{aligned} \tag{23}$$

where $\pi_a(l)$ is the equilibrium listing matching probability and $\kappa(l)$ is the total rental cost ($\hat{\tau}_b R_a$). I show later that both terms do not depend directly on τ_L. The term $\hat{\tau}_b = 1+(1-\beta\delta)(\tau-\tau_L)$ is the gross tenant-paid commission rate from equation (15) that considers the possibility of lease renewal. The disagreement payoff is assumed to be $(1-\beta\delta)^{-1}(c_{v0}+c_{v1}q)$ for a landlord with a rental of quality q and 0 for a broker. Note that the total surplus $BP_a + BP_L = (1-\beta\delta)^{-1}[\kappa(l)\pi_a(l)q - (c_{v0}+c_{v1}q)]$ does not depend on the choice of τ_L.

By adding (RE) to (PS), I can show that $\kappa(l) = [1+(1-\beta\delta)(\tau-\tau_L)]R_a(l;\tau_L)$ is decreasing in l by Corollary 6.3 and that $\pi_a(l)$ and $\kappa(l)$ are independent of τ_L. $R_a(l;\tau_L)$ is thus increasing in τ_L. The bargaining payoffs are monotonic in τ_L, with BP_a increasing and BP_L decreasing in τ_L. Hence, brokers prefer to list a rental as no-fee ($\tau_L = \tau$), while landlords prefer to list a rental as with-fee ($\tau_L = 0$). Consider the Nash bargaining

[54] While the coefficients on the housing amenities in the log rent regression differ from those in the regression of the no-fee status, I show in Appendix Figure C.18 that the predicted no-fee share and the rental quality are highly correlated (-0.76) to make the point that the predicted no-fee share captures the variation due to the rental quality.

[55] With the independence assumption, the disagreement payoff of a broker will not depend on the bargaining outcome (an agent of size l will be of size $l-1$ in case of disagreement with a landlord, which affects the listing value of other rentals).

problem to resolve the fee allocation, with the landlord bargaining power denoted by α.

$$\tau_L^*(l,q) \in \arg\max_{\tau_L \in [0,\tau]} \; BP_L(l,q,\tau_L)^{\alpha} BP_a(l,q,\tau_L)^{1-\alpha}$$

I characterize the bargaining solution below.

Proposition 8.1. *The commission paid by a landlord $\hat{\tau}_L(l,q)$ is increasing in the agent size.*

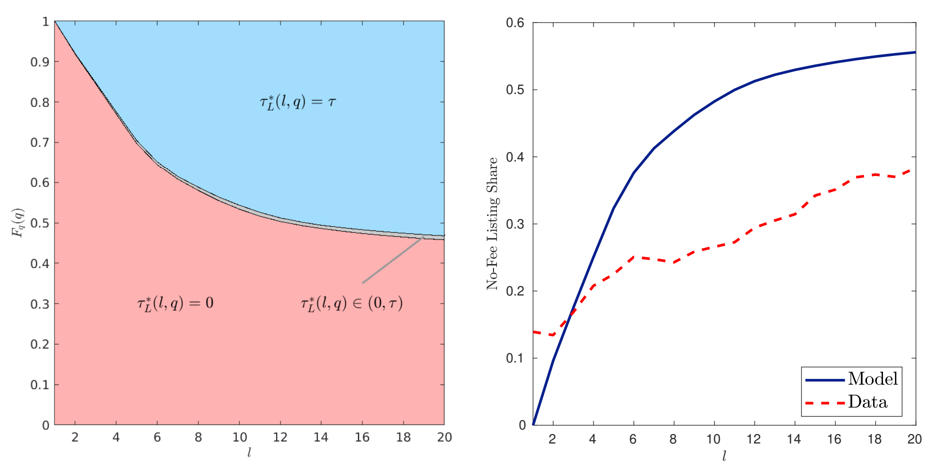
Proof. See Appendix A.10. □

I show in the proof that if $\tau_L^*(l,q) \in [0,\tau]$ is interior, it takes the following form.

$$\tau_L^*(l,q) = \tau \left[1 - \frac{1}{1-\alpha} \left(1 - \frac{c_{v0} + c_{v1} q}{LV_0(l,q)} \right)^{-1} \right] + \frac{1}{1-\beta\delta}, \text{ with } LV_0(l,q) = \kappa(l)\pi_a(l)q \tag{24}$$

where $LV_0(l,q)$ is the listing value in the case of zero broker's fee ($\tau_L = \tau = 0$). The commission rate paid by a landlord is increasing in the listing value $LV_0(l,q)$ and decreasing in the outside option $c_{v0} + c_{v1}q$. If $\tau_L^*(l,q)$ is interior, it is increasing in l and q. While the mean rental quality $q(l)$ is decreasing in the agent size in equilibrium, The direct effect of the agent size is dominant and leads $\tau_L^*(l,q(l))$ to be increasing in l.

The model properties in Section 6 are applicable to the extended model. Endogenizing fee allocation has a direct impact on the quality-adjusted rent, with indirect effects on the rest of the equilibrium objects. As the commission component $\hat{\tau}_b = 1 + (1-\beta\delta)(\tau - \tau_L)$ and the rent component R_a of the total rental cost $\hat{\tau}_b R_a$ are both decreasing in the agent size, relaxing the assumption of constant allocation of the broker's fee will flatten the gradient of the quality-adjusted rent as a decreasing function of the agent size. The evidence suggests that the choice of the no-fee status contributes to the agent impact to explain part of the variation of rent and listing duration across brokers.



a Landlord-paid Commission Rate

b No-Fee Listing Share

Figure 13: The landlord-paid commission rate $\tau_L^*(l,q) \in [0,\tau]$ and the no-fee listing share. No-fee indicates whether the broker's fee is paid by a landlord. Panel 13a: $F_q(q)$ is the the cumulative density distribution of the rental quality. Panel 13b: The model series of the no-fee share is $\tau_L^{**}(l)/\tau = E_q[\tau_L^*(l,q(l))/\tau | l, \hat{Q}]$.

I calibrate the bargaining parameter α to target the mean share of no-fee listings and get $\alpha = 0.89$. The model counterpart of the no-fee share is the fee paid by landlords as a share of the total broker's fee

$\tau^{-1} \sum_l a(l)\tau_L^{**}(l)$. I calculate $\tau_L^{**}(l) = E_q[\tau_L^*(l, q(l))|l, \hat{Q}]$ by simulating the rental quality feasible to an agent of size l, subject to the landlord choice of brokers.

In Figure 13a, I show that the landlord-paid commission rate $\tau_L^*(l, q) \in [0, \tau]$ is a corner solution in most of the cases. The greater the agent size of a broker or the higher the rental quality, the higher the likelihood of a rental to be listed as no-fee ($\tau_L^*(l, q) = \tau$). In Figure 13b, I compare the data and model series of the no-fee listing share. The no-fee share in the data is flatter than the model counterpart, suggesting that small brokers list too many rentals as no-fee while large brokers list too few rentals as no-fee.[56]

9 Conclusion

In this paper, I document new empirical facts about the brokerage sector in the rental housing market. Rental brokers differ substantially in the listing outcomes. The key empirical finding is that brokers with greater listing capacity, *i.e.* agent size, are associated with lower rents and shorter listing duration. The dispersion cannot be fully explained by the amenity difference of rentals and points to a sizable agent impact that a broker with greater capacity lists a rental at a lower rent. I find evidence that the listing incentive provided by the commission system to trade off the commission return and the listing liquidity is crucial to explain the agent impact. To quantitatively match the empirical findings, I develop a rental search model with a heterogeneous brokerage sector and apply it to evaluate the general equilibrium impacts of rental market policies. The model features a search-and-matching process in which the tenant coordination friction interacts with the brokers' capacity constraints that differentiate their ability to coordinate tenant search by reducing the likelihood of facing a binding capacity constraint. I highlight the endogeneity of the search friction and show that the endogenous agent distribution of the listing capacity summarizes how frictional the rental market is. The rental market will be more frictional, if a market policy decreases the mean agent size and makes tenant search harder to coordinate in aggregate.

[56] If I allow the landlord bargaining power to vary across brokers of different agent sizes, the data series of the no-fee share is consistent with the case where the landlord bargaining power α is an increasing function of the agent size.

References

Albrecht, J., Gautier, P. A. and Vroman, S. (2006). Equilibrium directed search with multiple applications. *The Review of Economic Studies*, **73** (4), 869–891.

—, — and — (2016). Directed search in the housing market. *Review of Economic Dynamics*, **19**, 218–231.

Anenberg, E. (2016). Information frictions and housing market dynamics. *International Economic Review*, **57** (4), 1449–1479.

Anglin, P. M. and Arnott, R. (1991). Residential real estate brokerage as a principal-agent problem. *The Journal of Real Estate Finance and Economics*, **4** (2), 99–125.

—, Rutherford, R. and Springer, T. M. (2003). The trade-off between the selling price of residential properties and time-on-the-market: The impact of price setting. *The Journal of Real Estate Finance and Economics*, **26** (1), 95–111.

Bar-Isaac, H. and Gavazza, A. (2015). Brokers' contractual arrangements in the manhattan residential rental market. *Journal of Urban Economics*, **86**, 73–82.

Barwick, P. J. and Pathak, P. A. (2015). The costs of free entry: an empirical study of real estate agents in greater boston. *The RAND Journal of Economics*, **46** (1), 103–145.

—, — and Wong, M. (2017). Conflicts of interest and steering in residential brokerage. *American Economic Journal: Applied Economics*, **9** (3), 191–222.

Belkin, L. (1983). Brokers monopolize rental cavancies. *New York Times*, https://www.nytimes.com/1983/10/30/realestate/brokers-monopolize-rental-vacancies.html?searchResultPosition=1.

Ben-Shahar, D. (2001). A study of the brokerage cost allocation in a rental housing market with asymmetric information. *The Journal of Real Estate Finance and Economics*, **23** (1), 77–94.

Berger, E. M. and Schmidt, F. (2019). *Inattention in the Rental Housing Market: Evidence from a Natural Experiment*. Tech. rep.

Brastow, R. T., Springer, T. M. and Waller, B. D. (2012). Efficiency and incentives in residential brokerage. *The Journal of Real Estate Finance and Economics*, **45** (4), 1041–1061.

Burdett, K., Shi, S. and Wright, R. (2001). Pricing and matching with frictions. *Journal of Political Economy*, **109** (5), 1060–1085.

Carlson, J. (2016). Nyc is one of the only cities where renters pay a broker's fee. *Gothamist*, https://gothamist.com/news/nyc-is-one-of-the-only-cities-where-renters-pay-a-brokers-fee.

Carmody, D. (1984). Hard to find, harder to afford: a decent manhattan apartment. *New York Times*, https://www.nytimes.com/1984/07/19/nyregion/hard-to-find-harder-to-afford-a-decent-mahatten-apartment.html?searchResultPosition=43.

Carrillo, P. E. (2012). An empirical stationary equilibrium search model of the housing market. *International Economic Review*, **53** (1), 203–234.

Carroll, W. (1989). Fixed-percentage commissions and moral hazard in residential real estate brokerage. *The Journal of Real Estate Finance and Economics*, **2** (4), 349–365.

Diaz, A. and Jerez, B. (2013). House prices, sales, and time on the market: A search-theoretic framework. *International Economic Review*, **54** (3), 837–872.

Edelstein, R. and Green, R. K. (2018). Real estate agents and brokerage. *Routledge Companion to Real Estate Investment*, p. 7.

Elder, H. W., Zumpano, L. V. and Baryla, E. A. (1999). Buyer search intensity and the role of the residential real estate broker. *The Journal of Real Estate Finance and Economics*, **18** (3), 351–368.

Ferré-Sadurní, L. (2019). $500 to apply for an apartment? so much for the $20 cap. *New York Times*, https://www.nytimes.com/2019/09/03/nyregion/apartment-rental-application-fees.html.

Forgey, F. A., Rutherford, R. C. and Springer, T. M. (1996). Search and liquidity in single-family housing. *Real Estate Economics*, **24** (3), 273–292.

Genesove, D. and Han, L. (2012). Search and matching in the housing market. *Journal of Urban Economics*, **72** (1), 31–45.

Gilbukh, S. and Goldsmith-Pinkham, P. S. (2019). Heterogeneous real estate agents and the housing cycle. *Available at SSRN 3436797*.

Glower, M., Haurin, D. R. and Hendershott, P. H. (1998). Selling time and selling price: The influence of seller motivation. *Real estate economics*, **26** (4), 719–740.

Haag, M. and Ferré-Sadurní, L. (2020). Surprise for new york renters: No more broker fees. *New York Times*, https://www.nytimes.com/2020/02/05/nyregion/nyc-landlord-rental-broker-fees.html.

Han, L. and Hong, S.-H. (2011). Testing cost inefficiency under free entry in the real estate brokerage industry. *Journal of Business & Economic Statistics*, **29** (4), 564–578.

— and — (2016). Understanding in-house transactions in the real estate brokerage industry. *The RAND Journal of Economics*, **47** (4), 1057–1086.

— and Strange, W. C. (2015). The microstructure of housing markets: Search, bargaining, and brokerage. In *Handbook of Regional and Urban Economics*, vol. 5, Elsevier, pp. 813–886.

— and — (2016). What is the role of the asking price for a house? *Journal of Urban Economics*, **93**, 115–130.

Haurin, D. (1988). The duration of marketing time of residential housing. *Real Estate Economics*, **16** (4), 396–410.

Haurin, D. R., Haurin, J. L., Nadauld, T. and Sanders, A. (2010). List prices, sale prices and marketing time: an application to us housing markets. *Real Estate Economics*, **38** (4), 659–685.

Hendel, I., Nevo, A. and Ortalo-Magné, F. (2009). The relative performance of real estate marketing platforms: Mls versus fsbomadison. com. *American Economic Review*, **99** (5), 1878–98.

Hsieh, C.-T. and Moretti, E. (2003). Can free entry be inefficient? fixed commissions and social waste in the real estate industry. *Journal of Political Economy*, **111** (5), 1076–1122.

Hu, L. (2020). Landlords, not tenants, must now pay broker fees in new york. *Spectrum News*, https://www.ny1.com/nyc/all-boroughs/news/2020/02/06/landlords--not-tenants--must-now-pay-broker-fees-in-new-york#.

Krainer, J. (2001). A theory of liquidity in residential real estate markets. *Journal of urban Economics*, **49** (1), 32–53.

Krishna, V. (2009). *Auction theory*. Academic press.

Levitt, S. D. and Syverson, C. (2008). Market distortions when agents are better informed: The value of information in real estate transactions. *The Review of Economics and Statistics*, **90** (4), 599–611.

Miceli, T. J. (1991). The multiple listing service, commission splits, and broker effort. *Real Estate Economics*, **19** (4), 548–566.

Miller, N. and Sklarz, M. (1987). Pricing strategies and residential property selling prices. *Journal of Real Estate Research*, **2** (1), 31–40.

Moen, E. R. (1997). Competitive search equilibrium. *Journal of political Economy*, **105** (2), 385–411.

Montgomery, J. D. (1991). Equilibrium wage dispersion and interindustry wage differentials. *The Quarterly Journal of Economics*, **106** (1), 163–179.

Munneke, H. J. and Yavas, A. (2001). Incentives and performance in real estate brokerage. *The Journal of Real Estate Finance and Economics*, **22** (1), 5–21.

NAR (2019). 2019 member profile report, national association of realtor. https://www.nar.realtor/sites/default/files/documents/2019-member-profile-highlights-05-09-2019.pdf.

New York State Department of Labor (2019). Occupational wages. https://labor.ny.gov/stats/lswage2.asp.

Ngai, L. R. and Tenreyro, S. (2014). Hot and cold seasons in the housing market. *American Economic Review*, **104** (12), 3991–4026.

Niedermayer, A. and Wang, C. (2018). A search model of rental markets: Who should pay the commission? *International Journal of Industrial Organization*, **58**, 214–235.

NYCHVS (2017). 2017 new york city housing and vacancy survey. https://www.census.gov/programs-surveys/nychvs.html.

Parker, W. (2020). Ban on broker fees sends new york city apartment rental firms reeling. *Wall Street Journal*, https://www.wsj.com/articles/ban-on-brokers-fees-sends-new-york-city-apartment-rental-firms-reeling-11581163201.

Peters, M. (1984). Bertrand equilibrium with capacity constraints and restricted mobility. *Econometrica: Journal of the Econometric Society*, pp. 1117–1127.

— (1991). Ex ante price offers in matching games non-steady states. *Econometrica: Journal of the Econometric Society*, pp. 1425–1454.

Piazzesi, M., Schneider, M. and Stroebel, J. (2015). *Segmented housing search*. Tech. rep., National Bureau of Economic Research.

Plitt, A. (2019). The state legislature's new democratic majority pushed through landmark tenant protections. *CURBED NY*, https://ny.curbed.com/2019/6/14/18679507/rent-regulation-new-york-state-reform-legislation-passed.

Rascoff, S. and Humphries, S. (2015). *Zillow Talk: Rewriting the Rules of Real Estate*. Grand Central Publishing.

RentCafe (2018). Renters became the majority population in 22 big us cities. https://www.rentcafe.com/blog/rental-market/market-snapshots/change-renter-vs-owner-population-2006-2016/.

Ricciulli, V. (2020). No more broker's fees for nyc renters: Here's what that means. *CURBED NY*, https://ny.curbed.com/2020/2/6/21125413/new-york-rent-laws-broker-fees-real-estate.

Rogerson, R., Shimer, R. and Wright, R. (2005). Search-theoretic models of the labor market: A survey. *Journal of Economic Literature*, **43** (4), 959–988.

Rutherford, R., Springer, T. and Yavas, A. (2004). The impact of contract type on broker performance: submarket effects. *Journal of Real Estate Research*, **26** (3), 277–298.

Rutherford, R. C., Springer, T. M. and Yavas, A. (2005). Conflicts between principals and agents: evidence from residential brokerage. *Journal of financial Economics*, **76** (3), 627–665.

Shi, L. and Tapia, C. (2016). The disciplining effect of concern for referrals: Evidence from real estate agents. *Real Estate Economics*, **44** (2), 411–461.

Spivack, C. and Ricciulli, V. (2020). Nyc's broker fee system is changing: Here's what that means for you. *CURBED NY*, https://ny.curbed.com/2020/2/11/21132836/nyc-broker-fees-law-real-estate-tenants-rights.

Statista (2019). Multifamily property rent as a percentage of household income in selected cities in the united states in 2019. https://www.statista.com/statistics/416494/multifamily-property-rent-as-share-of-household-income-usa-by-city/.

Stull, W. J. (1978). The landlord's dilemma: Asking rent strategies in a heterogeneous housing market. *Journal of Urban Economics*, **5** (1), 101–115.

Sun, K. and Kallergis, K. (2020). Broker fees for nyc rentals mystified outsiders. here's how other us cities do it. *The RealDeal*, https://therealdeal.com/2020/02/07/broker-fees-for-nyc-rentals-mystified-outsiders-heres-how-other-us-cities-do-it/.

Urban Institute (2019). Rents are too high. here are three ways to get the data we need to fix that. https://www.urban.org/urban-wire/rents-are-too-high-here-are-three-ways-get-data-we-need-fix.

Wachter, S. (1987). *Research in Law and Economics*, Greenwich, Connecticut: JAI Press, vol. 10, chap. Residential Real Estate Brokerage: Rate Uniformity and Moral Hazard, Austin Jaffee (Ed).

Wezerek, G. (2020). Do you rent in new york? you may soon catch a break. *New York Times*, https://www.nytimes.com/2020/02/25/opinion/new-york-brokers-fee-ban.html.

Wheaton, W. C. (1990). Vacancy, search, and prices in a housing market matching model. *Journal of political Economy*, **98** (6), 1270–1292.

Williams, J. T. (1998). Agency and brokerage of real assets in competitive equilibrium. *The Review of Financial Studies*, **11** (2), 239–280.

Wright, R., Kircher, P., Julien, B. and Guerrieri, V. (2019). Directed search and competitive search: A guided tour. *Journal of Economic Literature*.

Yavaş, A. (1994). Economics of brokerage: an overview. *Journal of Real Estate Literature*, **2** (2), 169–195.

Yavaş, A. and Yang, S. (1995). The strategic role of listing price in marketing real estate: theory and evidence. *Real Estate Economics*, **23** (3), 347–368.

Yinger, J. (1981). A search model of real estate broker behavior. *The American Economic Review*, **71** (4), 591–605.

Zumper, Z. (2020). Zumper national rent report. https://www.zumper.com/blog/zumper-national-rent-report-february-2020/.

A Proof

A.1 Proof of Lemma 1

Lemma 1. Given θ, $N(l,\theta)$ and $\pi_b(l,\theta)$ are increasing and concave in l. $\pi_a(l,\theta)$ is decreasing in l.

Proof. In recursive form, the local demand N can be expressed as

$$N(l+1,\theta) = N(l,\theta) + 1 - \sum_{y=0}^{l} \frac{e^{-\theta}\theta^y}{y!}, \text{ with } N(0,\theta) = 0 \text{ and } l \geq 0 \tag{A.25}$$

which implies that N is an increasing function of l. The monotonicity of π_b in l comes from equation (6) and the monotonicity of N in l. Hence, $N(l,\theta)$ and $\pi(l,\theta)$ are increasing in l. I prove the concavity by showing the second order difference of N is negative.

$$[N(l+1,\theta) - N(l,\theta)] - [N(l,\theta) - N(l-1,\theta)] = -\frac{e^{-\theta}\theta^l}{l!} < 0$$

Using equation (6), I can similarly show that $\pi_b(l,\theta) = N(l,\theta)/\theta$ is concave in l.

To prove that $\pi_a(l,\theta)$ is decreasing in l, it is sufficient and necessary to prove

$$\frac{l+1}{l} > \frac{N(l+1,\theta)}{N(l,\theta)} \Leftrightarrow N(l,\theta) > l - l\sum_{y=0}^{l} \frac{e^{-\theta}\theta^y}{y!} \Leftrightarrow \sum_{y=0}^{l-1} \frac{e^{-\theta}\theta^y}{y!} y + \frac{e^{-\theta}\theta^l}{l!} > 0$$

where I use the recursive form of N in equation (A.25) in the first step, and apply the analytical form of N in the second step. Because the last equality is true, I prove that $\pi_a(l,\theta)$ is decreasing in l. □

A.2 Proof of Lemma 2

Lemma 2. $\varepsilon(l,\theta)$ is decreasing in θ and increasing in l, with $0 \leq \varepsilon(l,\theta) \leq 1$, $\varepsilon(l,0) = 1$ and $\varepsilon(l,\infty) = 0$.

Proof. Using equation (6), I rewrite $\varepsilon(l,\theta)$ as follows.

$$\varepsilon(l,\theta) = \frac{q_{l-1}(\theta)}{e^\theta \pi_b(l,\theta)} = \frac{q_{l-1}}{q_{l-1} + \frac{l}{\theta}(e^\theta - q_l)} = \frac{1}{1 + \frac{l}{\theta}(e^\theta - q_l)/q_{l-1}}, \text{ where } q_l(\theta) = \sum_{y=0}^{l} \frac{\theta^y}{y!}$$

To prove the elasticity is decreasing in θ, it is sufficient to prove that the following term in the denominator is increasing in θ.

$$\frac{e^\theta - q_l}{\theta q_{l-1}} l = \lim_{T\to\infty} \frac{\frac{\theta^{l+1}}{(l+1)!} + \frac{\theta^{l+2}}{(l+2)!} + \dots + \frac{\theta^T}{T!}}{\theta[1 + \theta + \frac{\theta^2}{2!} + \dots + \frac{\theta^{l-1}}{(l-1)!}]} l$$

Because the degree of the polynomial in the numerator is higher than that in the denominator, the right side is 0 if $\theta = 0$ (applying L' Hospital rule once) and is infinite if $\theta = \infty$ (applying L' Hospital rule l times).

To show the fraction is increasing in θ, I divide the numerator and the denominator by θ^l.

$$\frac{e^\theta - q_l}{\theta q_{l-1}} l = \lim_{T\to\infty} \frac{\frac{\theta^1}{(l+1)!} + \frac{\theta^2}{(l+2)!} + \ldots + \frac{\theta^{T-l}}{T!}}{\theta^{-l} + \theta^{-l+1} + \frac{\theta^{-l+2}}{2!} + \ldots + \frac{1}{(l-1)!}} l$$

The numerator is increasing in θ, while the denominator is decreasing in θ. The left side of the equation above is increasing in θ. Hence, I prove that $\varepsilon(l,\theta)$ is decreasing in θ. Because the left side is non-negative, it is straightforward to derive that the elasticity lies in the unit interval.

To prove $\varepsilon(l,\theta)$ is increasing in l, I prove that

$$e^{-\theta} q_{l-1}(\theta) \le \varepsilon(l,\theta) < e^{-\theta} q_l(\theta)$$

Notice that the following equality is true.

$$\sum_{k=0}^{l-1} q_k + \theta q_{l-1} = \left[l \cdot 1 + (l-1)\theta + (l-2)\frac{\theta^2}{2!} + \ldots + \frac{\theta^{l-1}}{(l-1)!} \right]$$
$$+ \left[\theta + 2\frac{\theta^2}{2!} + \ldots + l\frac{\theta^l}{l!} \right] = l \left[1 + \theta + \frac{\theta^2}{2!} + \ldots + \frac{\theta^l}{l!} \right] = l q_l$$

I can derive the second inequality as follows.

$$\varepsilon(l,\theta) = \frac{\theta q_{l-1}(\theta)}{e^\theta N(l,\theta)} = \frac{\left[\sum_{k=0}^{l-1} q_k + \theta q_{l-1}\right] - \sum_{k=0}^{l-1} q_k}{l e^\theta - \sum_{k=0}^{l-1} q_k} = \frac{q_l - \frac{1}{l}\sum_{k=0}^{l-1} q_k}{e^\theta - \frac{1}{l}\sum_{k=0}^{l-1} q_k} < e^{-\theta} q_l$$

To derive the first inequality, notice that

$$\varepsilon(l,\theta) = \frac{e^{-\theta} q_{l-1}(\theta)}{\pi_b(l,\theta)} \ge e^{-\theta} q_{l-1}(\theta)$$

Hence, I can show that

$$e^{-\theta} q_{l-1}(\theta) \le \varepsilon(l,\theta) < e^{-\theta} q_l(\theta) \Rightarrow \epsilon(l,\theta) < \varepsilon(l+1,\theta)$$

□

A.3 Proof of Lemma 3

Lemma 3. $N(l,\theta)$ and $\pi_a(l,\theta)$ are increasing and concave in θ. $\pi_b(l,\theta)$ is decreasing in θ.

Proof. Using equation (A.25), the derivative of N with respect to θ can be written as follows.

$$N_\theta(l,\theta) = N(l-1,\theta) + 1 - N(l,\theta) = e^{-\theta} q_{l-1}(\theta), \text{ where } q_l(\theta) = \sum_{y=0}^{l} \frac{\theta^y}{y!} \tag{A.26}$$

Hence, $N(l,\theta)$ is increasing in θ. By Lemma 2, I can show by differentiating both sides of equation (6) that the tenant matching probability π_b is decreasing in θ.

$$\frac{\partial \pi_b(l,\theta)}{\partial \theta} = -\frac{N}{\theta^2}[1-\varepsilon(l,\theta)] < 0$$

To show the concavity of N with respect to θ, it is sufficient to show $N(l, t\theta + (1-t)0) > tN(l,\theta) + (1-t)N(l,0)$ for any θ and $0 < t < 1$. Notice that $N(l,0) = 0$. Using equation (6), I have $N(l,t\theta) = t\theta\pi_b(l,t\theta) > t\theta\pi_b(l,\theta) = tN(l,\theta)$. The monotonicity and concavity of $\pi_a(l,\theta)$ follows from the relationship between π_a and N: $\pi_a(l,\theta) = N(l,\theta)/l$. □

A.4 Proof of Lemma 4

Lemma 4. The quality-adjusted search value $\hat{u}_b(l,\eta)$ is decreasing in η.

Proof. I prove by contradiction. Suppose for some l, there exist $\eta_1 < \eta_2$ such that $\hat{u}_b(l,\eta_1) < \hat{u}_b(l,\eta_2)$. First of all, note that $\eta_1 < \eta_2$ implies that $\theta_1 < \theta_2$ and $\pi_b(l,\theta_1) > \pi(l,\theta_2)$ by Lemma 3. The reservation equation (RE), together the two inequalities about u_b and π_b above implies that $\hat{v}_R(l,\eta_1) > \hat{v}_R(l,\eta_2)$. The definition of the reserve value (15) further implies that $\hat{R}_a(l,\eta_1) > \hat{R}_a(l,\eta_2)$. I would like to use the price setting equation (PS) to derive a contradiction by showing the inequality of rent should be reversed.

I want to show the three components on the right side of the price setting equation is smaller under η_1 than under η_2. Note that $\varepsilon(l,\theta)$ is decreasing in θ. I have $\theta_1[1-F(\hat{v}_R(l,\eta_1))] < \theta_2[1-F(\hat{v}_R(l,\eta_2))]$ and thus $1/\varepsilon(l,\theta_1[1-F(\hat{v}_R(l,\eta_1))]) < 1/\varepsilon(l,\theta_2[1-F(\hat{v}_R(l,\eta_2))]$. In addition, I can show $r(\hat{v}_R(l,\eta_1)) < r(\hat{v}_R(l,\eta_2))$ because the distribution $F(v)$ has a weakly increasing hazard rate. The second to last step is to show the following function G is decreasing in v_R.

$$G(v_R;C) \equiv \frac{\kappa(v_R;C)[1-F(v_R)]}{h(v_R)}, \text{ where } \kappa(v_R;C) \text{ satisfies}$$
$$C = \frac{\hat{\beta}_s\delta}{1-\beta\delta}\kappa(v_R;C)\int_{v_R}^{\infty}[1-F(v)]dv \text{ and } C \text{ is a constant}$$

Note that the function κ is increasing in v_R and C. By differentiate the κ with respect to v_R and apply integration by parts, I can show that the function $G(v_R;C)$ is decreasing.

$$G'(v_R;C) = \frac{1}{h}\left[\frac{\kappa'(v_R)}{\kappa(v_R)} - h - \frac{h'}{h}\kappa(v_R)[1-F(v_R)]\right] = \frac{1}{h}\left[\frac{1-F(v_R)}{\int_{v_R}[1-F(v)]dv} - h - \frac{h'}{h}\right]$$
$$\int_{v_R}[1-F(v)]dv = \int_{v_R}\frac{f(v)}{h(v)}dv = \frac{[1-F(v_R)]}{h(v_R)} - \int_{v_R}[1-F(v)]\frac{h'(v)}{h(v)^2}dv$$
$$\geq \frac{[1-F(v_R)]}{h(v_R)} - \frac{h'(v_R)}{h(v_R)^2}\int_{v_R}[1-F(v)]dv \Rightarrow \int_{v_R}[1-F(v)]dv > \frac{h}{h^2+h'}[1-F(v_R)]$$
$$G'(v_R;C) \leq \frac{1}{h}\left[\frac{h^2+h'}{h} - h - \frac{h'}{h}\right] = 0 \Rightarrow G(\hat{v}_R(l,\eta_1)) \leq G(\hat{v}_R(l,\eta_2))$$

Here the inequality comes from the concavity of the hazard rate in Assumption 1 by showing $h'(v)/h(v) \leq$

$h'(v_R)/h(v_R)$ and $h(v) \geq h(v_R)$ for $v \geq v_R$.

$$\frac{d}{dv}\left(\frac{h'(v)}{h(v)}\right) = \frac{h''(v)h(v) - (h'(v))^2}{h(v)^2} \leq 0 \Rightarrow \frac{h'(v_R)}{h(v_R)^2} \geq \frac{h'(v)}{h(v)^2}, \text{ for } v \geq v_R$$

Let $C_1 = \hat{\beta}_s\delta(1-\beta_s)\hat{u}_b(l,\eta_1) + \hat{\beta}_s\delta c_b$ and $C_2 = \hat{\beta}_s\delta(1-\beta_s)\hat{u}_b(l,\eta_2) + \hat{\beta}_s\delta c_b$. I have

$$\begin{aligned}
&\frac{\hat{\pi}_b(l,\eta_1)[1-F(\hat{v}_R(l,\eta_1))]}{h(\hat{v}_R(l,\eta_1))} = \frac{\kappa(\hat{v}_R(l,\eta_1);C_1)[1-F(\hat{v}_R(l,\eta_1))]}{h(\hat{v}_R(l,\eta_1))} \\
&< \frac{\kappa(\hat{v}_R(l,\eta_2);C_1)[1-F(\hat{v}_R(l,\eta_2))]}{h(\hat{v}_R(l,\eta_2))} < \frac{\kappa(\hat{v}_R(l,\eta_2);C_2)[1-F(\hat{v}_R(l,\eta_2))]}{h(\hat{v}_R(l,\eta_2))} = \frac{\hat{\pi}_b(l,\eta_2)[1-F(\hat{v}_R(l,\eta_2))]}{h(v_R(l,\eta_2))}
\end{aligned}$$

The first and the last equalities are due to equation (RE). The first inequality results from the fact that $G(v_R;C)$ is decreasing in v_R. The second inequality is because κ is increasing in C.

As the three pieces on the right side of the price setting equation (PS) is smaller under η_1 than under η_2, I have $\hat{R}_a(l_1,\eta_1) < \hat{R}_a(l_2,\eta_2)$, which contradicts the inequality derived from the reservation equation that $\hat{R}_a(l_1,\eta_1) > \hat{R}_a(l_2,\eta_2)$. Hence, $\hat{u}_b(l,\eta)$ is decreasing in η. □

A.5 Proof of Proposition 6.1

Proposition 6.1. The tenant-agent ratio $\theta(l)$ and the effective tenant-agent ratio $\hat{\theta}(l)$ are increasing in l.

Proof. I prove the monotonicity of $\theta(l)$ by contradiction. Suppose there exist l_1 and l_2 with $l_1 < l_2$, but $\theta_1 \geq \theta_2$. Because the tenant meeting probability is decreasing in θ, $\pi_b(l_1,\theta_1) \leq \pi_b(l_1,\theta_2) < \pi_b(l_2,\theta_2)$. The reservation equation (RE) and the indifference condition (18) imply that $\hat{v}_R(l_1,\eta_1) < \hat{v}_R(l_2,\eta_2)$. The definition of the reserve value (15) leads to $\hat{R}_a(l_1,\eta_1) < \hat{R}_a(l_2,\eta_2)$. I want to show the inequality of the equilibrium rent is otherwise, by showing the product of three components on the right side of the price setting equation (PS) is bigger under l_1 than under l_2.

Because $\hat{v}_R(l_1,\eta_1) < \hat{v}_R(l_2,\eta_2)$, $r(\hat{v}_R(l_1,\eta_1)) > r(\hat{v}_R(l_2,\eta_2))$. Using the monotonicity of the elasticity in Lemma 2, $\theta_1[1-F(\hat{v}_R(l_1,\eta_1))] > \theta_2[1-F(\hat{v}_R(l_2,\eta_2))]$ implies that $1/\epsilon(l_1,\theta_1[1-F(\hat{v}_R(l_1,\eta_1))]) > 1/\epsilon(l_1,\theta_1[1-F(\hat{v}_R(l_1,\eta_1))]) > 1/\epsilon(l_2,\theta_2[1-F(\hat{v}_R(l_2,\eta_2))])$. As I have shown in the proof of Lemma 4 the monotonicity of the function G, I have the following inequality.

$$\begin{aligned}
&\frac{\hat{\pi}_b(l_1,\eta_1)[1-F(\hat{v}_R(l_1,\eta_1))]}{h(\hat{v}_R(l_1,\eta_1))} = \frac{\kappa(\hat{v}_R(l_1,\eta_1);C)[1-F(\hat{v}_R(l_1,\eta_1))]}{h(\hat{v}_R(l_1,\eta_1))} \\
&> \frac{\kappa(\hat{v}_R(l_2,\eta_2);C)[1-F(\hat{v}_R(l_2,\eta_2))]}{h(\hat{v}_R(l_2,\eta_2))} = \frac{\hat{\pi}_b(l_2,\eta_2)[1-F(\hat{v}_R(l_2,\eta_2))]}{h(\hat{v}_R(l_2,\eta_2))}
\end{aligned}$$

where $C = \hat{\beta}_s\delta(1-\beta_s)u_b + \hat{\beta}_s\delta c_b$ is a constant and u_b is the equilibrium value of a searching tenant which is identical across submarkets. Three inequalities implies that $\hat{R}_a(l_1,\eta_1) > \hat{R}_a(l_2,\eta_2)$ which contradicts the inequality I derive from the reservation equation. Hence, I show that $\theta(l) = \eta(l)l$ is increasing in l.

To prove $\hat{\theta}(l)$ is increasing in l, I prove by contradiction. Suppose there exist l_1 and l_2 with $l_1 < l_2$, but

$\hat{\theta}_1 \geq \hat{\theta}_2$. By Lemma 2, it implies that $\varepsilon(l_1, \theta_1) < \varepsilon(l_2, \theta_2)$. Because I have shown that $\theta_1 < \theta_2$, I can infer that $v_{R1} < v_{R2}$. Using the reservation equation (RE) and the definition of the reserve value (15), I have $\pi_{b1} < \pi_{b2}$ and $R_{a1} < R_{a2}$. On the other hand, $v_{R1} < v_{R2}$ implies that $r(v_{R1}) > r(v_{R2})$ by the monotone hazard rate in Assumption 1 and that $G(v_{R1}; C) > G(v_{R2}; C)$ by the same argument in the first part of the proof. However, the price setting equation (PS) will then imply that $R_{a1} > R_{a2}$, which is a contradiction to what I derive from the reservation equation. Hence, $\theta(l)$ is increasing in l.

A corollary of Proposition 6.1 is that $u_b(l_1, \theta) < u_b(l_2, \theta)$ if $l_1 < l_2$. I prove by contradiction. Suppose there are exist l_1 and l_2 with $l_1 < l_2$, but $u_b(l_1, \theta) \geq u_b(l_2, \theta)$ or $\hat{u}_b(l_1, \theta/l_1) \geq \hat{u}_b(l_2, \theta/l_2)$. From the proof above, I know that $l_1 < l_2$ results in $\theta_1 < \theta_2$. Notice that

$$u_b(l_1, \theta_1) = \hat{u}_b\left(l_1, \frac{\theta_1}{l_1}\right) \geq \hat{u}_b\left(l_2, \frac{\theta_1}{l_2}\right) > \hat{u}_b\left(l_2, \frac{\theta_2}{l_2}\right) = u_b(l_2, \theta_2)$$

The first and the last equalities come from the definition of $U_b(l, \theta)$ and $\hat{u}_b(l, \eta)$. The first inequality evaluates the conjectured inequality at θ_1, while the second equality uses $\theta_1 < \theta_2$ and Lemma 4. However, this cannot be part of the equilibrium, because the values of a searching tenant across submarkets are not equalized. Hence, I have $u_b(l_1, \theta) < u_b(l_2, \theta)$ if $l_1 < l_2$. ☐

A.6 Proof of Proposition 6.2

Proposition 6.2. For $l_1, l_2 \in \mathbb{L}$ and $l_1 < l_2$, if (1) $\hat{\pi}_b(l, \eta)$ increases in l, and (2) $Pr^{ES}(l_1, R_a) < Pr^{ES}(l_2, R_a)$ for $R_a \in S_R(l_1, l_2)$, then in the directed search equilibrium,

(a) large brokers expect more tenants per listing: $\eta(l_1) < \eta(l_2)$

(b) large brokers prefer lower quality-adjusted rents: $\hat{R}_a(l_1, \eta(l_1)) > \hat{R}_a(l_2, \eta(l_2))$

Proof. I focus on the case where $l_0 = 2$. For $l_0 > 2$, I can first focus on two arbitrary submarkets l_1 and l_2 with a fixed number of tenants in the combined market, and then discuss how tenants choose into or out of the combined market, keeping the relative relationship inside the combined market unchanged.

I first characterize the random search equilibrium. Under random search by tenants, the tenant matching probabilities in two submarkets are equalized: $\hat{\pi}_b(l_1, \eta^{RS}(l_1)) = \hat{\pi}_b(l_2, \eta^{RS}(l_2))$. Because $\hat{\pi}_b(l_1, \eta) < \hat{\pi}_b(l_2, \eta)$ by assumption and $\hat{\pi}_b(l_1, \eta)$ is decreasing in η by Lemma 4, I have $\eta^{RS}(l_1) < \eta^{RS}(l_2)$. Using the condition of equalized search values across submarkets, I can use equations (RE) and (15) to show that the quality-adjusted rent R_a and the reserve value $\tilde{v}_R(R_a)$ are constant across submarkets. However, the levels of R_a and $\tilde{v}_R$ are not pinned down under those conditions.

The first order derivative of the agent problem (12) in submarket l is as follows.

$$FOC(l, R_a) = R_a N(l, \hat{\eta}^{RS}(l, R_a)) \left(\frac{1}{R_a} - \frac{\hat{\varepsilon}(l, \hat{\eta}^{RS}(l; R_a))}{r(\tilde{v}_R(R_a))} \frac{d\tilde{v}_R}{dR_a} \right)$$

$$\text{where } \hat{\eta}^{RS}(l; R_a) = \eta^{RS}(l)[1 - F(\tilde{v}_R(R_a))], \; \frac{d\tilde{v}_R}{dR_a} = \hat{\tau}_b \left(1 + \frac{\hat{\beta}_s \delta}{1 - \beta\delta} \pi_b^{RS}[1 - F(\tilde{v}_R)] \right)^{-1}$$

Given R_a in the random search equilibrium, the terms in the parenthesis including $1/R_a$, $r(\tilde{v}_R(R_a))$ and $d\tilde{v}_R/dR_a$ are constant across submarkets, with the exception of $\hat{\varepsilon}(l, \hat{\eta}^{RS}(l; R_a))$. I apply the definition of the demand elasticity and rewrite $\hat{\varepsilon}$ as follows.

$$\hat{\varepsilon}(l_1, \hat{\eta}^{RS}(l_1; R_a)) = \frac{exp(-\hat{\eta}_1^{RS} l_1) q_{l_1 - 1}(\hat{\eta}_1^{RS} l_1)}{\hat{\pi}_b(l_1, \hat{\eta}_1^{RS})} = Pr^{ES}(l_1, R_a)$$
$$< Pr^{ES}(l_2, R_a) = \frac{exp(-\hat{\eta}_2^{RS} l_2) q_{l_2 - 1}(\hat{\eta}_2^{RS} l_2)}{\hat{\pi}_b(l_2, \hat{\eta}_2^{RS})} = \hat{\varepsilon}(l_2, \hat{\eta}^{RS}(l_2; R_a))$$

where the first and last equalities are based on equations (A.26) and (6) and the inequality is by the monotonicity assumption on the conditional probability. Because I consider the case with fixed mass of tenants in submarkets l_1 and l_2, the following inequality must hold for $R_a \in S_R(l_1, l_2)$, with at least one equality to be strict.

$$FOC(l_1, R_a) \geq 0 \geq FOC(l_2, R_a) \tag{A.27}$$

Notice that the random search outcome is identical to the outcome of a constrained directed search equilibrium where rent is restricted to be a constant across submarkets. To see the relationship, given a constant R_a, equal search values of tenants results in constant reserve value by equation (15) and constant tenant matching probability by equation (RE). Hence, once brokers are allowed to differentiate their rental pricing based on the listing capacity, equation (A.27) indicates that rent in submarket l_1 (l_2) will be adjusted above (below) R_a.

$$\hat{R}_a(l_1, \eta(l_1)) > \hat{R}_a(l_2, \eta(l_2))$$

With lower rent in submarket l_2 in the direct search equilibrium, tenants will find the search value in submarket l_2 higher, leading to an increase in the number of tenants in submarket l_2 until search values are equalized. As a result,

$$\eta(l_1) < \eta^{RS}(l_1) < \eta^{RS}(l_2) < \eta(l_2)$$

□

A.7 Proof of Corollary 6.3

Corollary 6.3. In the directed search equilibrium, the larger the agent size ($l_1 < l_2$),

(a) the lower the reserve value: $\hat{v}_R(l_1, \eta(l_1)) > \hat{v}_R(l_2, \eta(l_2))$

(b) the smaller the tenant matching probability: $\hat{\pi}_b(l_1, \eta(l_1)) > \hat{\pi}_b(l_2, \eta(l_2))$

(c) the higher the effective tenant-listing ratio: $\hat{\eta}(l_1) < \hat{\eta}(l_2)$

(d) the larger the listing matching probability: $\hat{\pi}_a(l_1, \hat{\eta}(l_1)) < \hat{\pi}_a(l_2, \hat{\eta}(l_2))$

(e) the greater the landlord listing value: $\hat{\Pi}_L(l_1, \theta(l_1), q) < \hat{\Pi}_L(l_2, \theta(l_2), q)$

Proof. (a) I can derive the inequality of reserve value $\hat{v}_R(l, \eta(l))$ from equation (15).

(b) I can derive the inequality of the tenant matching probability $\hat{\pi}_b(l, \eta(l))$ from equation (RE).

(c) I prove by contradiction to show the inequality of the effective tenant-listing ratio $\hat{\eta}(l)$. Suppose $\hat{\eta}(l_1) \geq \hat{\eta}(l_2)$. Then, combine the identity $\hat{\eta}(l) = \eta(l)[1 - F(\hat{v}_R(l, \eta(l)))]$ and $\eta(l_1) < \eta(l_2)$ from Proposition 6.2, I have $\hat{v}_R(l_1, \eta(l_1)) \leq \hat{v}_R(l_2, \eta(l_2))$, which contradicts $\hat{v}_R(l_1, \eta(l_1)) > \hat{v}_R(l_2, \eta(l_2))$. Hence, $\hat{\eta}(l)$ is increasing in l.

(d) I prove the inequality of the listing matching probability $\hat{\pi}_a(l, \hat{\eta}(l))$. Because $\hat{\pi}_b(l, \eta)$ is increasing in l by the assumption in Proposition 6.2, $\hat{\pi}_a(l, \eta) = \eta\hat{\pi}_b(l, \eta)$ is increasing in l. As $\pi_a(l, \theta)$ is increasing in $\theta = \eta l$ by Lemma 3, $\hat{\pi}_a(l, \eta)$ is increasing in η. Because $\hat{\eta}(l_1) < \hat{\eta}(l_2)$ for $l_1 < l_2$, I have $\hat{\pi}_a(l_1, \hat{\eta}(l_1)) < \hat{\pi}_a(l_2, \hat{\eta}(l_2))$.

(e) I show that the landlord listing value $\hat{\Pi}_L(l, \theta(l), q)$ is increasing in l. Define the reserve value $\tilde{v}_R(l, R_a)$ that incorporates the impact of the equilibrium tenant-agent ratio $\theta(l)$ as follows.

$$\tilde{v}_R(l, R_a) - \hat{\tau}_b R_a = -\hat{\beta}_s \delta c_b + \frac{\hat{\beta}_s \delta}{1 - \beta\delta} \hat{\pi}_b(l, \eta(l)) \int_{\tilde{v}_R(l, R_a)}^{\infty} [1 - F(v)] dv$$

Because $\hat{\pi}_b(l_1, \eta(l_1)) > \hat{\pi}_b(l_2, \eta(l_2))$ for $l_1 < l_2$, $\tilde{v}_R(l, R_a)$ is decreasing in l. Rewrite the agent maximization problem (12) as follows, with the optimal rent denoted by $R^*_{a,l}$.

$$R^*_{a,l} \hat{\pi}_a(l, \eta(l)[1 - F(\tilde{v}_R(l, R^*_{a,l}))])$$

I use the expression above to show that the landlord listing value $\hat{\Pi}_L(l, \theta(l), q)$ is increasing in l. Note that $\eta(l)$ and $1 - F(\tilde{v}_R(l, R^*_{a,l}))$ are increasing in l. As I have shown in the first part of the proof that $\hat{\pi}_a(l, \eta)$ is increasing in both arguments, the landlord listing value above is increasing in l given $R^*_{a,l}$. Similar to the mechanism of the Envelope Theorem, the agent impact through $R^*_{a,l}$ has zero first-order effect on the expected broker profit, because it is already accounted for by the optimality condition.

□

A.8 Proof of Lemma 5

Lemma 5. Brokers with $l \geq \hat{L}(q)$ are accepted. If $c_{v0} > 0$ and c_{v1} is sufficiently small, $\hat{L}(q)$ is decreasing.

Proof. Because the net value $\hat{\Pi}_L(l,\theta(l),q) - c_{v0} - c_{v1}q$ is increasing in the agent size l (Corollary 6.3), a landlord accepts a broker she meets if $l \geq \hat{L}(q)$ and declines a broker if $l < \hat{L}(q)$, with $\hat{L}(q)$ to be the minimum acceptable agent size.

$$\begin{aligned}\mathcal{L}(q) &= \{l : \chi_L(l,q) = 1\} = \{l : \hat{\Pi}_L(l,\theta(l),1) - c_{v1} \geq c_{v0}/q\} \\ &= \{l : \hat{\Pi}_L(l,\theta(l),1) \geq \hat{\Pi}_L(\hat{L}(q),\theta(\hat{L}(q)),1)\} = \{l : l \geq \hat{L}(q)\}\end{aligned}$$

For $q_1 < q_2$, the first line indicates that if $c_{v0} > 0$ and c_{v1} is sufficiently small ($c_{v1} < \hat{\Pi}_L(1,\theta(1),1)$), then $\mathcal{L}(q_1) \subseteq \mathcal{L}(q_2)$ and both sets are non-empty. For other cases, if $c_{v0} = 0$, $\hat{L}(q)$ does not depend on q. If $c_{v0} \neq 0$ and c_{v1} is too large, either $\mathcal{L}(q_1)$ and $\mathcal{L}(q_2)$ are empty ($c_{v0} > 0$), or $\mathcal{L}(q_2) \subseteq \mathcal{L}(q_1)$ ($c_{v0} < 0$). With $\mathcal{L}(q_1) \subseteq \mathcal{L}(q_2)$, I have in the second line that $\hat{L}(q)$ is decreasing in q. □

A.9 Proof of Proposition 6.4

Proposition 6.4. The mean rental quality $q(l) = \phi E(q|l,\hat{Q}) + (1-\phi)E(q)$ is decreasing in the agent size l.

Proof. It is equivalent to prove $E(q|l,\hat{Q})$ is decreasing in l. For $l_1, l_2 \in \mathbb{L}$ and $l_1 < l_2$, denote $\hat{Q}_l = \hat{Q}(l)$ and I have $\hat{Q}_1 \geq \hat{Q}_2$ by Lemma 5. By equation (22), I have $Pr^S(q < \hat{Q}_l|l,\hat{Q}) = 0$. I want to show that, for all $\hat{q}$, $\sum_{q\geq\hat{q}} Pr(q|l_1,\hat{Q}) \geq \sum_q Pr(q|l_2,\hat{Q})$, which I divide into two cases.

$$\text{If } \hat{q} \geq \hat{Q}_1,\ \sum_{q\geq\hat{q}} Pr^S(q|l_1,\hat{Q}) = \frac{\sum_{q\geq\hat{q}} Pr(q)}{\sum_{q\geq\hat{Q}_1} Pr(q)} \geq \frac{\sum_{q\geq\hat{q}} Pr(q)}{\sum_{q\geq\hat{Q}_1} Pr(q) + \sum_{\hat{Q}_1>q\geq\hat{Q}_2} Pr(q)} = \sum_{q\geq\hat{q}} Pr^S(q|l_2,\hat{Q})$$
$$\text{If } \hat{Q}_2 \leq \hat{q} < \hat{Q}_1,\ \sum_{q\geq\hat{q}} Pr^S(q|l_1,\hat{Q}) = 1 \geq \sum_{q\geq\hat{q}} Pr^S(q|l_2,\hat{Q})$$

In the first case, I use $\sum_{\hat{Q}_1>q\geq\hat{Q}_2} Pr(q) \geq 0$ for the inequality. In sum, I show that $\forall\hat{q}$, $\sum_{q\geq\hat{q}} Pr^S(q|l_1,\hat{Q}) \geq \sum_q Pr^S(q|l_2,\hat{Q})$ for $l_1 < l_2$. $Pr^S(q|l_1,\hat{Q})$ first-order stochastic dominates $Pr^S(q|l_2,\hat{Q})$. Hence, I conclude that the mean rental quality conditioning on the landlord choice is decreasing in the agent size, $E(q|l_1,\hat{Q}) \geq E(q|l_2,\hat{Q})$.

□

A.10 Proof of Proposition 8.1

Proposition 8.1. The commission paid by a landlord $\hat{\tau}_L(l,q)$ is increasing in the agent size.

Proof. If the solution is interior, the first order condition of the bargaining problem is

$$\frac{\alpha}{1-\alpha}\frac{BP_a(l,q,\tau_L)}{BP_L(l,q,\tau_L)} = -\frac{\partial BP_a/\partial\tau_L}{\partial BP_L/\partial\tau_L} = 1 \tag{A.28}$$

For the last equality, note that the fee allocation does not affect the surplus.

$$BP_L + BP_a = (1-\beta\delta)^{-1}[\kappa(l)\pi_a(l)q - (c_{v0} + c_{v1}q)] \Rightarrow \frac{\partial BP_L}{\partial\tau_L} + \frac{\partial BP_a}{\partial\tau_L} = 0$$

Equation (A.28) implies that $BP_a(l,q,\tau_L) = (1-\alpha)[BP_L(l,q,\tau_L) + BP_a(l,q,\tau_L)]$. If an interior solution exists, I solve the optimal $\tau_L^*(l,q)$ using equation (23).

$$\begin{aligned}
BP_a &= (1-\alpha)(BP_L + BP_a) = (1-\alpha)(1-\beta\delta)^{-1}\left[\kappa(l)\pi_a(l)q - (c_{v0} + c_{v1}q)\right] \\
BP_L &= \alpha(BP_L + BP_a) \\
\Rightarrow \tau_L^*(l,q) &= \tau\left[1 - \frac{1}{1-\alpha}\left(1 - \frac{c_{v0} + c_{v1}q}{\kappa(l)\pi_a(l)q}\right)^{-1}\right] + \frac{1}{1-\beta\delta} \in (0,\tau)
\end{aligned}$$

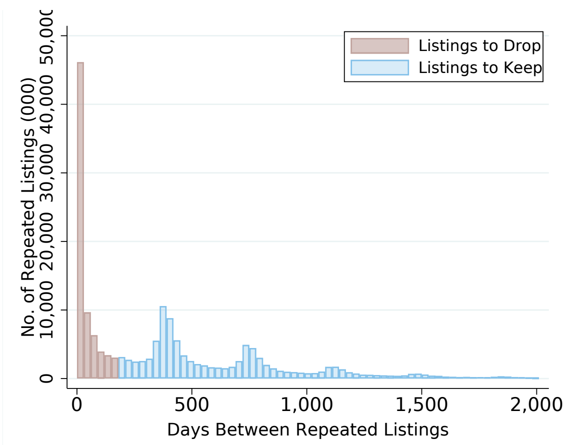
Given a constant level of a constant level of τ_{L0}, $\hat{\Pi}_L(l,1) = [(1-\beta\delta)^{-1} - \tau_{L0}]\kappa(l)\pi_a(l)$ is increasing in l by Corollary 6.3. By adding (RE) to (PS), I can show that the reserve value $v_R(l)$ does not depend on the fee allocation. Neither do $\kappa(l)$ and $\pi_a(l)$ that are functions of $v_R(l)$. I thus have $\kappa(l)\pi_a(l)$ to be independent of τ_L and to be increasing in l. Hence, $\hat{\tau}_L(l,q)$ is increasing in l and q. □

B Data Appendix

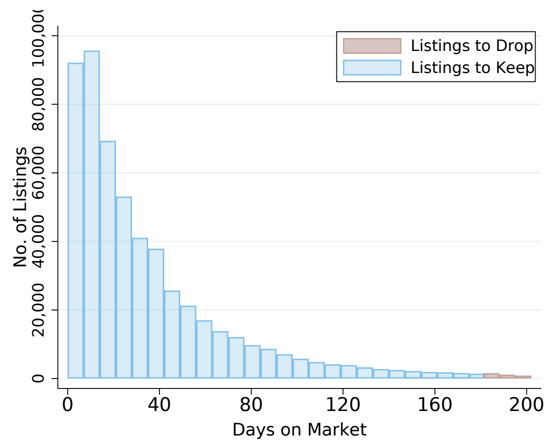
B.1 Data Filtering

To get a workable listing-agent matched data set from StreetEasy, I detect observations (1) with missing initial or last listed rent or date, (2) with inconsistent listed dates (*e.g.* the last listed date predates the initial lasted date). I use the rent history (a JSON object with the updated rent and date of the rent update) to infer the correct initial and last listed rent and date if the detected fields are missing or inconsistent. I drop the observations that has no sufficient information to infer the correct rents or dates.

One concern of the listings on a public platform is the issue of duplicates. I find that some rental units are taken down and re-listed with no changes in a very short period of time. Multiple listing records produced in this way should be regarded as one. Not many properties are turned over every year, as the moving cost in NYC is expensive.



a Days between Repeated Listings



b Days on Market

Figure B.1: Days between repeated listings and days on market. The width of a bin is 30 days in Panel 1a and 7 days in Panel 1b. The sample is the rental listings (2010-2017) in Manhattan.

To exclude the duplicated listings, I first identify repeated listings that are tied to the same property address from 2010 to 2017 and drop the listings if the number of days to the next repeated listing (if it exists) is fewer than 180 days (12% of the raw sample). The threshold is well above the days on market of an average listing ($<$ 50 days). The typical length of a rental contract in NYC is one or two years, so the threshold excludes potential duplicated listings and leaves enough room for properties to go back to the rental market through early termination by tenants (*e.g.* due to job change or family migration). I exclude properties with more than 10 bedrooms or 10 bathrooms (0.2% of raw sample), which is not typical in Manhattan. Furthermore, I drop stale listings whose days on market exceeds 180 days (6% of the raw sample). Because listing behaviors of agents is my main focus, I exclude listings without the agent identifiers.

In Appendix Figure B.1, Panel 1a shows the distribution of the number of days between two consecutive repeated listings. 28% of the listings in the raw sample are repeated listings, with 12% of the raw sample detected as duplicates. Panel 1b shows the distribution of the days on market, with the sample in the right tail excluded due to the stale listings.

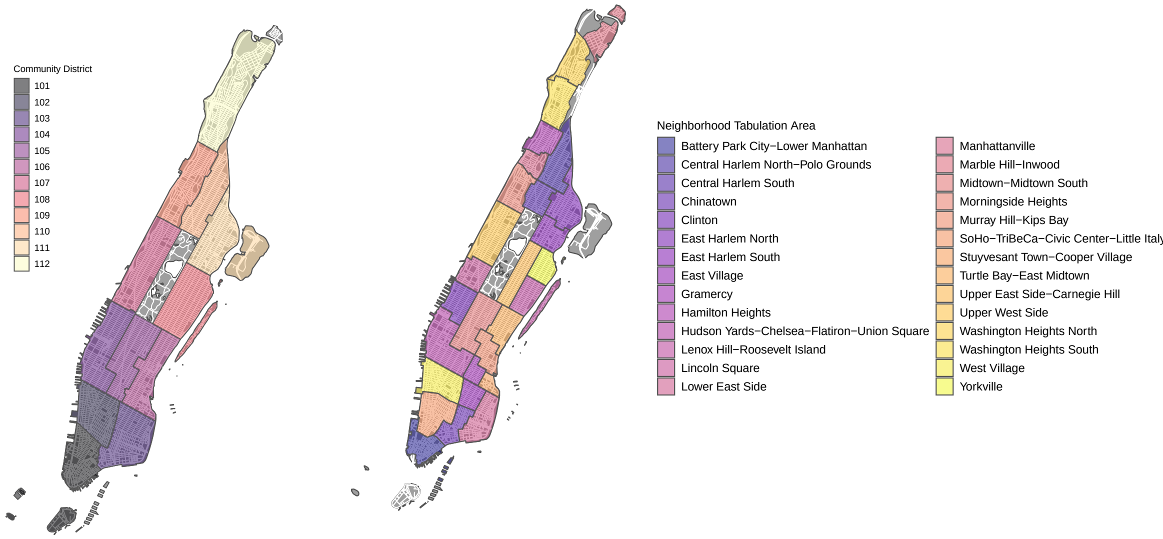
B.2 Rental Data Source and Reliability

Existing studies of the US rental markets are constrained by the breadth, the depth or the timeliness of the rental data and rely more on the private proprietary data sources, different from the studies of US sales markets that rely on the public deed transfer records of accessible online or at the county recorder's offices in most US states.

Major public rental data such as American Community Survey and American Housing Survey rely on a sparse sample of households in a neighborhood, focusing more on the market breadth than the depth, and cannot capture the short-term market trend. The concern of the micro rental data from private firms is that the sample may bias towards large, multi-family and expensive housing units. I think the issue is minor in my data sample, because the share of multi-family housing is more than 98% in Manhattan (Rascoff and Humphries, 2015) and the summary statistics of housing characteristics in my sample are similar to those from NYCHVS (2017). See the discussion on the issues of the rental market data by Urban Institute (2019).

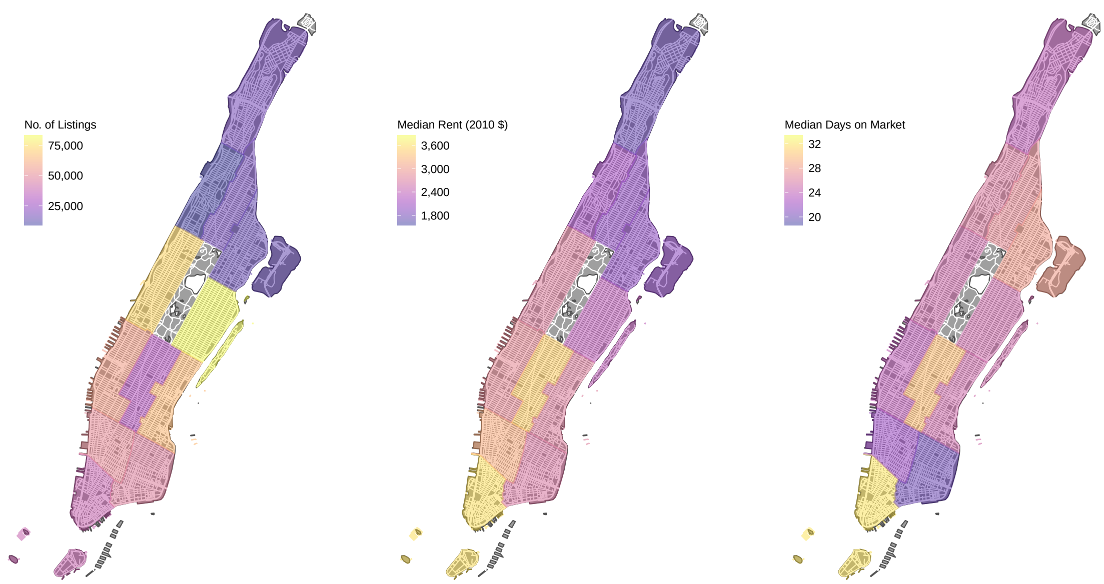
I use the rental listing data from a private firm (StreetEasy). I focus on Manhattan because the quality and the coverage of the listings are the best among all boroughs. I study the listing behavior before 2017, because StreetEasy changed the listing fee policies from the second half of 2017. Moreover, the platform started to face the direct competition with NYC's first multiple listings site: Residential Listing Service (RLS) launched in late 2017 and empowered by Real Estate Board of New York (REBNY).

C Additional Figures and Tables



a Community District **b** Neighborhood Tabulation Area (NTA)

Figure C.1: Division of New York Manhattan by Community District (12) or by neighborhood (28, excluding the Central Park). Divisions are defined by NYC Department of City Planning.



a No. of Listings **b** Median Rent (2010 $) **c** Median Days on Market

Figure C.2: Heat maps of the number of listings, rent, and days on market by community district in Manhattan. The sample is rental listings by brokers (2010-2017) in Manhattan. Rent refers to the last listed rent (2010 $). Community districts are defined by the NYC Department of City Planning.

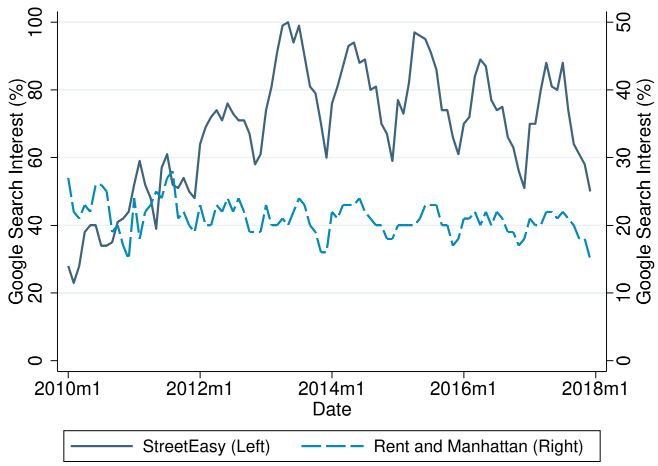
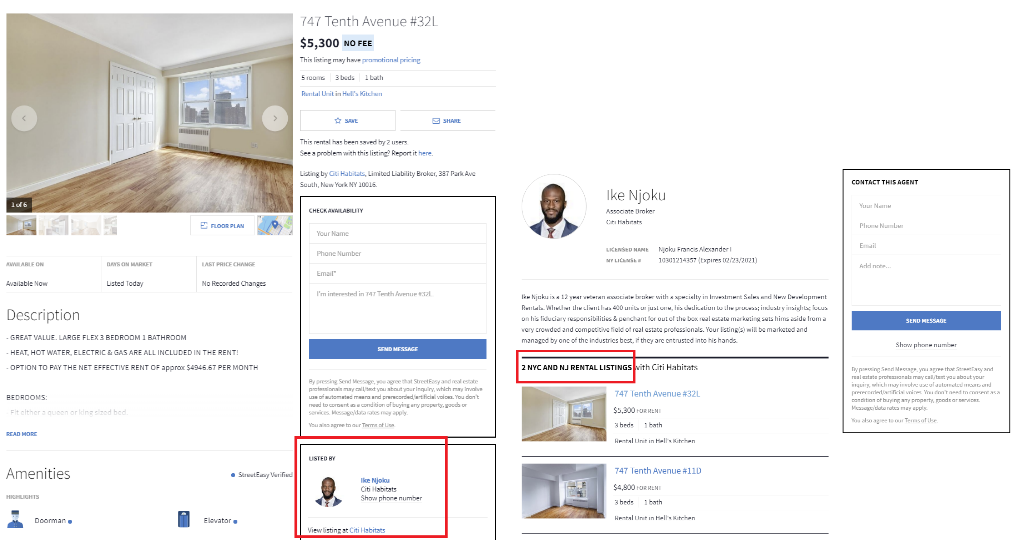


Figure C.3: Google Trend of "StreetEasy" and "Rent and Manhattan" for 2010-2017. The index represents search interest relative to the highest point on the chart for the given region and time. A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular.



a Example: Webpage of a Brokerage Listing

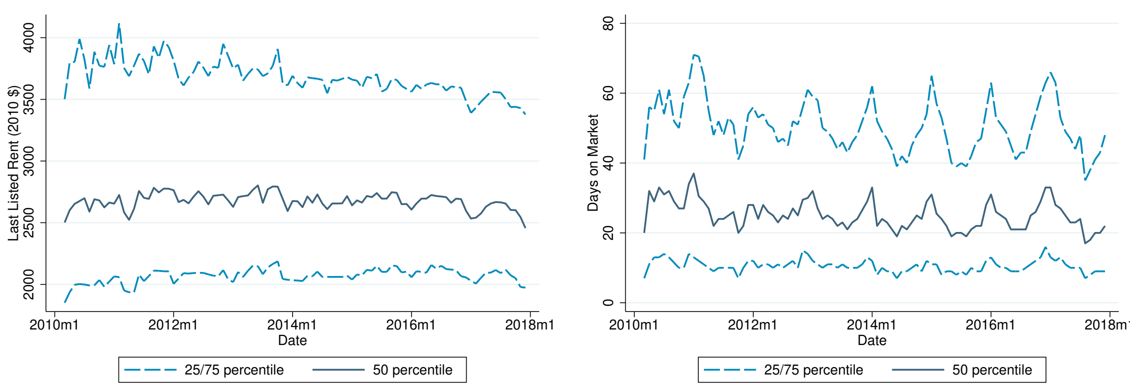
b Example: Webpage of a Listing Broker

Figure C.4: Screenshots of a rental listing page and a listing broker page. The screenshots are taken from www.streeteasy.com in January 2020.

a Listed Rent Movement (%)

b Last-Initial Rent Ratio (%)

Figure C.5: Time trend of the listed rent movement and the last-initial rent ratio. The sample is the listings by brokers (2010-2017) in Manhattan. The last-initial rent ratio is based on the subsample of listings whose last listed rents differ from the initial rents.



a Last Listed Rent (2010 $)

b Days on Market

Figure C.6: Time trend of the last listed rent and days on market (2010-2017), by percentile. The sample is the listings by brokers (2010-2017) in Manhattan.

Table C.1: Distribution of Listing Characteristics

	Listings by Brokers						
Listing Characteristics	Mean	SD	Pct.10	Pct.25	Pct.50	Pct.75	Pct.90
Last Listed Rent (2010 $)	3,510	4,022	1,697	2,084	2,673	3,663	5,603
Initial Listed Rent (2010 $)	3,592	4,153	1,717	2,110	2,718	3,736	5,752
Days on Market	37	38	4	10	24	50	90
Listing Stock of Agent	13	18	2	3	7	14	28
Monthly Volume of Agent	6	8	1	1	3	7	13
Is No-fee Listing	0.26	0.44	0	0	0	1	1
No. of Bedrooms	1.33	1.01	0	1	1	2	3
No. of Bathrooms	1.19	0.53	1	1	1	1	2
Has Doorman	0.41	0.49	0	0	0	1	1
Has Elevator	0.54	0.50	0	0	1	1	1
Has Fireplace	0.11	0.31	0	0	0	0	1
Has Dishwasher	0.40	0.49	0	0	0	1	1
Is Furnished	0.06	0.24	0	0	0	0	0
Has Gym	0.29	0.45	0	0	0	1	1
Allows Pets	0.56	0.50	0	0	1	1	1
Has Washer Dryer	0.26	0.44	0	0	0	1	1
Has Garage	0.21	0.41	0	0	0	0	1
Has Roof Deck	0.25	0.43	0	0	0	1	1
Has Concierge	0.22	0.42	0	0	0	0	1
Has Pool	0.12	0.32	0	0	0	0	1
Has Garden	0.13	0.34	0	0	0	0	1
Has Childrens' Playroom	0.10	0.30	0	0	0	0	0
Has Rent-Stabilized Unit	0.59	0.49	0	0	1	1	1

Note: The sample is the rental listings by brokers (2010-2017) in Manhattan. Initial and last listed rents are adjusted to 2010 dollars.

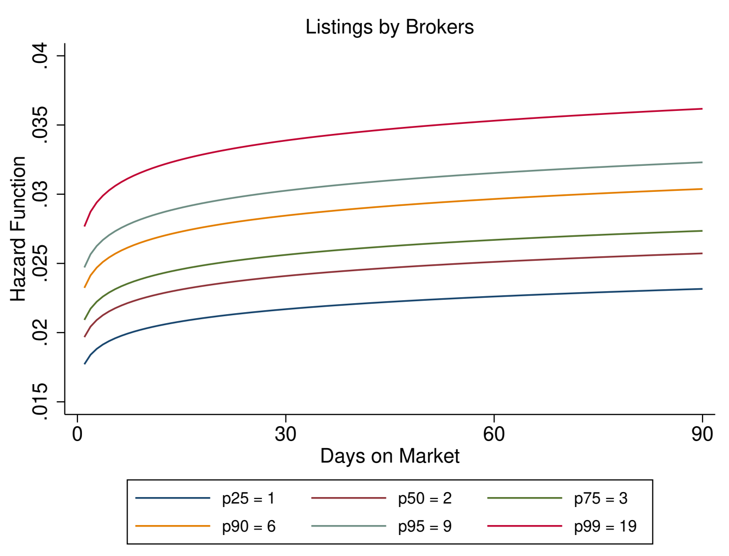


Figure C.7: Hazard functions of listings by brokers at the selected percentiles of agent distribution. The survival model controls the housing amenities and the location-date fixed effect. For the control variables, see Appendix Table C.1. The sample is rental listings by brokers (2010-2017) in Manhattan.

Table C.2: Reduced-Form Models of Rent and Days on Market (DOM)

	(1) Log Rent	(2) Log Rent	(3) Log Rent	(4) Log Rent	(5) Log DOM	(6) Log DOM	(7) Log DOM	(8) Log DOM
Agent Size Dummies		(Omitted)		(Omitted)		(Omitted)		(Omitted)
Is No-fee Listing		0.070***		0.011***		-0.007		-0.019**
		(0.006)		(0.003)		(0.009)		(0.008)
No. of Bedrooms			0.210***	0.211***			0.023***	0.031***
			(0.002)	(0.001)			(0.004)	(0.003)
No. of Bathrooms			0.352***	0.347***			0.151***	0.128***
			(0.005)	(0.005)			(0.006)	(0.006)
Has Doorman			0.065***	0.059***			0.149***	0.131***
			(0.003)	(0.003)			(0.008)	(0.007)
Has Elevator			0.121***	0.114***			0.114***	0.090***
			(0.003)	(0.003)			(0.006)	(0.006)
Has Fireplace			0.073***	0.070***			0.067***	0.047***
			(0.003)	(0.003)			(0.008)	(0.007)
Has Dishwasher			0.023***	0.024***			-0.070***	-0.045***
			(0.002)	(0.002)			(0.006)	(0.005)
Is Furnished			0.137***	0.130***			0.410***	0.375***
			(0.004)	(0.004)			(0.011)	(0.011)
Has Gym			0.051***	0.051***			-0.019**	-0.003
			(0.003)	(0.003)			(0.008)	(0.007)
Allows Pets			0.009***	0.010***			0.023***	0.020***
			(0.002)	(0.002)			(0.006)	(0.005)
Has Washer Dryer			0.079***	0.077***			0.020***	0.008
			(0.003)	(0.003)			(0.007)	(0.007)
Has Garage			0.001	0.000			0.011	-0.002
			(0.002)	(0.002)			(0.008)	(0.008)
Has Roof Deck			0.000	0.001			0.007	0.008
			(0.003)	(0.003)			(0.007)	(0.006)
Has Concierge			0.022***	0.023***			0.029***	0.021***
			(0.004)	(0.004)			(0.008)	(0.007)
Has Pool			0.006*	0.004			0.042***	0.038***
			(0.003)	(0.003)			(0.008)	(0.007)
Has Garden			0.020***	0.018***			0.049***	0.030***
			(0.002)	(0.002)			(0.007)	(0.006)
Has Childrens' Playroom			0.016***	0.013***			0.031***	0.030***
			(0.004)	(0.004)			(0.009)	(0.008)
Has Rent-Stabilized Unit			-0.106***	-0.093***			-0.218***	-0.156***
			(0.003)	(0.003)			(0.007)	(0.006)
Sample	2010-2017	2010-2017	2010-2017	2010-2017	2010-2017	2010-2017	2010-2017	2010-2017
Housing Amenities			✓	✓			✓	✓
Agent Characteristics		✓		✓		✓		✓
Location-Date FE	✓	✓	✓	✓	✓	✓	✓	✓
Survival Distribution					Weibull (1.01)	Weibull (1.05)	Weibull (1.05)	Weibull (1.07)
Adjusted R^2	0.15	0.19	0.75	0.76	0.05	0.09	0.12	0.14
N	396,537	396,537	396,537	396,537	396,537	396,537	396,537	396,537

Note: clustered-robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010. Errors are clustered by the neighborhood and the quarterly date. The sample is the rental listings by brokers (2010-2017) in Manhattan. The agent size dummies are used to allow the non-parametric impact of the agent size on the listing outcomes. The location-date fixed effect allows models to condition on the community district and the quarterly date. Rent refers to the last listed rent (2010 $). Accelerated failure time models under the Weibull survival distribution are estimated, with the parameter reported in the parenthesis.

Table C.3: Listing Characteristics by Agent Size Percentile

	min - p25	p25 - p50	p50 - p75	p75 - p90	p90 - p95	p95 - p99	p99 - max
No. of Bedrooms	1.32	1.33	1.33	1.33	1.32	1.33	1.34
No. of Bathrooms	1.32	1.33	1.30	1.22	1.16	1.14	1.13
Has Doorman	0.61	0.60	0.55	0.46	0.37	0.34	0.33
Has Elevator	0.74	0.72	0.67	0.58	0.50	0.48	0.47
Has Fireplace	0.14	0.15	0.14	0.12	0.11	0.10	0.09
Has Dishwasher	0.37	0.37	0.37	0.39	0.39	0.41	0.42
Is Furnished	0.13	0.12	0.11	0.08	0.06	0.04	0.04
Has Gym	0.42	0.41	0.38	0.32	0.26	0.23	0.24
Allows Pets	0.60	0.60	0.59	0.57	0.54	0.54	0.57
Has Washer Dryer	0.33	0.35	0.32	0.29	0.25	0.24	0.21
Has Garage	0.31	0.30	0.29	0.23	0.20	0.18	0.17
Has Roof Deck	0.35	0.34	0.32	0.27	0.23	0.21	0.23
Has Concierge	0.34	0.34	0.31	0.25	0.19	0.17	0.18
Has Pool	0.17	0.18	0.17	0.14	0.11	0.09	0.09
Has Garden	0.18	0.19	0.16	0.14	0.12	0.11	0.11
Has Childrens' Playroom	0.15	0.15	0.14	0.11	0.08	0.07	0.08
Is No-fee Listing	0.14	0.12	0.14	0.20	0.25	0.28	0.39
Has Rent-Stabilized Unit	0.38	0.38	0.41	0.52	0.62	0.68	0.71
Atypicality Index	0.32	0.32	0.32	0.32	0.33	0.33	0.32

Note: The sample is the rental listings by brokers (2010-2017) in Manhattan.

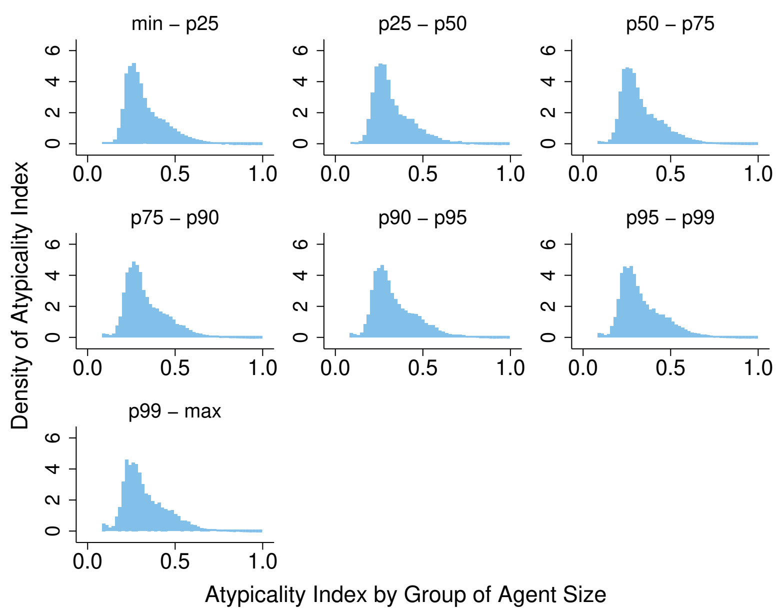
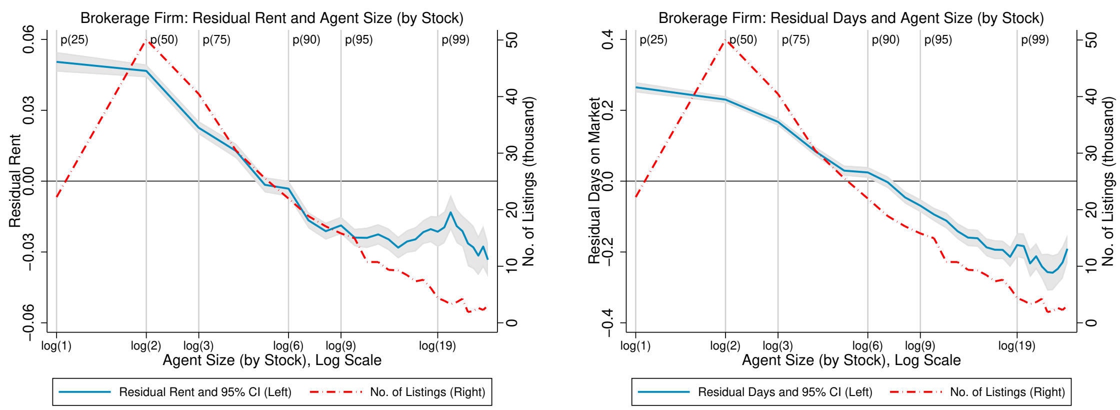


Figure C.8: Distribution of the atypicality index by the agent size group. The sample is rental listings by brokers (2010-2017) in Manhattan. The definition of the atypicality index follows Han and Strange (2016).

Table C.4: Linear and Logit Probability Models of No-fee Status

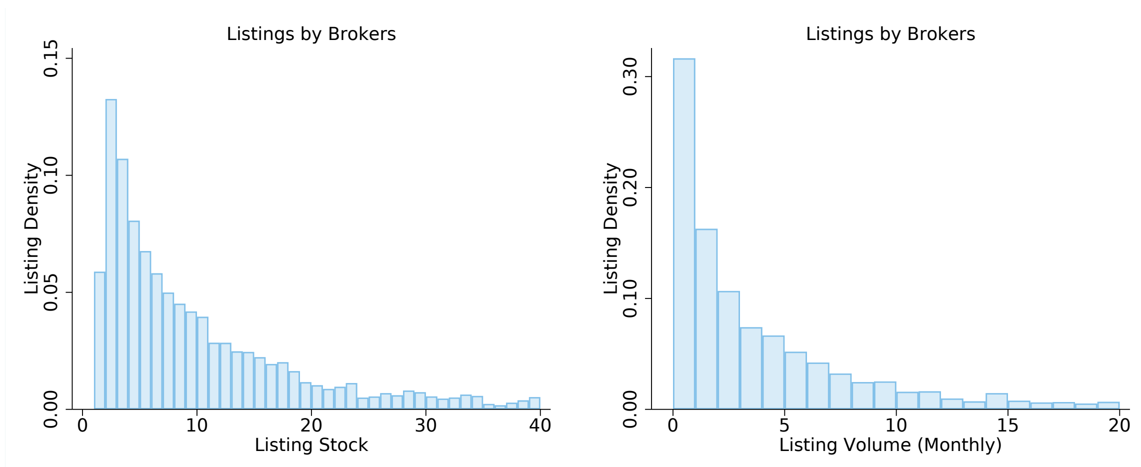
	(1) Is No-Fee Linear	(2) Is No-Fee Linear	(3) Is No-Fee Linear	(4) Is No-Fee Linear	(5) Is No-Fee Logit	(6) Is No-Fee Logit	(7) Is No-Fee Logit	(8) Is No-Fee Logit
Agent Size Dummies		(Omitted)		(Omitted)		(Omitted)		(Omitted)
No. of Bedrooms			0.025***	0.023***			0.160***	0.155***
			(0.002)	(0.002)			(0.010)	(0.009)
No. of Bathrooms			-0.049***	-0.039***			-0.325***	-0.275***
			(0.003)	(0.003)			(0.020)	(0.019)
Has Doorman			-0.012**	-0.002			-0.056*	-0.004
			(0.005)	(0.004)			(0.033)	(0.029)
Has Elevator			0.030***	0.033***			0.199***	0.219***
			(0.005)	(0.004)			(0.029)	(0.026)
Has Fireplace			-0.025***	-0.017***			-0.193***	-0.157***
			(0.004)	(0.003)			(0.028)	(0.025)
Has Dishwasher			0.082***	0.068***			0.478***	0.427***
			(0.004)	(0.003)			(0.021)	(0.019)
Is Furnished			-0.086***	-0.059***			-0.578***	-0.411***
			(0.007)	(0.005)			(0.045)	(0.040)
Has Gym			0.116***	0.111***			0.665***	0.682***
			(0.006)	(0.005)			(0.034)	(0.032)
Allows Pets			0.013***	0.014***			0.085***	0.097***
			(0.003)	(0.003)			(0.021)	(0.019)
Has Washer Dryer			0.006	0.013***			0.045*	0.100***
			(0.004)	(0.004)			(0.026)	(0.022)
Has Garage			0.009*	0.016***			0.035	0.089***
			(0.005)	(0.004)			(0.029)	(0.026)
Has Roof Deck			0.072***	0.072***			0.403***	0.430***
			(0.005)	(0.004)			(0.029)	(0.025)
Has Concierge			0.029***	0.023***			0.160***	0.136***
			(0.007)	(0.006)			(0.038)	(0.034)
Has Pool			-0.046***	-0.044***			-0.257***	-0.250***
			(0.005)	(0.004)			(0.030)	(0.027)
Has Garden			0.021***	0.029***			0.118***	0.174***
			(0.005)	(0.004)			(0.029)	(0.026)
Has Childrens' Playroom			-0.038***	-0.035***			-0.188***	-0.182***
			(0.006)	(0.006)			(0.035)	(0.031)
Has Rent-Stabilized Unit			0.066***	0.038***			0.409***	0.256***
			(0.005)	(0.004)			(0.030)	(0.026)
Sample	2010-2017	2010-2017	2010-2017	2010-2017	2010-2017	2010-2017	2010-2017	2010-2017
Housing Amenities			✓	✓			✓	✓
Agent Characteristics		✓		✓		✓		✓
Location-Date FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.10	0.16	0.14	0.20	0.09	0.14	0.13	0.18
N	396,537	396,537	396,537	396,537	396,537	396,537	396,537	396,537

Note: clustered-robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010. Errors are clustered by the neighborhood and the quarterly date. Exponentiated coefficients are reported for the logit models. Adjusted R-squared and pseudo R-squared are reported for the linear probability and the logit models respectively. The sample is the rental listings by brokers (2010-2017) in Manhattan.



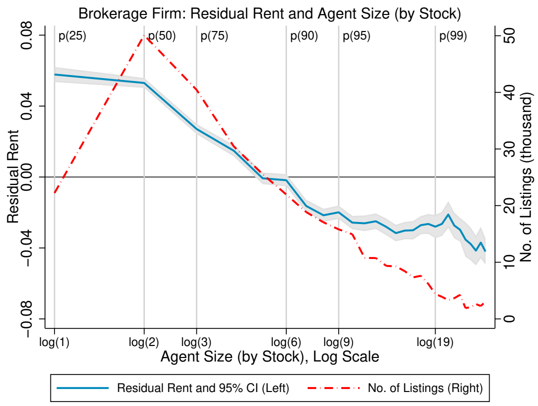
a Residual Rent (2010 $) **b** Residual Listing Days

Figure C.9: Residual rent, residual listing days and agent size (log deviation from the mean). The percentiles of the agent distribution are reported, with the bottom 90% of rentals covered. The residual rent (listing days) are adjusted for the housing amenities and the location-date effect using Model 3 (Model 7) in Table 4. For the control variables, see Appendix Table C.1. Rent refers to the last listed rent (2010 $). The sample is rental listings by brokers (2010-2017) in Manhattan.

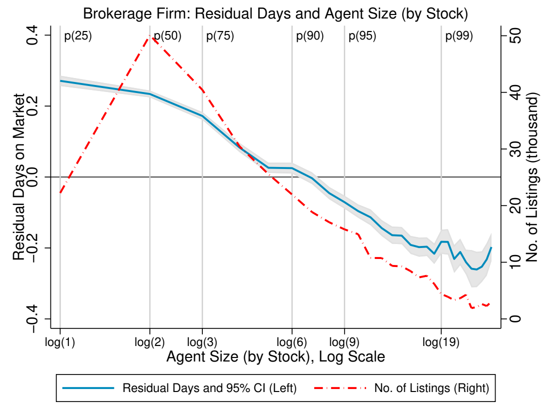


a Agent Size (by Listing Stock) **b** Agent Size (by Monthly Volume)

Figure C.10: Listing distribution by the agent size. See equation (1) and Fn.16 for the definitions of the agent size. The sample is rental listings by brokers (2010-2017) in Manhattan.

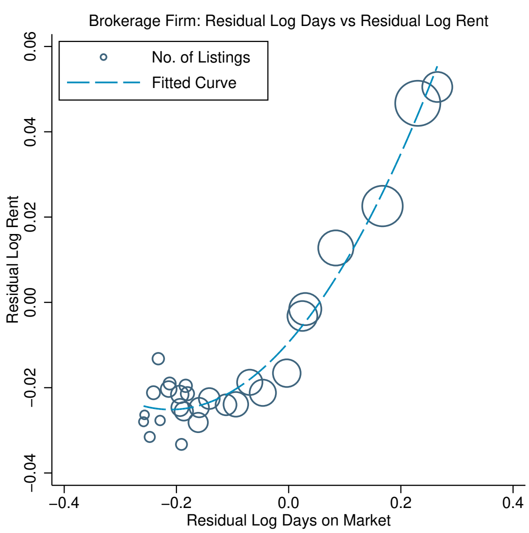


a Residual Initial Rent (2010 $)

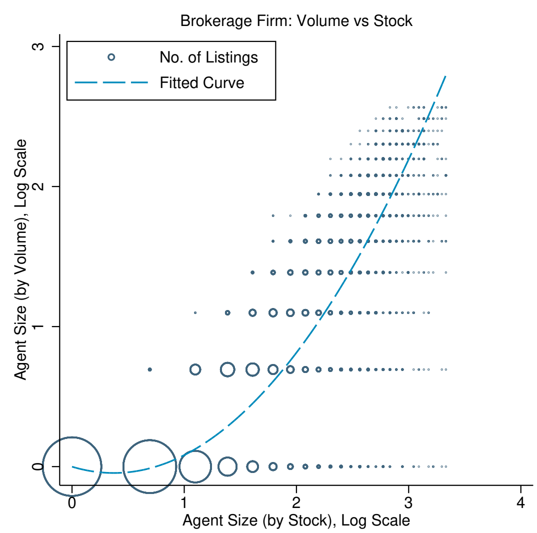


b Residual Listing Days

Figure C.11: Residual initial rent, residual listing days and the agent size. The percentiles of the agent distribution are reported, with the bottom 90% of rentals covered. The residual initial rents (listing days) are adjusted for the housing amenities and the location-date effect (using the initial listing dates). For the control variables, see Appendix Table C.1. Initial rents are adjusted to 2010 dollars. The sample is rental listings by brokers (2010-2017) in Manhattan.

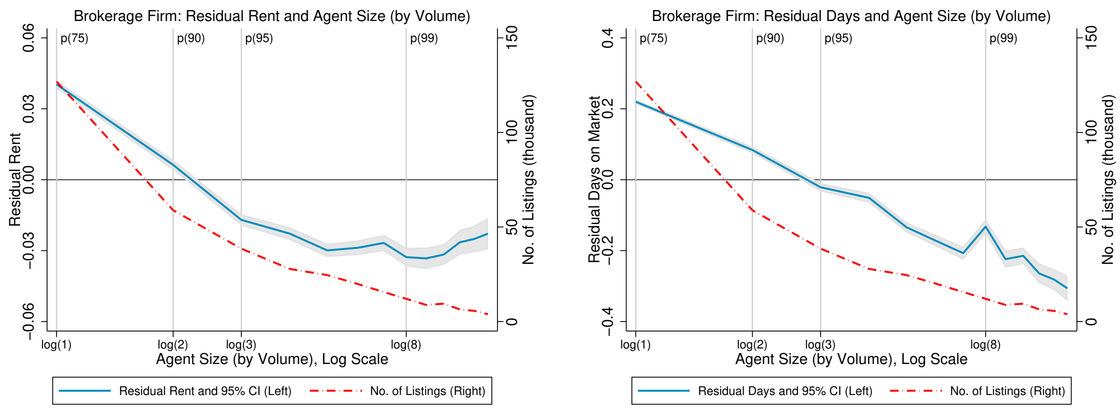


a Residual Log Rent vs Residual Log Days



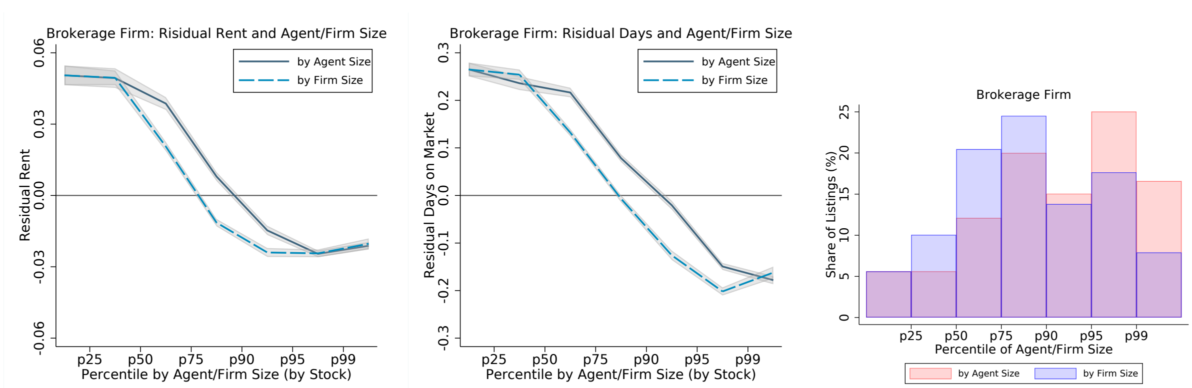
b Listing Stock vs Listing Volume

Figure C.12: Residual rent, residual listing days and the correlation between stock and volume measures of the agent size. The sample is the rental listings by brokers (2010-2017) in Manhattan. Panel 12a: Each circle represents a discrete agent size level. The size of the circles represents the number of listings. The residual log rent and the residual log listing days take out the variation due to the housing amenities and the location-date fixed effect and are based on Models 3 and 7 in Appendix Table C.2. Panel 12b: a circle is a pair of stock and volume measures of the agent size.



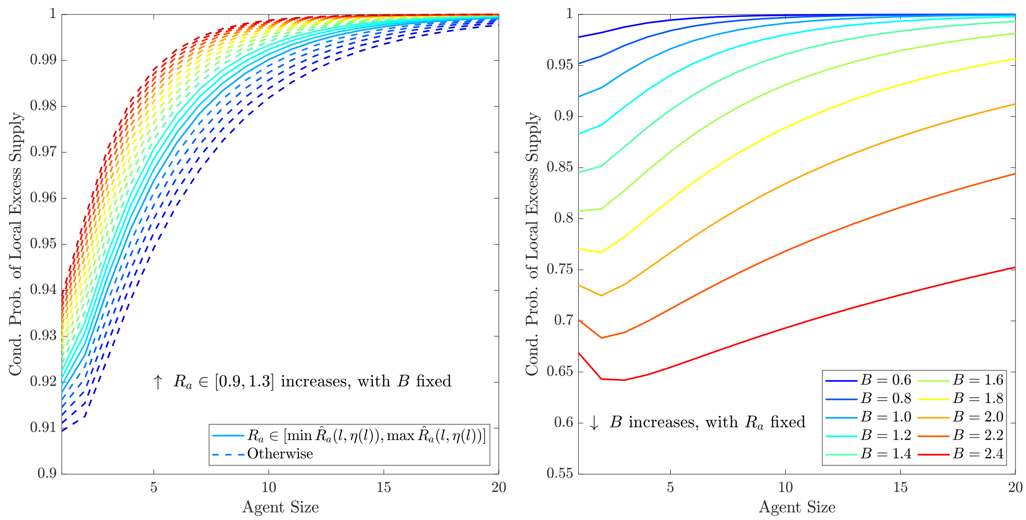
a Residual Rent (2010 $) **b** Residual Listing Days

Figure C.13: Residual rent, residual listing days and the agent size (monthly listing volume). See Fn.16 for the definition of the listing volume. The percentiles of the agent distribution are reported, with the bottom 90% of rentals covered. The residual rent and listing days are adjusted for the housing amenities and the location-date effect. For the control variables, see Appendix Table C.1. Rent refers to the last listed rent (2010 $). The sample is rental listings by brokers (2010-2017) in Manhattan.



a Residual Rent (2010 $) **b** Residual Listing Days **c** Listing Distribution

Figure C.14: Residual rent, residual listing days and listing distribution. The definition of the firm size is similar to that of the agent size in equation (1) but aggregate listings at the brokerage firm level. The residual rents (listing days) are adjusted for the housing amenities and the location-date effect. For the control variables, see Appendix Table C.1. Rent refers to the last listed rent (2010 $). The sample is rental listings by brokers (2010-2017) in Manhattan.



a Response of $Pr^{ES}(l; R_a)$ to R_a **b** Sensitivity of $Pr^{ES}(l; R_a)$ to B

Figure C.15: Comparative statics: probability of local excess supply conditional on a successful match $Pr^{ES}(l; R_a)$. The parameters are based on Table 6. Panel 15a shows the response of $Pr^{ES}(l; R_a)$ to $R_a \in [0.9, 1.3]$, with B evaluated at the equilibrium. The solid lines lie in the range of the $\hat{R}_a(l, \eta(l))$, while the dashed lines are out of the range. Panel 15b shows the sensitivity of $Pr^{ES}(l; R_a)$ to $B \in [0.6, 2.4]$, given R_a evaluated at the weighted mean value across brokers.

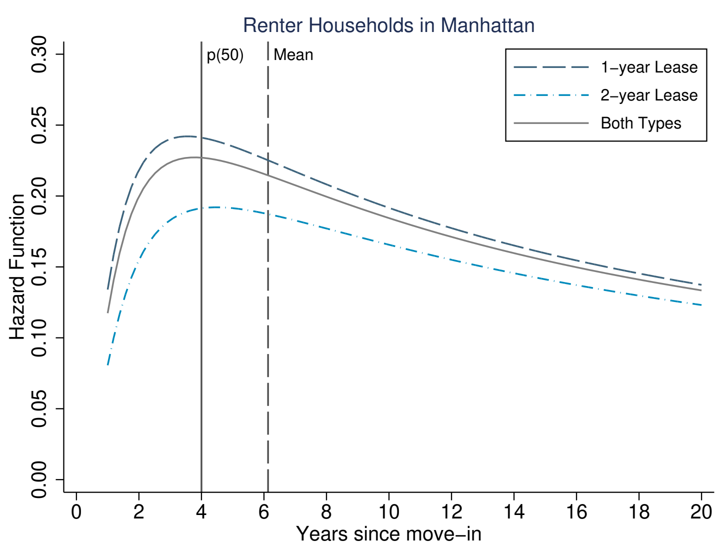


Figure C.16: Turnover hazard of renter households in Manhattan by lease type. The survival model controls renter and housing characteristics (log household income, log household size, log householder age, immigration status of the householder, indicator of lease type (1- or 2-year), the housing type (single-family, condominium, cooperative), the borough of the housing unit). The sample is the renter households from the 2017 New York City Housing and Vacancy Survey who moved in the current units less than 20 years and signed either a 1- or 2-year lease.

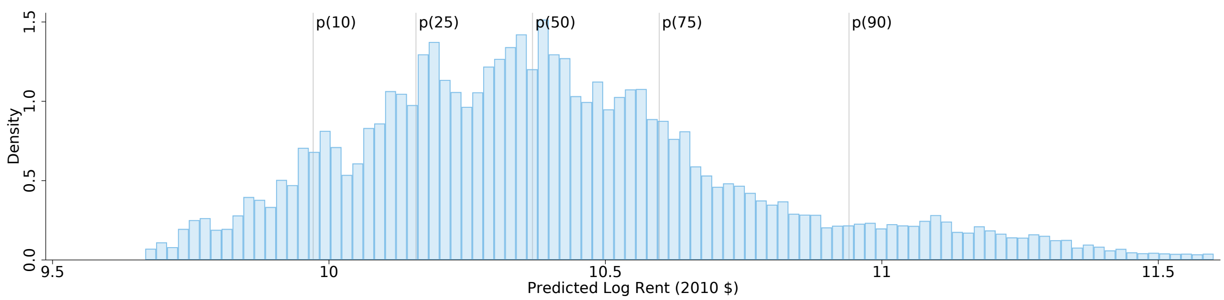


Figure C.17: Log rental quality distribution $Pr(\ln q)$. $\ln q$ is the log annualized rent. The percentiles of the distribution are reported. I estimate a hedonic rent model (Model 3, Table 4) that controls the housing amenities and the location-date effect. The log rental quality $\ln q$ is defined as the predicted rent, which is a linear combination of the observed characteristics weighted by the hedonic prices. The sample used in the hedonic rent model is rental listings by brokers (2010-2017) in Manhattan. The distribution uses the subsample of brokers whose agent sizes are greater than 15 to adjust for the selection bias of housing amenities.

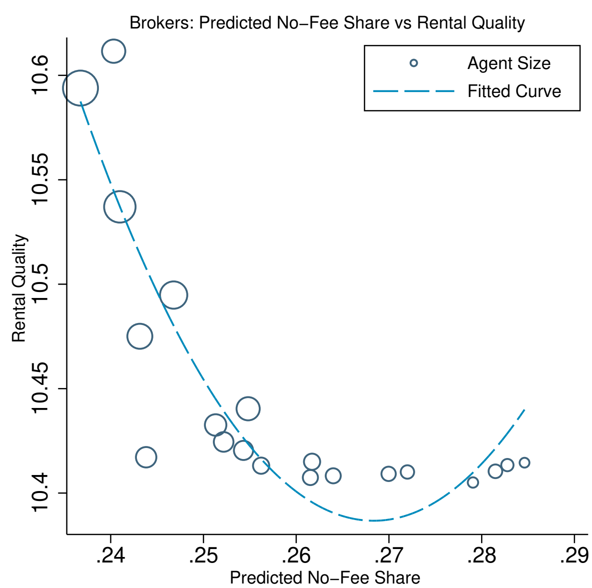


Figure C.18: Predicted no-fee listing share and rental quality. Each circle represents a discrete agent size level. The size of the circle captures the number of listings. The predicted no-fee share accounts for the listing variation due to the housing amenities and the location-date fixed effect and is based on Model 3 in Appendix Table C.4. The rental quality is the predicted log annual rent and is based on Model 3 in Table 4. The sample is rental listings (2010-2017) by brokers in Manhattan.

D Rental Listings by Property Managers

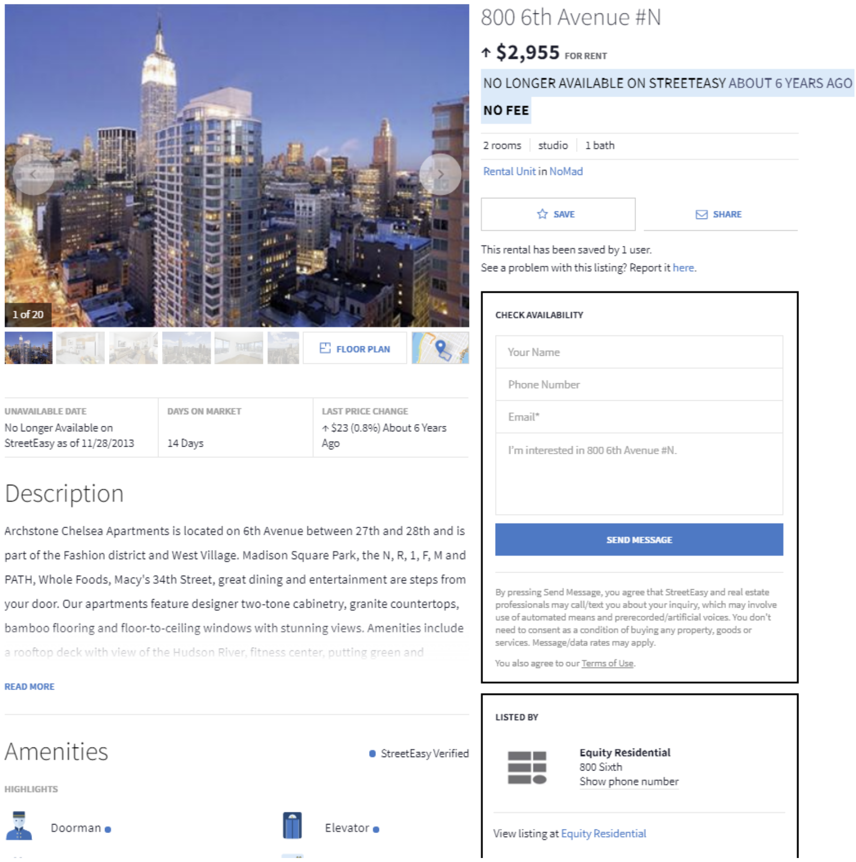
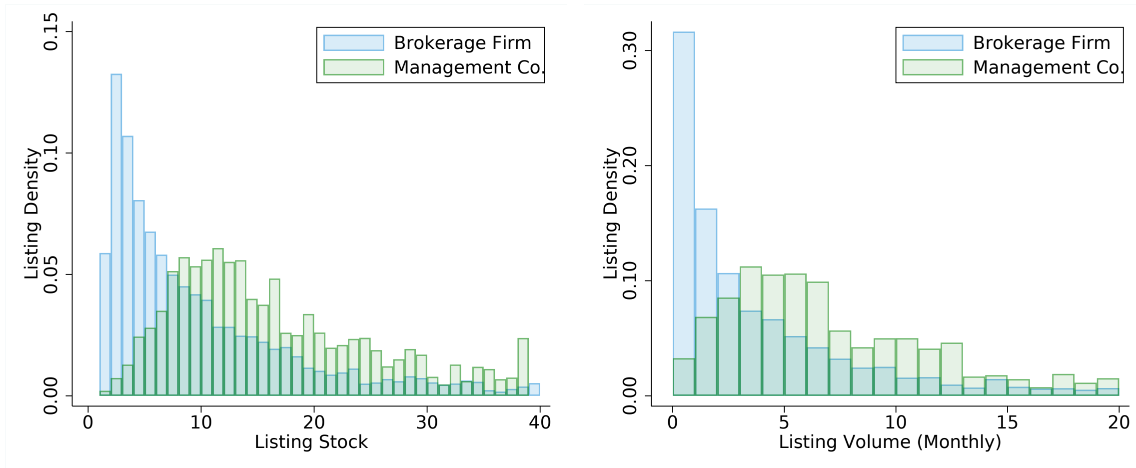


Figure D.1: Screenshots of a rental listings by a property manager. The screenshot is taken from www.streeteasy.com in January 2020.

Table D.1: Listing Summary Statistics by Year

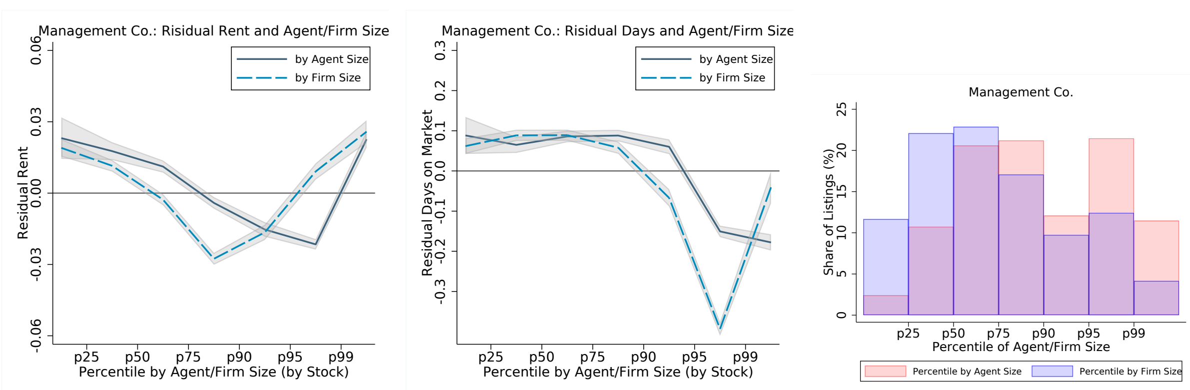
	Year								
Listings by Property Managers	2010	2011	2012	2013	2014	2015	2016	2017	Total
No. of Listings	5,201	7,041	9,339	12,821	17,772	18,452	19,694	18,275	15,713
No. of Buildings	255	421	584	886	1,029	1,116	1,278	1,325	1,007
No. of Neighborhoods	22	26	26	27	27	28	28	28	27
No. of Community Districts	11	12	12	12	12	12	12	12	12
No. of Property Managers	90	150	170	230	292	354	378	338	289
No. of Management Co.	33	42	51	63	77	82	88	86	73
Median Initial Rent (2010 $)	3,238	3,338	3,398	3,245	3,240	3,386	3,351	3,212	3,300
Median Last Rent (2010 $)	3,227	3,311	3,374	3,211	3,216	3,359	3,292	3,177	3,267
Median Days on Market	7	9	14	16	16	20	21	18	17

Note: The sample is the rental listings by property managers (2010-2017) in Manhattan. Initial and last listed rents are adjusted to 2010 dollars. Neighborhoods are defined by NYC Department of City Planning.



a Agent Size (by Listing Stock) **b** Agent Size (by Monthly Volume)

Figure D.2: Listing distribution by the agent size and the listing source (brokerage firm, management company). See equation (1) and Fn.16 for the definitions of the agent size (stock or volume measures). The sample is the rental listings (2010-2017) in Manhattan.



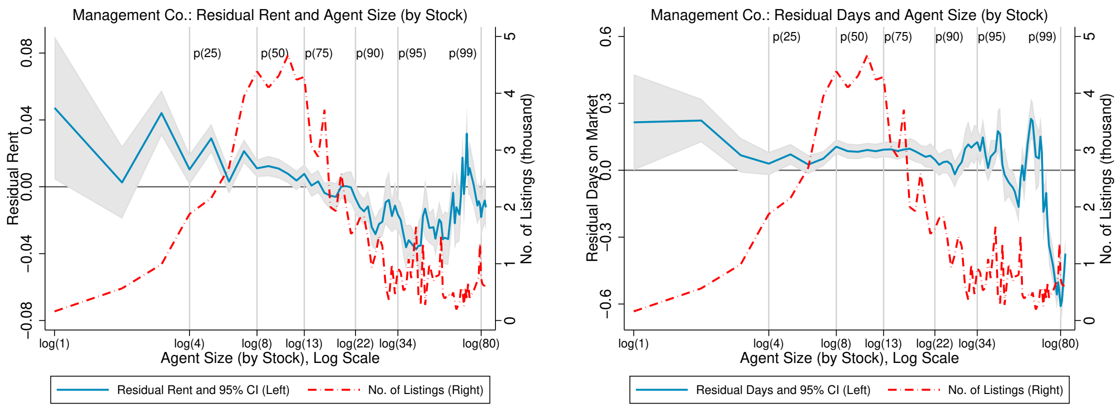
a Log Rent (2010 $) **b** Log Days on Market **c** Listing Distribution

Figure D.3: Residual rent, residual listing days and listing distribution. The definition of the firm size is similar to that of the agent size in equation (1) but aggregate listings at the management company level. The residual rents (listing days) are adjusted for the housing amenities and the location-date effect. For the control variables, see Appendix Table D.4. Rent refers to the last listed rent (2010 $). The sample is rental listings by property managers (2010-2017) in Manhattan.

Table D.2: Agent Summary Statistics by Year

	Year								
Property Managers	2010	2011	2012	2013	2014	2015	2016	2017	Total
Agent Size	10.8	9.8	10.5	14.2	15.2	11.9	11.6	10.9	12.1
Listing Volume (Monthly)	4.8	3.9	4.6	4.6	5.1	4.3	4.3	4.5	4.5
No. of Listings/Agent	57.8	46.9	54.9	55.8	60.9	52.1	52.1	54.1	54.2
No. of Buildings/Agent	3.3	3.6	3.9	4.5	4.2	4.0	4.4	4.6	4.2
No. of Neighborhoods/Agent	2.1	2.0	2.0	2.0	1.9	1.8	1.8	1.8	1.9
No. of Community Districts/Agent	1.8	1.7	1.6	1.7	1.6	1.5	1.6	1.5	1.6

Note: The sample is the listing property managers of rentals in New York Manhattan on StreetEasy (2010-2017). Agent-level averages are reported. Neighborhoods are defined by the Neighborhood Tabulation Area (NTA) by NYC Department of City Planning.



a Residual Rent (2010 $)

b Residual Listing Days

Figure D.4: Residual rent, residual listing days and agent size (log deviation from the mean). The percentiles of the agent distribution are reported, with the bottom 90% of rentals covered. The residual rent (listing days) are adjusted for the housing amenities and the location-date effect. For the control variables, see Appendix Table D.4. Rent refers to the last listed rent (2010 $). The sample is rental listings by property managers (2010-2017) in Manhattan.

Table D.3: Rents and Days on Market by Agent Size Quartile and Year

	Property Managers: Median Rent (2010 $)								
Agent Size Quartile	2010	2011	2012	2013	2014	2015	2016	2017	Total
min - Q1	3,358	3,352	3,187	3,227	3,438	3,270	3,131	3,521	3,290
Q1 - Q2	3,033	3,426	3,784	3,364	3,398	3,340	3,377	3,273	3,348
Q2 - Q3	3,146	3,392	3,514	3,465	3,490	3,513	3,451	3,385	3,453
Q3 - max	3,268	3,259	3,323	3,120	3,121	3,311	3,239	3,081	3,203
	Property Managers: Median Days on Market								
Agent Size Quartile	2010	2011	2012	2013	2014	2015	2016	2017	Total
min - Q1	21	19	13	21	23	21	23	14	19
Q1 - Q2	12	20	17	20	15	23	21	15	19
Q2 - Q3	10	14	18	21	21	22	22	19	20
Q3 - max	7	8	14	14	15	18	21	18	15

Note: The sample is the rental listings by property managers (2010-2017) in Manhattan. Rent refers to the last listed rent (2010 $).

Table D.4: Distribution of Listing Characteristics

	Listings by Property Managers						
Listing Characteristics	Mean	SD	Pct.10	Pct.25	Pct.50	Pct.75	Pct.90
Last Listed Rent (2010 $)	3,719	1,963	2,143	2,648	3,266	4,252	5,585
Initial Listed Rent (2010 $)	3,770	2,003	2,177	2,676	3,297	4,308	5,672
Days on Market	27	30	3	7	16	37	66
Listing Stock of Agent	41	65	7	11	19	47	84
Monthly Volume of Agent	19	22	3	5	9	24	56
No. of Bedrooms	1.15	0.89	0	1	1	2	2
No. of Bathrooms	1.22	0.48	1	1	1	1	2
Has Doorman	0.72	0.45	0	0	1	1	1
Has Elevator	0.80	0.40	0	1	1	1	1
Has Fireplace	0.07	0.26	0	0	0	0	0
Has Dishwasher	0.49	0.50	0	0	0	1	1
Is Furnished	0.00	0.07	0	0	0	0	0
Has Gym	0.68	0.47	0	0	1	1	1
Allows Pets	0.74	0.44	0	0	1	1	1
Has Washer Dryer	0.29	0.45	0	0	0	1	1
Has Garage	0.36	0.48	0	0	0	1	1
Has Roof Deck	0.46	0.50	0	0	0	1	1
Has Concierge	0.54	0.50	0	0	1	1	1
Has Pool	0.21	0.41	0	0	0	0	1
Has Garden	0.21	0.41	0	0	0	0	1
Has Childrens' Playroom	0.23	0.42	0	0	0	0	1
Is No-fee Listing	0.97	0.18	1	1	1	1	1
Has Rent-Stabilized Unit	0.66	0.48	0	0	1	1	1

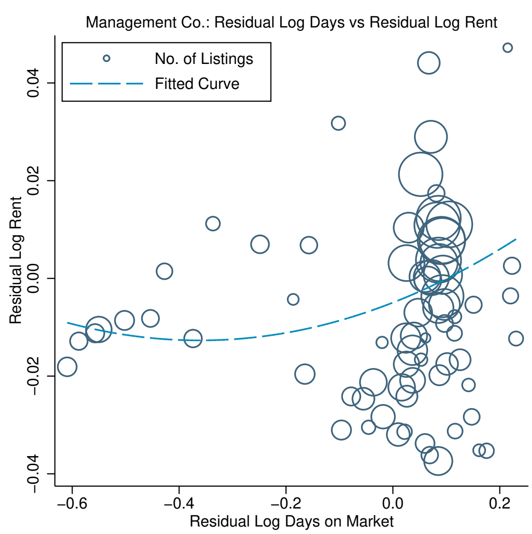
Note: The sample is the rental listings by property managers in New York Manhattan (2010-2017) on StreetEasy. Initial and last listed rents are adjusted to 2010 dollars.

Table D.5: Hedonic Regressions of Rent and Days on Market (DOM)

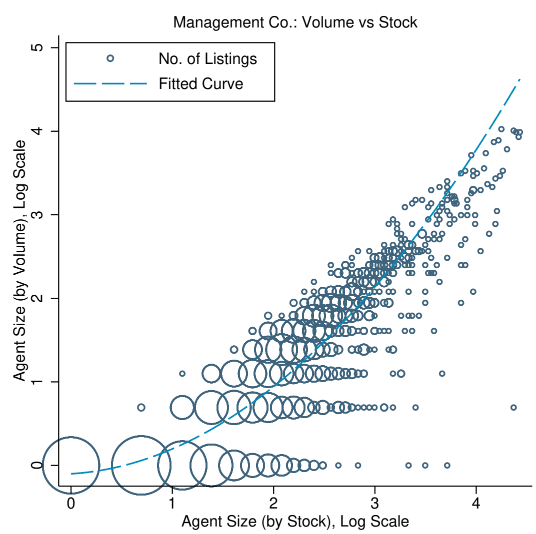
	Listings by Property Managers			
	(1) Log Rent	(2) Log DOM	(3) Log Rent	(4) Log DOM
Log Agent Size	-0.030***	-0.110***	-0.004***	-0.138***
	(0.001)	(0.004)	(0.001)	(0.004)
Sample	2010-2017	2010-2017	2010-2017	2010-2017
Housing Amenities	No	No	Yes	Yes
Location-Date FE	Yes	Yes	Yes	Yes
Survivor Distribution		Weibull (1.02)		Weibull (1.04)
Adjusted R^2	0.13	0.09	0.77	0.11
N	108,595	108,595	108,595	108,595

Note: clustered-robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010. Errors are clustered by the neighborhood and the quarterly date. The sample is the rental listings by property managers (2010-2017) in Manhattan. The location-date fixed effect allows models to condition on the community district and the quarterly date. The rent refers to the last listed rent (2010 $). Accelerated failure time models under the Weibull survival distribution are estimated, with the parameter reported in the parenthesis. For the list of housing amenities, see Appendix Table D.4.

Figure D.5: Hazard functions of listings by property managers at the selected percentiles of agent distribution. The survival model controls the housing amenities and the location-date fixed effect. For the control variables, see Appendix Table D.4. The sample is rental listings by property managers (2010-2017) in Manhattan.



a Residual Rent vs Residual Days



b Agent Stock vs Agent Volume

Figure D.6: Residual rent, residual listing days and the correlation between stock and volume measures of the agent size. The sample is the rental listings by property managers (2010-2017) in Manhattan. Panel 6a: Each circle represents a discrete agent size level. The size of the circles represents the number of listings. The residual log rent and the residual log listing days take out the variation due to the housing amenities and the location-date fixed effect. Panel 6b: a circle is a pair of stock and volume measures of the agent size.