

New Listings and Housing Market Congestion*

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Abstract

This paper studies how new listings affect properties already on the market through the housing search process. I develop a sequential-search model that generates a stock–flow matching pattern and predictions about how congestion varies with entrant characteristics and incumbent listing age. Using detailed micro-level data, I find that a new listing reduces incumbent buyer visits by 15–18% and weekly sale probability by 11–14%, with little effect on list or sale prices. Consistent with the model, congestion is stronger for more price-competitive entrants and recently listed incumbents, and is also larger when properties are closer substitutes and local markets are smaller. The findings support a search-based mechanism in which new listings reshape buyers’ search orderings and redistribute matching opportunities across sellers, primarily through the liquidity rather than the price margin.

Keywords: New Listing; Congestion; Search and Matching; Sale Probability

JEL Classification: R31, R21, D83

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1 Introduction

When a new property enters the housing market, how does it affect properties already on the market for sale? In a frictionless market, the arrival of an additional listing would be absorbed through adjustments in demand and prices. In a frictional housing market, however, search is costly: buyers inspect only a limited number of properties and therefore must rank available listings and decide which ones to visit. Moreover, housing search is highly segmented, so these choices are made within relatively narrow local markets and are directed by observable property characteristics (Albrecht et al., 2016; Han and Strange, 2016; Piazzesi et al., 2020). A new listing can therefore affect not only prices but also the ordering of properties in buyers' search processes. By entering ahead of incumbent properties, it can reduce their probabilities of being visited and sold, generating congestion for sellers already on the market. This search-based mechanism provides a micro-foundation for the seller-side congestion documented in housing markets (Anenberg and Ringo, 2026). The congestion issue is particularly important for home sellers. Housing is typically the largest asset on a household's balance sheet, while selling a home is an illiquid process with substantial uncertainty about how long the property will remain on the market.

To theoretically explain these congestion externalities, I develop a sequential-search framework in the spirit of Weitzman (1979), in which buyers follow an optimal search strategy. A newly listed property initially receives a spike in visits and sale opportunities from the stock of buyers already searching in the market, but these opportunities decline rapidly as the existing buyer stock is depleted, generating a mechanism similar to stock-flow matching. At the same time, the entrant is inserted into buyers' search sequences and pushes incumbent properties to lower positions, reducing their probabilities of being visited and sold and thereby generating congestion. The model also predicts stronger congestion from more price-competitive entrants and among recently listed incumbents, which compete more directly with new listings for the existing stock of buyers.

This mechanism is difficult to observe with standard housing data, which typically record listings and transactions but not the underlying search process. As a result, there is limited direct evidence on whether and how new supply reshapes buyer search. I test these predictions using detailed micro-level data from a major Chinese housing platform that link property listings and transactions to individual buyer visits. These data allow me to directly observe how buyer attention is reallocated following new-listing entry, providing a direct test of the model's search mechanism, and to decompose changes in sale probabilities into changes in the probability of receiving a visit and changes in the probability of purchase

conditional on a visit. The latter captures the matching margin after a buyer has inspected a property and learned its match-specific value. I exploit variation in the timing of new-listing arrivals across buildings and residential complexes and examine their effects on properties already on the market.

I find substantial negative congestion externalities from new-listing arrivals. Following the arrival of a new listing in the same building, existing properties receive approximately 15–18% fewer buyer visits and experience an 11–14% decline in their weekly probability of sale. This shows that this decline is driven primarily by fewer buyer visits rather than by a lower probability of purchase conditional on a visit, indicating that congestion operates mainly through the reallocation of buyer attention rather than through deterioration in post-visit match quality. The congestion externality also extends beyond the building itself: new listings reduce the sale probability of existing properties in other buildings within the same residential complex. Despite the substantial decline in liquidity, I find no significant price response. Existing sellers neither adjust their listing prices nor sell at lower transaction prices following the arrival of a new listing. Thus, the congestion effect operates primarily through the liquidity margin rather than the price margin: increased competition reduces buyer attention and delays transactions without generating meaningful price adjustments.

I find substantial heterogeneity in the magnitude of the congestion effect, consistent with the sequential-search model. First, congestion is stronger when the new listing is priced below incumbent properties, suggesting that more price-competitive entrants are more likely to move ahead of incumbents in buyers' search sequences. Second, the negative congestion effect is concentrated among recently listed incumbent properties. This pattern is consistent with the model's stock-flow matching mechanism: recent incumbents still compete with the entrant for the existing stock of active buyers, whereas older listings rely more heavily on newly arriving buyers. Third, the effect is substantially stronger when the new and incumbent properties are closer substitutes. In particular, the decline in buyer visits and sale probabilities is larger when the two properties are on the same floor or have the same floor area. Fourth, congestion is weaker in larger markets. When more properties are already available, the arrival of one additional listing represents a smaller proportional expansion of the local choice set and therefore has a smaller effect on each incumbent property.

I also examine how new-listing entry affects buyer behavior. Importantly, the congestion effect does not simply reflect a fixed pool of buyers being divided among more properties. I find that new listings attract additional buyers into the local market. Nevertheless, incumbent properties receive fewer visits and become less likely to sell. New listings therefore simultaneously expand the local buyer

pool and divert buyer attention toward newly available properties. The decline in incumbent liquidity despite increased buyer entry suggests that the congestion effect dominates the potential benefit from the expansion of local demand.

Related Literature. This paper is most closely related to [Anenberg and Ringo \(2026\)](#), who document congestion in the for-sale housing market. My findings are consistent with theirs in showing that congestion operates primarily through lower sale probabilities rather than lower prices. I complement their analysis in three ways. First, I develop a sequential-search model that provides a micro-foundation for congestion by showing how new listings can push incumbent properties to lower positions in buyers' search sequences. Second, the model generates additional predictions about the incidence of congestion, including stronger effects from more attractive entrants and for recently listed incumbents, both of which I test empirically. Third, I directly identify the buyer-visit margin and decompose the decline in sale probabilities into visits and purchase conditional on a visit. The decline is driven primarily by fewer visits, consistent with the model's search-ranking mechanism. Together, these results provide a micro-level foundation for housing-market congestion and show how the organization of buyer search determines which incumbent sellers are most exposed to new supply.

This paper also contributes to the literature on the local effects of changes in housing supply. Existing studies show that new housing supply can affect nearby rents and house prices through changes in supply, competition, and neighborhood composition, with mixed findings. [Li \(2021\)](#), [Asquith et al. \(2023\)](#), and [Mense \(2025\)](#) find that new housing supply lowers nearby rents, whereas [González-Pampillón \(2022\)](#) documents increases in nearby house prices associated with reductions in crime and increases in neighborhood income. Other work documents highly localized spillovers generated by changes in the quality or availability of nearby housing, including renovation, rehabilitation, and foreclosure ([Anenberg and Kung, 2014](#); [Campbell et al., 2011](#); [Ganduri and Maturana, 2024](#); [Hartley, 2014](#); [Rossi-Hansberg et al., 2010](#); [Szumilo, 2020](#)). I contribute to this literature by studying local supply changes through the lens of search frictions. Rather than operating primarily through prices, I find that the arrival of new listings reallocates buyer attention and reduces the liquidity of incumbent properties: existing listings receive fewer visits and become less likely to sell, while listing and transaction prices respond little. These findings highlight a distinct channel through which local housing supply affects incumbent sellers, operating through buyer search and matching rather than the price margin.

This paper also contributes to the literature on how the joint entry and exit of buyers and sellers shape housing-market dynamics. Search-and-matching mod-

els emphasize market tightness—the ratio of buyers to sellers—as a central determinant of matching rates and market liquidity (Genesove and Han, 2012; Han and Strange, 2015). Empirically, Genesove and Han (2012) show that stronger demand reduces seller time on market and the number of properties visited by buyers, and use these responses to estimate a housing matching function. A related strand of work examines how changes in buyer and seller entry jointly shape housing-market activity and decomposes the distinct contributions of each side of the market (Anenberg and Ringo, 2024; Ngai and Sheedy, 2024). In addition, the sequencing of buying and selling decisions can affect housing-market dynamics by endogenously altering market tightness (Grindaker et al., 2026; Moen et al., 2019; Ngai and Sheedy, 2020). I contribute to this literature by examining a seller-side entry shock and tracing how it affects both buyer entry and seller outcomes. New listings attract additional buyers into the local market and raise market tightness, but incumbent properties nevertheless receive fewer visits and become less likely to sell. This pattern shows that the expansion in buyer demand is more than offset, from the perspective of incumbent sellers, by the reallocation of buyer attention toward newly listed properties.

This paper also relates to the broader literature on search and matching in housing markets, particularly recent work using granular platform search data to directly observe buyer search behavior and the matching process. Related work on directed search shows that buyers allocate search toward properties based on observable listing characteristics, particularly asking prices (Albrecht et al., 2016; Han and Strange, 2016). One strand emphasizes stock-flow matching, whereby newly entering buyers and sellers interact differently with market participants that have remained unmatched (Coles and Smith, 2026; Gilbukh, 2023; Smith et al., 2026). A closely related literature studies sequential search (Armstrong, 2017; Weitzman, 1979). Building on Weitzman (1979), I develop a sequential-search framework that provides a micro-foundation for housing-market congestion and generates a stock-flow matching mechanism. The model explains how new listings reduce incumbent visits and sale probabilities and predicts which properties are most exposed to these congestion effects. More broadly, a growing literature uses detailed search data to study how buyers allocate attention across housing options. Gargano et al. (2023) document how online housing search responds to local house-price experiences, while Piazzesi et al. (2020) emphasize the segmentation of housing search across locations and property characteristics. van Dijk and Francke (2018) show that online interest in listed properties contains information about housing demand and predicts market liquidity and prices. My analysis contributes to this literature by using detailed search data from a housing brokerage platform to directly observe how the arrival of new supply reallocates buyer attention across

competing properties and affects seller liquidity.

The rest of the paper is organized as follows. Section 2 presents a model that motivates the empirical findings. Section 3 introduces the data and empirical strategy. Section 4 presents and discusses the empirical results. Section 5 concludes.

2 A Sequential Search Model

I use a simple static sequential-search model to illustrate how the arrival of a new listing generates congestion for properties already on the market. Buyers face a fixed set of properties and inspect them sequentially according to an optimal search rule.¹ The arrival of a new listing is modeled as an MIT shock that perturbs this choice set and changes the ranking of incumbent properties in buyers' search sequences. By shifting some incumbent properties to lower positions, the shock reduces their probabilities of being visited and of attracting latent buyer demand. The model therefore provides a comparative-static framework for analyzing how new-listing entry affects incumbent sellers through the search process.

2.1 Weitzman Search

Consider a market with a set of buyers $\mathcal{B}$ and a set of sellers $\mathcal{S}$, where $|\mathcal{S}| = S$ and $|\mathcal{B}| = B$. Each seller $k \in \mathcal{S}$ offers one property for sale. Buyer $i \in \mathcal{B}$ faces the set of available properties $\mathcal{S}$ and may inspect them sequentially before deciding which property to select.

For each property $k \in \mathcal{S}$, buyer i observes its list price p_k and a set of observable characteristics summarized by v_{ik} before inspection. Following Weitzman (1979), visiting a property entails a search cost $c > 0$. Upon visiting property k , buyer i learns an idiosyncratic buyer–property match component z_{ik} that is not observed before the visit. The utility from buying property k is

$$u_{ik} = v_{ik} - p_k + z_{ik}. \quad (1)$$

For simplicity, I assume that the transaction price is equal to the list price; this normalization does not affect the structure of the search problem. I assume that z_{ik}

¹Within a search episode, buyers take the set of available properties as fixed and transactions occur only after search decisions have been made. This timing abstracts from the possibility that a property is purchased by another buyer while an individual buyer is still searching, allowing the buyer's problem to retain the standard Weitzman structure with recall. The purpose of the model is therefore not to characterize the dynamic equilibrium of competing buyers and sellers, but to isolate the comparative-static effect of adding a new listing on buyer search and incumbent matching opportunities.

is independently drawn across buyer–property pairs from a common distribution F^z with support $[\underline{z}, \bar{z}]$. I further assume that reservation values are independently drawn across properties from a common continuous distribution F^r with support $[\underline{r}, \bar{r}]$. The same distribution applies to incumbent properties and potential new listings, so a new listing is an additional draw from the same reservation-value distribution. I assume that sellers set list prices so as to absorb, on average, observable differences in property value, such that

$$\mathbb{E}[v_{ik} - p_k] = 0. \quad (2)$$

The residual differences capture deviations of quality-adjusted value from this benchmark and are centered around zero.

Within a search period, the set of available properties $\mathcal{S}$ is fixed. Transactions are realized only after search decisions have been made. Buyers can recall any previously inspected property. After stopping search, buyer i selects the property that delivers the highest realized utility among those inspected, provided that this utility exceeds her outside option, which I normalize to zero.

Under optimal sequential search, buyer i ranks properties according to their Weitzman reservation values,

$$r_{ik} = v_{ik} - p_k + z^*, \quad (3)$$

where z^* solves

$$\int_{z^*}^{\bar{z}} (1 - F^z(z)) dz = c. \quad (4)$$

For each buyer i , let $m_{ik} \in \{1, \dots, S\}$ denote the rank of property k in the buyer's search sequence, where a lower rank corresponds to a higher reservation value. Thus, for any two properties k and j ,

$$m_{ik} < m_{ij} \iff r_{ik} > r_{ij}. \quad (5)$$

Under the optimal search rule of [Weitzman \(1979\)](#), buyer i visits properties in ascending order of m_{ik} and stops searching once the highest utility realized so far exceeds the reservation value of every remaining property. Let $\mathcal{N}_i$ denote the set of properties already visited. The stopping rule is

$$\max \left\{ u_{i0}, \max_{j \in \mathcal{N}_i} u_{ij} \right\} > \max_{k \notin \mathcal{N}_i} r_{ik}, \quad (6)$$

where u_{i0} denotes the outside option.

Following [Ursu et al. \(2025\)](#), I assume that every buyer makes at least one visit, so that

$$\max_{k \in \mathcal{S}} r_{ik} \geq u_{i0} \quad \forall i. \quad (7)$$

This search rule has two implications that are central to the analysis. Properties appearing later in the search sequence are less likely to be reached, because the buyer may stop at any earlier position. They are also less likely to become the buyer's most preferred property, because each earlier property provides an additional opportunity for the buyer to stop and select another property. The following lemmas formalize these two implications.

Lemma 1 (Visiting Probability and Rank). *Let $\nu_i(m)$ denote the probability that buyer i visits a property ranked m in her search sequence. Under the Weitzman search rule, the visiting probability is*

$$\nu_i(m) = \begin{cases} 1, & m = 1, \\ \prod_{s=1}^{m-1} \Pr(u_{is} < r_{im}), & m \geq 2. \end{cases} \quad (8)$$

The visiting probability is strictly decreasing in rank:

$$\nu_i(m) > \nu_i(m+1), \quad m = 1, \dots, S-1. \quad (9)$$

Proof. See Appendix A.1. □

The search order also determines which property ultimately delivers the highest utility to the buyer. A lower-ranked property is less likely to be reached before search stops and, conditional on being reached, must compete with all previously inspected properties. I therefore consider the probability that a property becomes buyer i 's most preferred option at the end of the search process.

Lemma 2 (Probability of Being the Most Preferred Property and Rank). *Let m_{ik} denote the rank of property k in buyer i 's search sequence, and let*

$$\delta_{ik} \equiv \Pr(\text{property } k \text{ becomes buyer } i\text{'s most preferred property}). \quad (10)$$

Under the Weitzman search rule, the probability of becoming the buyer's most preferred property is strictly decreasing in search rank. That is, for any two properties k and j ,

$$m_{ik} < m_{ij} \implies \delta_{ik} > \delta_{ij}. \quad (11)$$

Proof. See Appendix A.2. □

2.2 Duration Dependence

I next use the sequential-search framework to characterize how buyer visits and sale opportunities evolve with time on market. When a new property enters the

market, it is inserted into the search sequences of buyers who are already searching. For buyers who have already searched beyond the entrant's position, the new property immediately becomes their next available option, generating a spike in visits at entry. For other buyers, the property can be reached only in later periods and only if they continue searching to that position. Because both the probability of being visited and the probability of becoming a buyer's preferred property decline with search rank, as established in Lemmas 1 and 2, these later search opportunities become progressively less likely to generate visits and sales.

Figure 1 provides a snapshot of buyer–seller pairs at a particular point in the search process. Sellers S_1 – S_{10} are ordered by reservation value and visited sequentially. Since each buyer can and have to visit one property per period, search rank maps directly into the period in which a property can be reached.² The new listing N , shown in red, enters between S_3 and S_4 , while the gray cells indicate buyer–seller pairs already visited at the time of entry.

At the moment of entry, buyers B_4 – B_6 have already searched beyond the entrant's rank, new seller N becomes their next available option and is visited immediately. The expected number of visits in the first period is therefore 3. For buyer B_3 , the entrant occupies the second position in the remaining search sequence, so in period $t = 2$ it is reached with probability $\nu_3(2)$. Similarly, for buyer B_2 , the entrant is third in the remaining search sequence and is reached in period $t = 3$ with probability $\nu_2(3)$, while for buyer B_1 it is fourth and is reached in period $t = 4$ with probability $\nu_1(4)$. For $t > 4$, none of the buyers present at entry has a positive probability of visiting the entrant, so subsequent visits can only come from newly arriving buyers.³ Figure 2 summarizes the implied visit profile: a sharp spike at entry, followed by a rapid decline as the entrant is reached only at progressively lower positions in buyers' remaining search sequences, and eventually a small, approximately stable flow generated by newly arriving buyers.

Proposition 1 (Duration Dependence of Visits and Sale Probability). *Consider a fixed stock of buyers present when a new property enters the market and a small subsequent inflow of newly arriving buyers. Suppose that each buyer can inspect at most one additional property per period. The expected number of visits and the sale probability are*

²The duration mechanism requires a capacity constraint on buyer search: if buyers could inspect all properties simultaneously, search rank would not translate into differences in the timing of visits. For simplicity, I assume that each buyer can inspect one property per period; allowing a fixed number greater than one would only rescale the mapping between search rank and time. By contrast, I do not impose a capacity constraint on sellers, since the model abstracts from congestion on the buyer side: a listing may therefore receive visits from any number of buyers within the same period.

³I do not explicitly model this inflow; assuming that it is small relative to the initial buyer stock, it generates only a small expected flow of visits and does not materially affect the declining duration profile.

	S_1	S_2	S_3	N	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}
B_1											
B_2											
B_3											
B_4											
B_5											
B_6											

Figure 1: Illustration of a New Seller Entering Buyers' Search Sequences.

Notes: Rows denote buyers and columns denote sellers. Gray cells indicate incumbent sellers already visited by each buyer. The new seller N enters between S_3 and S_4 in the search ranking. Buyers B_1 – B_6 have already visited 0–5 incumbent sellers, respectively. Thus, for buyers who have already searched beyond the entrant's position, N becomes the next available option, while for the remaining buyers it is reached only if search continues to that position.

highest in the first period and decline strictly over subsequent periods in which the initial buyer stock continues to generate matching opportunities. The initial spike arises because buyers who have already searched beyond the entrant's rank can inspect it immediately. The subsequent decline follows from Lemmas 1 and 2: properties reached at lower positions in the remaining search sequence are less likely to be visited and less likely to become buyers' preferred properties. Once these initial search opportunities are exhausted, only newly arriving buyers generate further visits and matching opportunities. If this inflow is small relative to the initial buyer stock, expected visits and sale probabilities remain at a low level thereafter.

Proof. See Appendix A.3. □

2.3 Congestion

I now consider how a new listing can generate congestion for incumbent sellers. Consider an incumbent property $k \in \mathcal{S}$ with rank m_{ik} for buyer i immediately before the arrival of a new listing n . Before entry, the entrant's reservation value is not yet realized and is treated as a random draw from a continuous distribution F^r . Once the entrant is realized, its position in buyer i 's search sequence is determined by its reservation value.

Following entry, the rank of incumbent property k becomes

$$m'_{ik} = m_{ik} + \mathbf{1}\{r_{in} > r_{ik}\}. \quad (12)$$

Thus, the incumbent is pushed one position lower whenever the entrant has a higher reservation value.

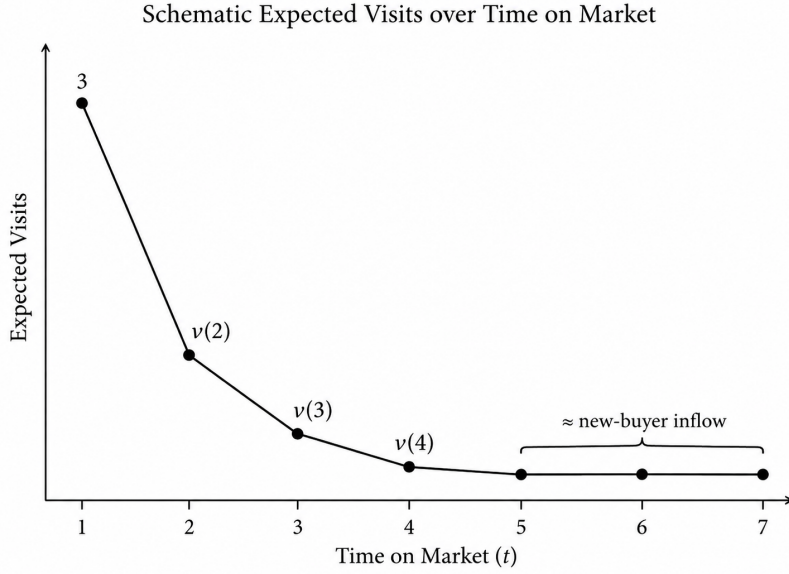


Figure 2: Illustration of Expected Visits over Time on Market

Notes: The figure provides a schematic illustration of the expected visit profile of a newly listed property. Upon entry, the property receives an initial spike in visits from buyers for whom it immediately becomes the next property in the remaining search sequence. In the example, this generates three expected visits in the first period. In subsequent periods, the property is reached only by buyers for whom it occupies progressively lower positions in the remaining search sequence, with visiting probabilities $\nu_i(2)$, $\nu_i(3)$, and $\nu_i(4)$. Once these initial search opportunities have been exhausted, later visits are generated by newly arriving buyers. Because this inflow is assumed to be small relative to the initial stock of buyers, it produces only a small and approximately stable flow of visits.

Because F^r is continuous, a realized reservation value lies in the interior of its support with probability one, so any incumbent property has a strictly positive probability of being ranked both above and below a subsequently drawn listing.

$$q_{ik} \equiv \Pr(r_{in} > r_{ik}) = 1 - F^r(r_{ik}) \in (0, 1). \quad (13)$$

where q_{ik} is the ex ante probability that the entrant ranks ahead of property k . Therefore, before the entrant is realized, property k remains at rank m_{ik} with probability $1 - q_{ik}$ and is pushed to rank $m_{ik} + 1$ with probability q_{ik} .

By Lemmas 1 and 2, both probabilities decline with rank. Hence, following the arrival of the new listing,

$$\begin{aligned} \bar{\nu}_{ik}^1 &\equiv \mathbb{E}[\nu_i(m'_{ik})] \\ &= \nu_i(m_{ik}) - q_{ik} [\nu_i(m_{ik}) - \nu_i(m_{ik} + 1)] < \nu_i(m_{ik}), \end{aligned} \quad (14)$$

and similarly,

$$\begin{aligned} \bar{\delta}_{ik}^1 &\equiv \mathbb{E}[\delta_i(m'_{ik})] \\ &= \delta_i(m_{ik}) - q_{ik} [\delta_i(m_{ik}) - \delta_i(m_{ik} + 1)] < \delta_i(m_{ik}). \end{aligned} \quad (15)$$

Aggregating across buyers, the expected number of visits received by property k before and after entry is

$$V_k^0 = \sum_{i \in \mathcal{B}} \nu_i(m_{ik}), \quad V_k^1 = \sum_{i \in \mathcal{B}} \bar{\nu}_{ik}^1. \quad (16)$$

I next aggregate preferred-property outcomes across buyers. Conditional on the common search environment, I assume that these buyer-specific outcomes are independent across buyers, reflecting independently distributed buyer–property match shocks. This independence applies to preferred-property outcomes rather than to realized transactions: several buyers may regard the same property as their most preferred property even though it can ultimately be sold to at most one buyer (Albrecht et al., 2016; Ngai and Sheedy, 2024).

The probability that property k becomes the most preferred property of at least one buyer is therefore

$$D_k^0 = 1 - \prod_{i \in \mathcal{B}} [1 - \delta_i(m_{ik})], \quad D_k^1 = 1 - \prod_{i \in \mathcal{B}} [1 - \bar{\delta}_{ik}^1]. \quad (17)$$

Proposition 2 (Congestion from New Listings). *The arrival of a new listing reduces both the expected number of buyer visits and the probability that an incumbent property becomes the most preferred property of at least one buyer:*

$$V_k^1 < V_k^0, \quad D_k^1 < D_k^0. \quad (18)$$

Proof. By Lemma 1,

$$\nu_i(m_{ik}) > \nu_i(m_{ik} + 1).$$

Hence equation (14) implies

$$\bar{\nu}_{ik}^1 < \nu_i(m_{ik})$$

Since the entrant has a positive probability of ranking ahead of property k for at least one buyer, summing across buyers gives

$$V_k^1 < V_k^0.$$

Similarly, Lemma 2 implies

$$\delta_i(m_{ik}) > \delta_i(m_{ik} + 1),$$

so equation (15) gives

$$\bar{\delta}_{ik}^1 < \delta_i(m_{ik})$$

Therefore, We have:

$$\prod_{i \in \mathcal{B}} (1 - \bar{\delta}_{ik}^1) > \prod_{i \in \mathcal{B}} (1 - \delta_i(m_{ik})),$$

which implies

$$D_k^1 < D_k^0.$$

□

To connect preferred-property outcomes to the sale outcome observed in the data, suppose that property k is sold whenever it becomes the most preferred available property of at least one buyer. If several buyers prefer the same property, a rationing mechanism determines which buyer obtains it but does not affect whether the property is sold. Under this market-clearing assumption, the listing-level sale probability is

$$\Pi_k = D_k. \quad (19)$$

Proposition 2 therefore implies

$$\Pi_k^1 \leq \Pi_k^0. \quad (20)$$

The propositions highlight a simple congestion mechanism. When a new listing enters ahead of an incumbent property, it pushes the incumbent to a lower position in buyers' search sequences. Lemmas 1 and 2 imply that lower-ranked properties are less likely to be visited and less likely to become buyers' preferred properties. New-listing entry therefore reduces both the buyer attention received by incumbent properties and their sale opportunities.

2.3.1 Discussion of Prices

The static model holds sellers' prices fixed and therefore isolates the pure search effect of new-listing entry. In this environment, an entrant that ranks ahead of an incumbent property pushes the incumbent to a lower position in buyers' search sequences, reducing its visits and sale probability. In practice, however, incumbent sellers face a trade-off after new-listing entry: they can keep their prices unchanged and accept a lower probability of being visited and sold, or reduce their prices to improve their position in buyers' search sequences.

A reduction in the list price raises the property's reservation value and moves it toward a higher position in the buyer's search sequence. Price adjustment therefore allows sellers to trade off sale price against liquidity, mitigating the congestion effect at the cost of accepting a lower price.

Corollary 1 (Price Adjustment and Congestion). *Suppose incumbent sellers can respond to new-listing entry through the price margin. A lower list price, or more generally a lower expected transaction price observed by buyers before inspection, raises the incumbent property's reservation value and improves its position in buyers' search sequences, thereby mitigating the decline in visits and matching probabilities. Sellers may therefore trade off price against liquidity in response to greater competition. Consequently, if this price-adjustment channel is quantitatively important, new-listing entry should be accompanied by lower list prices and lower sale prices as well.*

2.3.2 Discussion of Buyer Entry

The static model holds the number of buyers, B , fixed and therefore isolates the congestion effect generated by the reordering of buyers' search sequences. In practice, however, new listings may also attract additional buyers into the local market. If buyer entry responds positively to new-listing arrivals, the larger buyer pool increases both the expected number of visits and the probability that an incumbent property becomes the most preferred property of at least one buyer. This force works in the opposite direction of the congestion effect derived above.

To see this, let $\mathcal{B}^0$ denote the set of buyers already present in the market and let $\mathcal{E}$ denote buyers who enter in response to the new listing. With buyer entry, the post-entry outcomes become

$$\tilde{V}_k^1 = \sum_{i \in \mathcal{B}^0} \bar{\nu}_{ik}^1 + \sum_{i \in \mathcal{E}} \nu_i(m_{ik}), \quad (21)$$

and

$$\tilde{D}_k^1 = 1 - \prod_{i \in \mathcal{B}^0} (1 - \bar{\delta}_{ik}^1) \prod_{i \in \mathcal{E}} (1 - \delta_i(m_{ik})). \quad (22)$$

Relative to the fixed-buyer case, the additional terms generated by $\mathcal{E}$ raise both expected visits and matching opportunities. Thus, while Proposition 2 implies $V_k^1 < V_k^0$ and $D_k^1 < D_k^0$ holding the buyer pool fixed, buyer entry can partially or fully offset these declines.

Accordingly, the empirical effect of new-listing entry reflects the net impact of two opposing forces: the entrant pushes incumbent properties to lower positions in existing buyers' search sequences, while any additional buyers attracted to the market create new visiting and matching opportunities. I therefore examine empirically whether buyer entry responds to new-listing arrivals and whether this response offsets the congestion effect on incumbent properties.

2.4 The Heterogeneity of the Congestion

2.4.1 Price competitiveness

The magnitude of the congestion effect depends on where the entrant appears in buyers' search sequences. Since

$$r_{in} = v_{in} - p_n + z^*, \quad (23)$$

an entrant with a higher quality-adjusted net value, $v_{in} - p_n$, has a higher reservation value and is therefore more likely to rank ahead of incumbent properties. It consequently pushes more incumbents to lower positions in buyers' search sequences.

Corollary 2 (Stronger Congestion from More Attractive New Listings). *Consider two potential entrants, n and n' , such that*

$$v_{in} - p_n > v_{in'} - p_{n'} \quad (24)$$

for every buyer $i \in \mathcal{B}$. Then entrant n generates a strictly larger congestion effect on any incumbent property k :

$$V_k^1(n) < V_k^1(n'), \quad D_k^1(n) < D_k^1(n'). \quad (25)$$

Proof. Since reservation values are increasing in quality-adjusted net value,

$$v_{in} - p_n > v_{in'} - p_{n'} \implies r_{in} > r_{in'}.$$

Since F^r is continuous and incumbent reservation values lie in the interior of its support, it follows that

$$q_{ik}(n) = \Pr(r_{in} > r_{ik}) > \Pr(r_{in'} > r_{ik}) = q_{ik}(n').$$

Equations (14) and (15), together with Lemmas 1 and 2, imply that both the incumbent's expected visit probability and preferred-property probability are strictly decreasing in q_{ik} . Aggregating across buyers therefore gives

$$V_k^1(n) < V_k^1(n'), \quad D_k^1(n) < D_k^1(n').$$

□

2.4.2 The Listing Age of incumbent sellers

Proposition 1 implies a natural distinction between two types of incumbent sellers. Recently listed properties still receive visits and matching opportunities from buyers who were already searching when the property entered the market, whereas properties that have remained on the market sufficiently long have already exhausted most of these opportunities and rely primarily on newly arriving buyers. Figure 1 illustrates this distinction. In the example, S_4 – S_{10} can be viewed as relatively recent listings: they have been visited by at most two buyers and still have substantial exposure to the existing buyer stock. By contrast, S_1 – S_3 represent older listings that have already been reached by more buyers. When the new listing N enters between S_3 and S_4 , it pushes S_4 – S_{10} to lower positions in buyers' remaining search sequences, reducing their subsequent visiting and matching opportunities, while leaving S_1 – S_3 largely unaffected. The congestion effect should therefore be concentrated among relatively recent incumbent listings.

Corollary 3 (Congestion and Incumbent Listing Age). *Consider two incumbent properties. A recent incumbent still receives visits and matching opportunities from buyers already present in the market, whereas an old incumbent has exhausted these opportunities and relies only on newly arriving buyers. New-listing entry reduces the visits and sale probability of the recent incumbent by entering ahead of it and pushing it to lower positions in the search sequences of existing buyers. By contrast, this channel does not affect the old incumbent, whose opportunities from the existing buyer stock have already been exhausted.*

3 Data and Empirical Strategy

3.1 Housing Dataset

The dataset is from China's largest multiple listing service (MLS), which covers buyer visits to sellers, seller listings and listing price revisions, as well as transaction data from Beijing during August 2015 to July 2016. The agency company was established in Beijing and holds more than 50% of the market share in Beijing, making this dataset highly representative.

This data set contains five sub-datasets, including transaction records, visit records, property characteristics, buyer characteristics, and price adjustment records. The basic information of the house records the property's floor area, number of rooms, year of construction, floor height, apartment complex, and neighborhood to which it belongs. The buyer's basic characteristics include the buyer's gender and the preferences filled in when the buyer registered, including upper and lower bounds on psychological price, floor area, and number of rooms. The visit data set records the visit time and the buyers and sellers involved in the visit. The price adjustment data records all price adjustment records of the seller, including the price before the price adjustment, the price after the price adjustment, and the price adjustment time. This also includes records of the seller's first listing. The transaction data set records the transaction price, transaction time, sellers, and buyers involved in the transaction.

3.2 Sample Construction

I construct the baseline estimation sample using a six-month observation window. I first identify properties that are already on the market at the beginning of the observation period, which I refer to as *existing listings*, and properties that enter during the observation period, which I refer to as *new listings*. The newly listed properties themselves are excluded from the estimation sample, as the analysis

focuses on how their arrival affects properties already on the market.⁴

In the baseline design, I define treatment within the same building. The treatment group consists of existing listings in buildings that experience exactly one new-listing arrival during the observation period, while the control group consists of existing listings in buildings with no new-listing arrivals. Buildings with multiple new-listing arrivals are excluded. Because the number of transactions within individual buildings is too small to estimate transaction-price effects precisely, I additionally conduct the price analysis at the residential-complex level.⁵ In this specification, a complex is treated if at least M new listings arrive within a week, while complexes with fewer than M new listings form the control group. I discuss the corresponding identification strategies in Section 3.4.

3.3 Summary Statistics

I first report descriptive patterns in the housing market over the sample period. From August 2015 to July 2016, both transaction prices and list prices per square meter increased steadily (see Figure A1). In contrast, the numbers of new listings and transactions remained relatively stable over time, apart from the sharp decline around the Chinese New Year. The number of new listings consistently exceeded the number of transactions, suggesting a gradual accumulation of for-sale inventory over the sample period.

Figure A2 further shows the evolution of aggregate buyer visits and market tightness. The total number of buyer visits remained relatively stable over time, again with the exception of the Chinese New Year period. Market tightness, measured as the ratio of total buyer visits to the number of active listings, declined over the sample period. This decline is consistent with the expansion of for-sale inventory relative to a relatively stable level of buyer attention.⁶ From the seller's

⁴The six-month window serves two purposes. First, the design requires a sufficient stock of existing listings against which subsequent new-listing arrivals can be studied. I therefore use properties listed during the preceding six months to construct this stock. Second, a longer observation window substantially reduces the number of buildings experiencing exactly one new-listing arrival, which would considerably restrict the baseline estimation sample.

⁵In China, a residential complex is typically a gated community consisting of several apartment buildings developed by the same developer and constructed around the same time. Properties within a complex share the same location and neighborhood amenities and are highly homogeneous in construction quality and architectural characteristics. Prices are therefore highly comparable within a complex, with most remaining differences arising from a small set of unit-level characteristics such as floor area, number of rooms, and floor level.

⁶One caveat is that, due to data limitations, I cannot fully observe properties that exit the market without a transaction. The measured stock of active listings may therefore be overstated, which may mechanically contribute to the observed increase in inventory and decline in measured market tightness.

perspective, this implies increasing competition for a limited pool of buyer attention, providing a useful setting in which to study congestion effects.

I construct the main estimation sample as a property-week panel. Table 1 reports summary statistics for the main variables. Panel A presents property-level characteristics, including housing attributes, the initial list price, and transaction outcomes. Panel B reports variables measured at the property-week level, including weekly buyer visits, list prices, the sale indicator, and the new-listing treatment indicator.

Table 1: Summary Statistics

Variables	<i>N</i>	Mean	Std. Dev.	Min	Max
<i>Panel A: Property-Level Characteristics</i>					
Total Buyer Visits	19,582	3.089	6.547	0	38
Sale Indicator	19,582	15.177	35.881	0	100
Log Initial List Price	19,582	14.917	0.585	13.122	16.787
Log Sale Price	2,891	14.824	0.514	13.874	16.380
Living Rooms	19,181	1.264	0.543	0	2
Bedrooms	19,472	2.429	0.874	1	5
Bathrooms	19,019	1.349	0.582	1	3
Log Floor Area	19,169	4.508	0.453	3.535	5.680
Floor Level	19,369	4.506	3.452	1	27
<i>Panel B: Property-Week Outcomes</i>					
Buyer Visits	520,784	0.122	0.700	0	29
Sale Probability	520,784	0.571	7.533	0	100
Log List Price	520,784	14.922	0.599	13.122	16.760
New Listing	520,784	0.292	0.455	0	1

Notes: Panel A reports summary statistics at the property level, while Panel B reports summary statistics for the property-week panel used in the baseline analysis. Total Buyer Visits is the total number of buyer visits received by a property. Sale Indicator equals 100 if the property is sold and zero otherwise. Sale Probability in Panel B equals 100 in the week in which a property is sold and zero otherwise. New Listing is an indicator equal to one after the arrival of a new listing in the same building.

3.4 Identification Strategy

The identification strategy closely follows [Anenberg and Ringo \(2026\)](#), who exploit the arrival of an individual new listing as a local supply shock and examine how

nearby transaction volume and prices respond following its arrival. Similarly, I exploit variation in the timing of new-listing arrivals to identify their effects on properties already on the market.

My baseline analysis defines exposure at the building level. This market definition is useful for both economic and identification reasons. First, properties within the same building share highly similar location and structural characteristics and are therefore likely to be close substitutes from the perspective of prospective buyers. The arrival of a new listing in the same building consequently represents a salient expansion of the buyer's available choice set. Second, the narrow definition permits a cleaner separation between treated and never-treated listings. Because new listings arrive frequently, defining exposure over a broader geographic area would generate repeated or overlapping treatments for many incumbent properties, leaving few observations that can serve as clean controls. I therefore examine how the arrival of a single new listing affects buyer visits and the probability of sale for incumbent listings in the same building.

I additionally implement a residential-complex-level design for two purposes. First, because relatively few transactions occur within individual buildings, the broader complex-level market provides a sufficiently large transaction sample to examine effects on sale prices. Second, it allows me to assess whether congestion extends beyond the same building. At this level, I define a treatment event as a week in which at least M new listings enter a complex. Treated complexes experience exactly one such event during the sample period, while control complexes have fewer than M new listings in every week; complexes experiencing multiple treatment events are excluded. I vary M across specifications to examine the effects of different intensities of new-listing entry. Section 4.4 presents the corresponding complex-level results.

The identifying assumption is that, absent new-listing entry, incumbent properties in treated and control buildings would have followed parallel short-run trends in buyer visits and sale probabilities, conditional on the fixed effects and controls included in the specification. This assumption does not require either the decision to list or its timing to be random. Homeowners may respond to aggregate or local housing-market conditions when deciding when to list; these common shocks are absorbed by the residential-complex-by-week fixed effects in my preferred specification. The remaining concern is therefore a building-specific time-varying shock that both induces a new listing and independently affects incumbent outcomes. I assess this possibility using event-study specifications that trace the dynamics of buyer visits and sale probabilities around new-listing entry. The absence of differential pre-trends provides support for the identifying assumption and helps rule out the possibility that listings systematically arrive in response to pre-existing

changes in incumbent outcomes.

3.5 Model Specification

I start the estimation with a canonical two-way fixed effect specification:

$$Y_{ibt} = \alpha + \beta NewListing_{bt} + X_i' \eta + \theta_{it} + \gamma_b + \rho_n \phi_t + \epsilon_{ibt}, \quad (26)$$

Y_{ibt} denotes the outcome of existing property i in building b in week t , including the number of buyer visits, the probability of sale, list price, and other seller outcomes. $NewListing_{bt}$ is an indicator equal to one once property i is exposed to a new-listing shock in building b at week t . X_i is a vector of time-invariant housing characteristics, including log floor area, floor level, and the numbers of bedrooms, bathrooms, and living rooms.⁷ θ_{it} denotes time-on-market fixed effects, which flexibly control for duration dependence in property outcomes by absorbing differences associated with the number of weeks property i has been on the market. Controlling for time on market is particularly important because buyer attention and sale outcomes exhibit strong duration dependence: properties that remain unsold for longer periods may systematically receive fewer visits and have lower probabilities of sale.

γ_b denotes building fixed effects, which absorb time-invariant differences across buildings.⁸ Finally, $\rho_n \times \phi_t$ denotes complex-by-week or neighborhood-by-week fixed effects, which flexibly absorb time-varying local market conditions common to properties within the same complex or neighborhood. My preferred specification includes complex-by-week fixed effects, thereby identifying the effect of a new-listing shock from variation across buildings within the same residential complex and week.

The causal identification relies on the parallel trends assumption: absent the arrival of a new listing, outcomes for treated and control properties would have

⁷Within the same building, these are the only characteristics that retain variation; other attributes, such as building age, amenities, and building height, are absorbed by building fixed effects.

⁸I include building fixed effects together with observable property characteristics rather than property fixed effects because my baseline specification is intended to capture changes in outcomes among the set of existing listings within a building following the arrival of a new listing. As properties are sold and exit the market, the composition of the at-risk listings naturally evolves over time. Property fixed effects would place greater weight on within-property changes for listings that remain observed over time, thereby abstracting from part of this evolution in the risk set. By contrast, building fixed effects allow the composition of existing listings to change before and after treatment, while observable property characteristics account for differences in the composition of listings and building fixed effects absorb persistent heterogeneity across buildings.

evolved similarly over time. I assess this assumption using an event-study specification that traces the dynamics of buyer visits and sale probabilities around the arrival of a new listing. The absence of differential trends prior to treatment would provide support for the identifying assumption and would also help rule out the possibility that new listings systematically arrive in response to pre-existing changes in the outcomes of incumbent properties. I therefore estimate the following event-study specification. T_b denotes the week in which building b receives a new listing. I normalize the week immediately preceding the new-listing shock ($\tau = -1$) as the omitted period. To avoid noisy estimates at the tails of the event-time distribution, I bin event times more than seven weeks before the shock into period -7 and those more than seven weeks after the shock into period 7 .

$$Y_{ibt} = \alpha + \sum_{\tau=-7, \tau \neq -1}^7 \beta_{\tau} \mathbb{I}(t - T_b = \tau) + X_i' \eta + \theta_{it} + \gamma_b + \rho_n \phi_t + \epsilon_{ibt}. \quad (27)$$

Recent advances in the DiD literature have shown that, under staggered treatment adoption, conventional two-way fixed effects (TWFE) estimators may be biased when treatment effects vary across cohorts or over time (Callaway and Sant’Anna, 2021; de Chaisemartin and D’Haultfœuille, 2020; Goodman-Bacon, 2021). In particular, TWFE estimates can combine heterogeneous treatment effects using potentially negative weights, which may distort the estimated average treatment effect. To address this concern, I report the conventional TWFE estimates together with the interaction-weighted estimator proposed by Sun and Abraham (2021), implemented using the `eventstudyinteract` command. This estimator constructs cohort-specific treatment effects using appropriate comparison groups and then aggregates them, thereby avoiding the problematic comparisons and negative weighting that can arise under conventional TWFE estimation.

4 Empirical Results

4.1 Duration Dependence of New Listings

I first examine a key implication of Proposition 1: newly listed properties should receive a concentration of visits and sale opportunities shortly after entry, followed by a rapid decline with time on market. In the sequential-search model, a new listing initially becomes available to a stock of buyers who are already searching, generating a spike in visits and matching opportunities upon entry. As these initial search opportunities are exhausted, the listing increasingly relies on the smaller flow of newly arriving buyers.

This duration pattern is important for two reasons. First, it provides a direct test of the model’s prediction about how visits and sale opportunities evolve with time on market. Second, it underlies the model’s prediction for congestion: recently listed incumbents still depend on the existing stock of buyers and are therefore more exposed to displacement by a new entrant, whereas older listings rely primarily on newly arriving buyers and should be less affected.

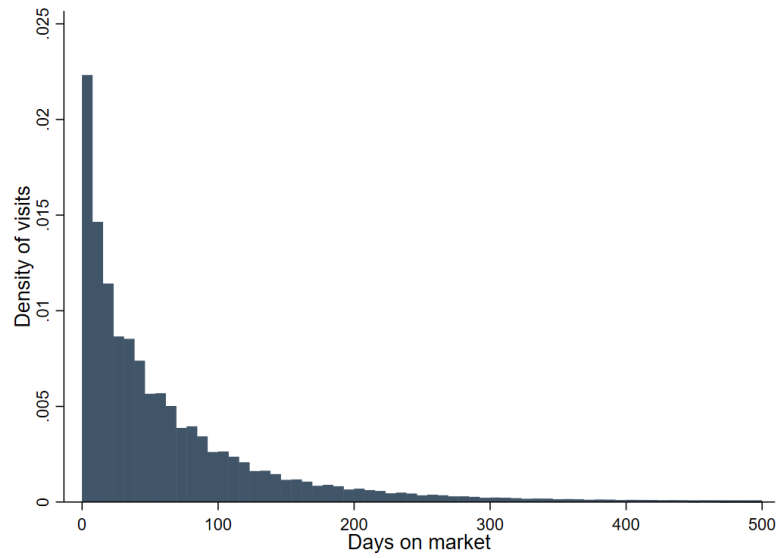
Figure 3 shows a clear duration pattern in both buyer visits and sale outcomes. Panel (a) shows that newly listed properties receive substantially more visits at the beginning of their listing spell, with visit intensity declining sharply as time on market increases. Panel (b) displays a similar pattern for sales: the sale hazard is highest shortly after listing and falls with duration. The close correspondence between the two patterns is consistent with the idea that the early sale advantage of new listings is generated by greater exposure to the existing stock of searching buyers. As that stock is progressively exhausted, both visits and sale opportunities decline and become increasingly dependent on newly arriving buyers.

4.2 Results of Congestion Effects

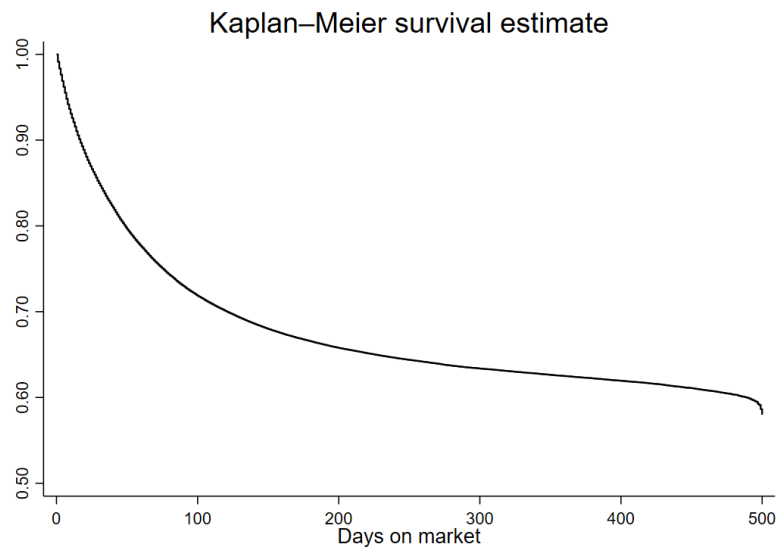
4.2.1 Visits and Sale Probability

I first test the main prediction of Proposition 2: the arrival of a new listing should reduce both the number of visits received by incumbent properties and their probability of sale. Table 2 reports the estimates under different specifications. Columns (1)–(3) examine the effect on the number of visits. Across all specifications, the coefficient on New Listing is negative and statistically significant at the 1% level. The magnitude remains similar after controlling for housing characteristics and progressively absorbing local time-varying shocks using neighborhood-by-week and complex-by-week fixed effects. The estimated effect ranges from -0.031 to -0.037 visits per week. Relative to the average of approximately 0.21 weekly visits among treated properties before treatment, these estimates correspond to a decline of approximately 15–18% in buyer visits following the arrival of a new listing in the same building. Figure 4 presents the corresponding event-study estimates. Before the new listing arrives, the treatment and control groups exhibit similar trends in weekly visits, providing support for the parallel-trends assumption. Following the arrival of the new listing, visits to existing properties decline after 1 week and remain below their pre-treatment level. The dynamic pattern therefore suggests that new listings divert buyer attention away from existing properties in the same building.

Columns (4)–(6) of Table 2 examine whether this loss of buyer attention trans-



(a) Density of Visits Over Time-on-Market



(b) Sale Hazard Over Time-on-Market

Figure 3: Visits and Sale Hazard Over Time-on-Market

Notes: Panel (a) shows the distribution of all visits over sellers' time-on-market. Panel (b) presents Kaplan-Meier survival estimates for property listings, where a sale is defined as the failure event. All properties enter the risk set at the time of listing and are right-censored at the end of August 2016, allowing us to characterize the time-to-sale process and the corresponding sale hazard.

lates into a lower probability of sale. The estimated coefficients are again consistently negative, ranging from -0.106 to -0.127 percentage points across specifications. Relative to an average weekly sale probability of 0.93% among treated properties before treatment, these estimates correspond to a decline of approximately $11\text{--}14\%$ in the weekly probability of sale. Figure 5 shows a similar dynamic pattern: sale probabilities exhibit no differential trends before treatment, begin to decline following the arrival of a new listing, and become significantly negative four weeks after the shock.

Taken together, these results provide evidence of a substantial congestion externality from new listings. The arrival of a competing listing in the same building reduces both buyer attention to existing properties and their probability of sale. The decline in visits provides direct evidence that new listings divert potential buyers away from existing listings, while the decline in sale probability shows that this loss of attention has economically meaningful consequences for sellers by slowing the sale process.

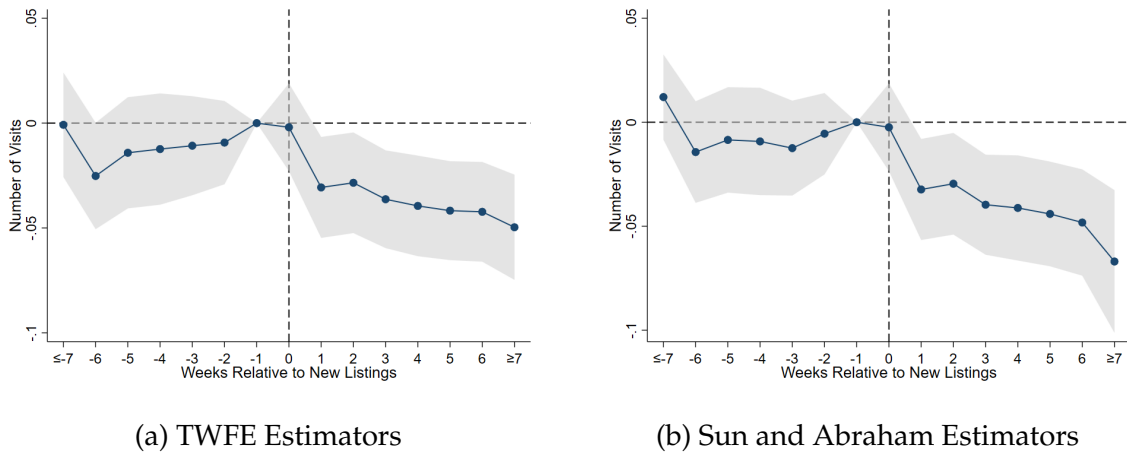


Figure 4: The Dynamic Effects of New Listings on Visits

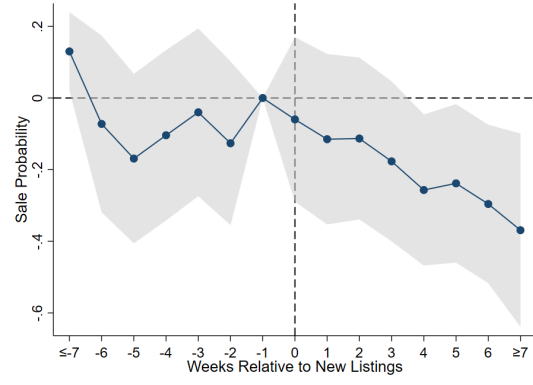
Notes: The figure shows the dynamic treatment effects of new listings shock within the same building on number of visits and sale probability.

4.2.2 Prices

Corollary 1 implies that incumbent sellers may respond to new-listing congestion by accepting lower sale prices in order to improve liquidity. I therefore first examine whether new-listing entry affects transaction prices. Because transaction prices are observed only for properties that sell, the number of transactions within narrowly defined buildings is relatively small. I therefore conduct the main transaction-price analysis at the residential-complex level, where the larger number of transactions allows for more informative estimation. Specifically, I define a



(a) TWFE Estimators



(b) Sun and Abraham Estimators

Figure 5: The Dynamic Effects of New Listings on Sales

Notes: The figure shows the dynamic treatment effects of new listings shock within the same building on number of visits and sale probability.

complex as treated if it experiences exactly one treatment event during the sample period, where a treatment event occurs when at least M new listings enter the complex within a week. Complexes with fewer than M new listings in every week throughout the observation period form the control group. Complexes that experience more than one such treatment event are excluded. I vary the threshold M across specifications to examine whether transaction prices respond to different intensities of new-listing entry.

Table 3 reports the results, and Figure A3 presents the corresponding event-study estimates. Across specifications, I find no significant effect of new-listing arrivals on transaction prices except in column (5). However, the corresponding event-study estimates in Figure A3 exhibit significant pre-treatment differences, casting doubt on a causal interpretation of this coefficient. Taken together, the evidence suggests that incumbent sellers do not systematically respond to new-listing congestion by accepting lower sale prices.

I also examine list-price responses at the building level using the baseline treatment definition. As shown in Figure A4, I find no evidence that incumbent sellers adjust their asking prices following the arrival of a new listing. Thus, despite substantial declines in buyer visits and sale probabilities, new-listing competition does not appear to induce meaningful price adjustments among incumbent properties. This finding is also consistent with Anenberg and Ringo (2026), who show that, after controlling for housing characteristics, both transaction prices and the ratio of transaction prices to list prices are largely unaffected by the arrival of new listings. Overall, the evidence suggests that the congestion effect of new listings operates primarily through the liquidity margin rather than the price margin. New listings reduce buyer attention and the probability of sale without generating eco-

Table 2: The Impact of New Listings on Visits and Sale Probability

	Number of Visits			Sale Probability		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A: TWFE Estimators</i>						
New Listing	-0.037*** (0.006)	-0.036*** (0.006)	-0.031*** (0.008)	-0.121*** (0.039)	-0.106*** (0.039)	-0.127*** (0.046)
<i>Panel B: Sun and Abraham (2021) Estimators</i>						
New Listing	-0.052*** (0.010)	-0.051*** (0.010)	-0.048*** (0.012)	-0.194** (0.079)	-0.187** (0.080)	-0.252*** (0.092)
<i>N</i>	487,200	487,170	459,273	487,200	487,170	459,273
Housing Attributes	✓	✓	✓	✓	✓	✓
Time-on-Market F.E.	✓	✓	✓	✓	✓	✓
Building F.E.	✓	✓	✓	✓	✓	✓
Week F.E.	✓	✓	✓	✓	✓	✓
Neighbor $\times$ Week F.E.		✓			✓	
Complex $\times$ Week F.E.			✓			✓

Notes: Panel A reports estimates from the two-way fixed effects specification. Panel B reports estimates using the interaction-weighted estimator of [Sun and Abraham \(2021\)](#), which accommodates treatment-effect heterogeneity across treatment cohorts and event time. The dependent variables are the number of buyer visits received by a property in a given week and an indicator for whether the property is sold in that week. Housing controls include floor level, floor area, and the numbers of kitchens, bedrooms, and living rooms. Standard errors are clustered at the building level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

nomically meaningful changes in either asking or transaction prices. Incumbent sellers therefore appear to absorb increased competition mainly through a longer expected time to sale rather than through lower prices.

4.3 Heterogeneity in Congestion Effects

I next examine heterogeneity in the congestion effect along four dimensions. The first two, the price competitiveness of the entrant and the listing age of incumbent properties, directly test predictions of the model. I then examine two additional dimensions, property substitutability and local market size, which help to characterize when congestion is likely to be more important.

4.3.1 Price Competitiveness of New Listings

Corollary 2 predicts stronger congestion from entrants with higher quality-adjusted net value. I test this prediction by comparing new listings whose price per square

Table 3: The Impact of New Listings on Sale Prices

$M =$	Treatment: At Least M New Listings at Complex-Week					
	1	2	3	4	5	6
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.092** (0.036)	0.006 (0.007)	0.001 (0.004)	-0.001 (0.004)	-0.008** (0.004)	-0.003 (0.004)
N	95	3,276	10,410	18,800	26,815	33,542
R^2	0.991	0.984	0.979	0.975	0.971	0.969
Housing Attributes	✓	✓	✓	✓	✓	✓
Complex F.E.	✓	✓	✓	✓	✓	✓
Week F.E.	✓	✓	✓	✓	✓	✓

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered at the residential complex level. This table reports the effects of new listings on sale prices at the residential complex level. In column M , a complex-week is classified as treated if at least N new properties are listed within the complex during that week, while complex-weeks with fewer than M new listings serve as the control group.

meter is lower versus higher than that of the incumbent property.⁹ A lower price per square meter makes the entrant more price competitive and more likely to rank ahead of the incumbent in buyers' search sequences. Because market prices rose continuously during the sample period, newly listed properties are typically more expensive than existing listings, as shown in Figure A1. Figure A5 shows that only about 13% of new listings are priced below the corresponding incumbent property, while some are priced as much as 70% higher.

Table 4 reports the estimated effects on buyer visits and sale probability. Consistent with Corollary 2, more price-competitive new listings generate substantially stronger congestion effects. A new listing priced below the incumbent property reduces weekly visits by about 0.13 and the weekly probability of sale by 0.88 percentage points. In contrast, a relatively more expensive new listing reduces weekly visits by only 0.03 and the sale probability by 0.19 percentage points. Thus, the effects of cheaper new listings on both visits and sale probability are approximately four times as large as those of more expensive new listings.

Figure 6 presents the corresponding event-study estimates separately for cheaper and more expensive new listings. For cheaper new listings, the pre-treatment co-

⁹Because the new and existing listings are located in the same building, they share nearly identical housing and location characteristics. Price per square meter therefore provides a simple measure of relative price competitiveness while accounting for differences in unit size.

efficients exhibit some upward movement, which warrants caution in interpreting the estimates. Importantly, however, the arrival of a cheaper new listing coincides with a sharp reversal of the pre-existing upward pattern in both buyer visits and sale probability, producing a clear discontinuous decline around the treatment date. I therefore interpret the event-study evidence as suggestive that the substantially larger effects of cheaper new listings are not simply driven by continuation of the pre-treatment trend.

Table 4: The Price Competitiveness of New Listings

	Number of Visits		Sale Probability	
	<i>Expensive</i>	<i>Cheap</i>	<i>Expensive</i>	<i>Cheap</i>
	(1)	(2)	(3)	(4)
New Listing	-0.031*** (0.008)	-0.130*** (0.028)	-0.193*** (0.047)	-0.882*** (0.176)
<i>N</i>	425,531	230,093	425,531	230,093
<i>R</i> ²	0.347	0.453	0.253	0.341
Housing Attributes	✓	✓	✓	✓
Time-on-Market F.E.	✓	✓	✓	✓
Building F.E.	✓	✓	✓	✓
Week F.E.	✓	✓	✓	✓
Complex × Week F.E.	✓	✓	✓	✓

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered at the building level. New listings are classified as *Cheap* (*Expensive*) if their price per square meter is lower (higher) than that of the corresponding existing listing. For the *Cheap* specifications, the treatment group consists of existing listings exposed to a cheaper new listing and is compared with the control group. For the *Expensive* specifications, the treatment group consists of existing listings exposed to a more expensive new listing and is compared with the same control group.

4.3.2 Listing Age of Incumbent Sellers

Corollary 3 provides a direct prediction about how congestion should vary with an incumbent property's time on market. Recently listed incumbents still receive visits and matching opportunities from buyers already active in the market. A new listing can therefore enter ahead of these properties in existing buyers' search sequences and push them to lower positions, reducing their probabilities of being visited and sold. By contrast, incumbents that have remained on the market for sufficiently long have exhausted most of these opportunities and rely primarily

on newly arriving buyers. The congestion effect should therefore be concentrated among relatively recent incumbents. This prediction is closely related to stock–flow matching: new listings and recent incumbents overlap substantially in the stock of buyers already searching, whereas older unmatched listings increasingly depend on the flow of new buyers (Anenberg and Ringo, 2026; Smith et al., 2026).

To test this prediction, I divide treated incumbent properties according to their time on market when the new listing arrives. I use the median time on market in the treated sample, 32 days, as the cutoff. Properties that have been listed for no more than 32 days at the time of treatment are classified as *Recent*, while those that have been on the market for more than 32 days are classified as *Old*. I then estimate the baseline specification separately for the two groups.

Table 5 reports the results. Consistent with Corollary 3, the negative congestion effect is concentrated among recently listed properties. For the *Recent* group, the arrival of a new listing reduces weekly buyer visits by 0.054 and the weekly sale probability by 0.155 percentage points. In contrast, the coefficients for the *Old* group are positive. These estimates should not be interpreted as evidence that new listings benefit older incumbents, however, because Figure 7 shows differential pre-treatment trends for this group, making a causal interpretation difficult.

The results therefore support the model’s prediction that congestion is most pronounced for incumbents that still share the existing buyer stock with the entrant. For older listings, whose matching opportunities depend increasingly on newly arriving buyers, I do not find credible evidence of a negative congestion effect.

4.3.3 Substitutability of New Listings

I next examine whether the congestion effect depends on the substitutability between the new listing and existing properties. If the negative externality operates through the diversion of buyer attention, its magnitude should depend on how closely the new listing competes with an existing property for the same buyers. A new listing that is similar to an existing property provides a closer alternative and should therefore divert more buyer attention from that property. I measure substitutability along two salient housing characteristics—floor area and floor level—which are the only housing attributes that vary within buildings. I separately compare the effects when the new and existing listings have the same versus different floor areas and when they are located on the same versus different floors. I expect the negative effect of new listings to be stronger when the two properties share these characteristics.

Table 6 reports the results. The heterogeneity in buyer visits is economically

Table 5: Heterogeneity by Time on Market

	Number of Visits		Sale Probability	
	<i>Recent</i>	<i>Old</i>	<i>Recent</i>	<i>Old</i>
	(1)	(2)	(3)	(4)
New Listing	-0.054*** (0.013)	0.025*** (0.008)	-0.155** (0.068)	0.197*** (0.046)
<i>N</i>	323,020	313,855	323,020	313,855
<i>R</i> ²	0.374	0.363	0.279	0.280
Housing Attributes	✓	✓	✓	✓
Building F.E.	✓	✓	✓	✓
Week F.E.	✓	✓	✓	✓
Complex $\times$ Week F.E.	✓	✓	✓	✓

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered at the building level. Treated incumbent properties are classified according to their time on market when the new listing arrives. *Recent* properties are those that have been listed for no more than 32 days, the median time on market in the treated sample, while *Old* properties are those that have been listed for more than 32 days. Each treatment group is compared with the control group of properties in buildings that experience no new-listing arrival during the sample period.

substantial. When the new and existing listings have the same floor area, the decline in visits is about four times as large as when their floor areas differ (-0.112 versus -0.027). A similarly pronounced pattern emerges for floor level: the reduction in visits is also about four times larger when the two properties are located on the same floor (-0.100 versus -0.025). These results suggest that new listings attract substantially more attention away from existing properties when they offer more comparable housing attributes. The results for sale probability generally point in the same direction. The effect is more than three times as large when the new and existing properties are located on the same floor (-0.375 versus -0.105). For floor area, the estimated effect is also economically large when the two properties have the same area (-0.168), although it is imprecisely estimated and statistically insignificant. Taken together, the consistently stronger effects on buyer visits, together with the corresponding pattern in sale probabilities, suggest that the congestion externality becomes more pronounced when new listings are closer substitutes for existing properties. This evidence is consistent with buyer-attention diversion as an important mechanism underlying the negative effect of new listings.

Table 6: The Substitutability of New Listings

	Number of Visits		Sale Probability	
	<i>Same</i>	<i>Different</i>	<i>Same</i>	<i>Different</i>
	(1)	(2)	(3)	(4)
<i>Panel A: Floor Area</i>				
New Listing	-0.099*** (0.023)	-0.023*** (0.008)	-0.319*** (0.113)	-0.117** (0.050)
<i>N</i>	216,957	428,705	216,957	428,705
<i>R</i> ²	0.413	0.337	0.320	0.246
<i>Panel B: Floor Level</i>				
New Listing	-0.090*** (0.022)	-0.020** (0.008)	-0.412*** (0.124)	-0.117** (0.049)
<i>N</i>	220,603	424,040	220,603	424,040
<i>R</i> ²	0.416	0.334	0.320	0.247
Housing Attributes	✓	✓	✓	✓
Time-on-Market F.E.	✓	✓	✓	✓
Building F.E.	✓	✓	✓	✓
Week F.E.	✓	✓	✓	✓
Complex × Week F.E.	✓	✓	✓	✓

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered at the building level. Panel A classifies treated listings according to whether the new listing has the same floor area as the corresponding existing listing. The *Same* (*Different*) specifications compare existing listings exposed to a new listing with the same (different) floor area with the control group. Panel B follows the same procedure based on floor level: the *Same* (*Different*) specifications compare existing listings exposed to a new listing on the same (different) floor with the control group.

Table 7: Market Size and the Congestion Effect of New Listings

	Number of Visits			Sale Probability		
	(1)	(2)	(3)	(4)	(5)	(6)
New Listing $\times$ Market Size	0.009* (0.005)	0.007* (0.004)	0.013** (0.005)	0.086*** (0.020)	0.071*** (0.020)	0.079*** (0.025)
New Listing	-0.056*** (0.013)	-0.051*** (0.012)	-0.057*** (0.014)	-0.267*** (0.068)	-0.215*** (0.068)	-0.242*** (0.079)
<i>N</i>	484,819	484,789	456,944	484,819	484,789	456,944
<i>R</i> ²	0.184	0.199	0.314	0.070	0.084	0.220
Housing Attributes	✓	✓	✓	✓	✓	✓
Time-on-Market F.E.	✓	✓	✓	✓	✓	✓
Building F.E.	✓	✓	✓	✓	✓	✓
Week F.E.	✓	✓	✓	✓	✓	✓
Neighbor $\times$ Week F.E.		✓			✓	
Complex $\times$ Week F.E.			✓			✓

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered at the building level. This table examines whether the effect of new listings varies with local market size. Market Size is measured by the number of existing listings in the building at the time the new listing enters the market. The interaction term, New Listing $\times$ Market Size, therefore captures how the effect of a new-listing arrival varies with the number of incumbent properties competing in the same building. A positive interaction coefficient indicates that the negative effect of a new listing becomes weaker as market size increases.

4.3.4 Market Size

I next examine whether the congestion effect varies with the size of the local market. Market size is important because the competitive impact of a new listing should depend not only on its arrival but also on the number of properties already available to buyers. In a smaller market, the addition of a single listing represents a larger proportional expansion of the relevant choice set and may therefore attract a larger share of buyer attention away from existing properties. By contrast, in a larger market with many competing listings, one additional property constitutes a relatively small change in the available inventory and should have a more limited effect on the allocation of buyer attention. I therefore expect the negative effect of new listings on existing properties to be stronger in smaller markets.

I measure market size by the number of existing listings in the building at the time a new listing enters the market and interact this measure with the new-listing indicator. The results are reported in Table 7. The interaction coefficients are consistently positive, indicating that the negative effects of new listings become weaker as market size increases. This pattern is consistent with the congestion mechanism: in a larger market, the arrival of one additional listing represents a smaller proportional expansion of the set of available properties and therefore di-



Figure 6: The Dynamic Effects of Heterogeneous Price Competitive New Listings

Notes: The figure shows how number of visits of the existing listings changes after new listings shock within the same building. The panel (a) shows the dynamics when houses are affected by more expensive new listing shocks, while the panel (b) illustrates the dynamics when houses are affected by cheaper new listing shocks.

verts less buyer attention from each existing listing.

4.4 Robustness

Multiple New Listings. The baseline analysis restricts the sample to buildings that experience either one or no new-listing arrival during the sample period. While this restriction provides a clean comparison that isolates the effect of a single new listing, it may introduce a sample-selection concern by excluding buildings with more active listing entry. To assess whether my findings depend on this restriction, I retain the full sample and allow buildings to experience multiple new-listing arrivals. For each building-week, I construct the cumulative number of new listings that have entered the building up to that week and regress incumbent properties' buyer visits, sale probability, and prices on this measure. This specification allows me to examine whether the baseline congestion pattern extends to



Figure 7: Dynamic Effects of New Listings by Incumbent Time on Market

Notes: This figure presents event-study estimates of the effects of new-listing arrivals on incumbent properties, separately by their time on market at the treatment date. *Recent* listings are properties that have been on the market for no more than 32 days when the new listing arrives, while *Old* listings have been on the market for more than 32 days. Panels (a) and (b) report the effects on buyer visits, and Panels (c) and (d) report the effects on sale probability.

the broader sample and to settings with repeated new-listing entry.

Table A4 and Table A5 present the results. Table A4 confirms that the cumulative number of new listings is significantly negatively associated with both buyer visits and the sale probability of existing listings. I find that each additional new listing is associated with 0.001–0.004 fewer weekly buyer visits and a 0.018–0.026 percentage-point decline in the weekly probability of sale. These coefficients are substantially smaller than those in the baseline specification because they capture the marginal effect of one additional new listing, rather than the average change associated with the arrival of the first new listing. Table A5 shows that the cumulative number of new listings is not significantly associated with the list prices of existing properties, but is positively associated with their transaction prices. I interpret the latter result with caution. Buildings experiencing more new-listing arrivals may be located in relatively active or appreciating local markets, where

both seller entry and transaction prices are higher. The positive association may therefore partly reflect endogenous variation in local market conditions rather than a causal price response to additional new listings.

Apartment Complex Level Evidence. To conduct robustness checks and examine the geographic scope of the congestion externality, I extend the analysis to the apartment-complex level.¹⁰ Applying the baseline treatment definition at this broader spatial level leaves relatively few eligible complexes, because new listings arrive frequently and many complexes experience multiple treatment events during the sample period. I therefore modify the treatment definition. Specifically, I define a complex as treated if it experiences at least N new listings within a week, while complexes with fewer than N new listings in every week throughout the observation period form the control group. I vary the threshold N across specifications to obtain sufficient treated and control observations and to examine how the congestion effect changes with the intensity of new-listing entry.

Tables A2 and A3 report the estimation results, and Figures A8 and A9 present the corresponding event-study estimates. I find that new-listing entry significantly reduces both buyer visits and the sale probability of existing properties within the same residential complex. As I increase the threshold N , the treatment group becomes smaller while the control group expands, resulting in larger estimation samples. Across specifications, the estimated effect on weekly buyer visits ranges from -0.010 to -0.039, broadly comparable to the building-level estimates of -0.037 to -0.044. The estimated effect on the weekly probability of sale ranges from -0.36 to -1.05 percentage points. Although these estimates are larger in magnitude than the corresponding building-level effects of approximately -0.10 to -0.14 percentage points, they consistently point to substantial negative congestion effects at the broader complex level.

Overall, I find that the apartment-complex-level estimates are qualitatively consistent with the baseline building-level results. These findings provide additional evidence that the congestion externality generated by new listings is not confined to properties within the same building but extends to competing properties in other buildings within the same residential complex. The results also show that concentrated entry by multiple new listings generates substantial congestion relative to periods with fewer new listings. Taken together, the evidence suggests that new-listing congestion operates over a broader local housing market than the in-

¹⁰A residential complex is a gated residential community consisting of multiple apartment buildings that are typically developed by the same developer and constructed around the same time. Properties within a complex are highly homogeneous in terms of location, construction quality, architectural style, and neighborhood amenities, with differences primarily arising from unit size and the number of rooms.

dividual building, while preserving the same qualitative pattern of reduced buyer attention and lower sale probabilities.

The Role of Transactions. A potential concern is that the baseline treatment measure may overstate exposure to a new listing when the newly listed property is sold shortly after entry. In the baseline specification, a property is considered exposed once a new listing enters the same building. However, once that new listing is sold, it no longer remains available to compete for buyer attention. Continuing to classify subsequent weeks as treated may therefore introduce measurement error and attenuate the estimated congestion effect toward zero. Figure A7 illustrates this issue: although a new-listing arrival initially increases the stock of properties for sale, the average increase in active inventory is less than one and declines over time, consistent with some new listings being sold relatively quickly.

To address this concern, I construct an indicator for whether the newly listed property has been sold. The indicator equals zero when the new listing first enters the market and switches to one in all weeks after that property is sold. I then include this variable together with the baseline new-listing indicator in the regression. Under this specification, the coefficient on the new-listing indicator captures the effect of the entrant while it remains active on the market, whereas the post-sale indicator captures the change in outcomes after the entrant exits. This allows me to separate the congestion generated by an active new listing from the effect associated with its subsequent sale.

Table A6 reports the results. Controlling for the sale of the newly listed property does not eliminate the negative effect of new-listing entry on incumbent properties. The new estimates remain closely aligned with the baseline results, providing further evidence that my findings are robust to accounting explicitly for the subsequent sale of the newly listed property.

4.5 Buyer Entry

Section 2.3.2 extends the model to allow for buyer entry. I next examine whether new-listing entry induces such a demand-side response in the local market. This distinction is important because the congestion effect may either reflect a fixed amount of buyer search being mechanically divided across more properties or arise even as new listings attract additional buyers. To distinguish between these possibilities, I measure buyer activity at the building-week level using the total number of property visits and the number of unique buyers generating these visits. Table 8 and Figure 8 show that new-listing entry significantly increases both measures. Thus, new listings do more than redistribute a fixed pool of buyer search: they also

attract additional buyers into the building.

I further examine whether this increase in buyer activity keeps pace with the expansion in available inventory. Market tightness, measured as visits or unique buyers per active listing, also rises following a new-listing arrival (Figure A10). Thus, new-listing entry increases buyer demand relative to the number of properties available for sale. Nevertheless, my baseline results show that incumbent properties receive fewer visits and become less likely to sell. Taken together, these findings imply that the additional buyer activity generated by new listings is disproportionately directed toward the newly listed property rather than shared with incumbent listings. The demand-side expansion therefore partially offsets, but does not overturn, the congestion effect on incumbent sellers.

One explanation is that newly listed properties attract particularly strong attention shortly after entry. Consistent with this mechanism, buyer visits and the sale hazard are highest immediately after listing and decline rapidly with time on market (see Figure 3). This pattern is also consistent with stock-flow matching: because a large stock of buyers is already actively searching when a new listing enters, the entrant immediately faces many potential matching opportunities and therefore receives particularly intense attention shortly after listing (Gilbukh, 2023; Smith et al., 2026). New-listing entry therefore both expands local buyer activity and reallocates matching opportunities toward newly available properties.

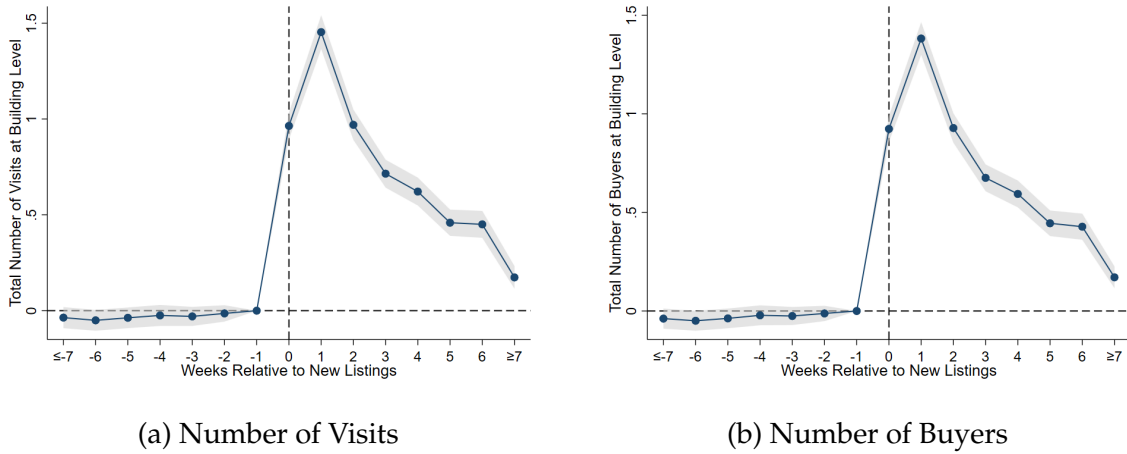


Figure 8: The Dynamic Effects of New Listings on Buyer Entry at Building Level

Notes: The figure shows the dynamic treatment effects of new listings shock within the same building on number of visits and number of buyers. *Number of Total Visits* is defined as the total number of property visits received by all listings within a building in a given week. *Number of Total Buyers* is the number of unique buyers associated with these visits in the same building-week.

Table 8: The Impact of New Listings on Buyer Entry

	Number of Total Visits			Number of Total Buyers		
	(1)	(2)	(3)	(4)	(5)	(6)
New Listing	0.625*** (0.019)	0.640*** (0.019)	0.682*** (0.023)	0.601*** (0.018)	0.615*** (0.018)	0.653*** (0.021)
<i>N</i>	321,725	321,695	273,851	321,725	321,695	273,851
<i>R</i> ²	0.232	0.255	0.430	0.235	0.257	0.431
Building F.E.	✓	✓	✓	✓	✓	✓
Week F.E.	✓	✓	✓	✓	✓	✓
Neighbor $\times$ Week F.E.		✓			✓	
Complex $\times$ Week F.E.			✓			✓

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered at the building level. *Number of Total Visits* is defined as the total number of property visits received by all listings within a building in a given week. *Number of Total Buyers* is the number of unique buyers associated with these visits in the same building-week.

5 Conclusion

This paper studies how new housing supply affects properties already on the market through the buyer search process. I use a sequential-search framework because a standard random-matching model can generate congestion when more sellers compete for a given pool of buyers, but is largely silent about which properties are most exposed to that congestion. Sequential search provides a richer mechanism: new listings enter buyers' search sequences, alter the relative positions of incumbent properties, and thereby change their probabilities of being visited and sold. The model therefore yields additional predictions about the incidence of congestion, including stronger effects from more attractive entrants and for recently listed incumbents that still share the existing stock of buyers with new listings.

The empirical evidence supports these predictions and helps distinguish the search mechanism from a generic increase in seller competition. More price-competitive entrants generate substantially larger congestion effects, and the negative effects are concentrated among relatively recent incumbent listings. The buyer-side evidence further shows that new listings can attract additional buyers into the local market while still reducing visits and sale probabilities for incumbent properties. Thus, congestion is not simply the mechanical consequence of dividing a fixed amount of demand among more sellers; it reflects how new supply changes the ordering and allocation of search across properties.

This perspective also provides a micro-foundation for the stock–flow matching

patterns observed in housing markets. Newly listed properties initially interact with the stock of buyers already searching and therefore receive a concentration of visits and matching opportunities shortly after entry. As those opportunities are exhausted, listings increasingly depend on the flow of newly arriving buyers. More broadly, the findings show that housing-market liquidity depends not only on the number of buyers and sellers, but also on where properties appear in buyers' search processes. Understanding this search allocation is therefore important for explaining both the aggregate congestion created by new supply and the unequal incidence of that congestion across incumbent sellers.

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Online Appendix

A Proof of Lemmas and Propositions

A.1 Proof of Lemma 1

Proof. The first-ranked house is visited with probability one. For $m \geq 2$, buyer i visits the house ranked m if and only if she has not stopped after visiting ranks $1, \dots, m-1$. This requires the highest realized utility among previously visited houses to be below the reservation index of the house ranked m :

$$\max_{s < m} u_{ik_s} < r_{ik_m}.$$

Equivalently,

$$u_{ik_s} < r_{ik_m} \quad \text{for all } s < m.$$

Since post-visit shocks are independent across houses, the visiting probability is

$$\Pr_{ik_m}^{\text{visit}}(m) = \prod_{s=1}^{m-1} \Pr(u_{ik_s} < r_{ik_m}).$$

For monotonicity, define

$$P_m = \Pr_{ik_m}^{\text{visit}}(m).$$

To visit rank $m+1$, buyer i must first visit rank m and then continue searching after rank m . Hence

$$P_{m+1} = P_m \cdot \Pr(\text{continue from rank } m \text{ to } m+1 \mid V_m),$$

where V_m is the event that buyer i visits rank m .

It remains only to show that this continuation probability is strictly smaller than one. Equation (4) defines the reservation threshold z^* . Since $c > 0$, we have $z^* < \bar{z}$. Given

$$r_{ik_m} = v_{ik_m} + z^* - p_{k_m} \quad \text{and} \quad u_{ik_m} = v_{ik_m} + z_{ik_m} - p_{k_m},$$

the condition $z^* < \bar{z}$ implies

$$\Pr(z_{ik_m} \geq z^*) > 0,$$

and therefore

$$\Pr(u_{ik_m} \geq r_{ik_m}) > 0.$$

Since the Weitzman indices are ordered as

$$r_{ik_m} \geq r_{ik_{m+1}},$$

the event $u_{ik_m} \geq r_{ik_m}$ implies that buyer i stops after visiting rank m , before rank $m + 1$ is reached. Thus,

$$\Pr(\text{continue from rank } m \text{ to } m + 1 \mid V_m) < 1.$$

Therefore,

$$P_{m+1} < P_m.$$

This proves that the visiting probability is strictly decreasing in rank. $\square$

A.2 Proof of Lemma 2

Proof. Fix buyer i and suppress the buyer subscript. Let A_m denote the event that the property ranked m becomes the buyer's most preferred property at the end of the search process. By definition,

$$\Pr(A_m) = \delta_i(m).$$

Consider any realization of match shocks under which the property ranked $m + 1$ becomes the buyer's most preferred property. Now construct a new realization by swapping only the shocks at ranks m and $m + 1$. Since the match shocks are i.i.d., the original and swapped realizations have the same probability law.

Because properties are ordered by reservation values,

$$r_i(m) \geq r_i(m + 1).$$

Since the reservation shock z^* is common across properties, this implies

$$v_i(m) - p(m) \geq v_i(m + 1) - p(m + 1).$$

Therefore, after assigning the original rank- $(m + 1)$ shock to rank m , the realized utility of rank m is weakly higher than the realized utility of the original rank- $(m + 1)$ winner:

$$v_i(m) - p(m) + z_{m+1} \geq v_i(m + 1) - p(m + 1) + z_{m+1}.$$

Moreover, rank m is visited before rank $m + 1$. Hence, if rank $m + 1$ can become the buyer's most preferred property under the original realization, then after the swap rank m can do so as well: it is reached earlier and, with the same winning shock, delivers weakly higher realized utility. Thus, every realization in A_{m+1} can be mapped into a realization in A_m . Since the swap preserves the joint distribution of shocks,

$$\Pr(A_m) \geq \Pr(A_{m+1}).$$

The inequality is strict. By Lemma 1, conditional on reaching rank m , there is a strictly positive probability that the buyer stops at rank m . On such realizations, rank m becomes the buyer's most preferred property while rank $m + 1$ is never reached. Hence there is a positive-probability set of realizations that belongs to A_m but has no counterpart in A_{m+1} . Therefore,

$$\Pr(A_m) > \Pr(A_{m+1}),$$

and thus

$$\delta_i(m) > \delta_i(m + 1), \quad m = 1, \dots, S - 1.$$

□

A.3 Proof of Proposition 1

Proof. Suppose there are S incumbent properties immediately before property k enters, so that the post-entry choice set contains $S + 1$ properties. Let m_{ik} denote the entrant's rank in buyer i 's optimal search sequence after entry, and let s_i denote the number of properties that buyer i has already inspected. Since buyer i can inspect at most one additional property per period, the period in which the entrant would be reached, conditional on search continuing sufficiently far, is

$$t_{ik} = \max\{1, m_{ik} - s_i\}. \quad (\text{A1})$$

Because the entrant's reservation value is an independent draw from the same continuous distribution as those of incumbent properties, its post-entry rank is exchangeable across the $S + 1$ positions. Hence,

$$\Pr(t_{ik} = t \mid s_i, S) = \begin{cases} \frac{s_i + 1}{S + 1}, & t = 1, \\ \frac{1}{S + 1}, & t = 2, \dots, S + 1 - s_i, \\ 0, & \text{otherwise.} \end{cases} \quad (\text{A2})$$

The first-period probability is larger because all global ranks $m_{ik} \leq s_i + 1$ make the entrant the buyer's next available property.

Let $\nu_i(t)$ denote the probability that buyer i , conditional on her search history at entry, continues searching sufficiently far to reach position t in the remaining search sequence. Applying Lemma 1 to this remaining sequence gives

$$\nu_i(1) = 1, \quad \nu_i(t) > \nu_i(t + 1). \quad (\text{A3})$$

The probability that buyer i visits property k in period t is therefore

$$v_{ikt} = \Pr(t_{ik} = t \mid s_i, S) \nu_i(t). \quad (\text{A4})$$

Aggregating across the stock of buyers present at entry,

$$V_{k1}^0 = \frac{1}{S+1} \sum_{i \in \mathcal{B}} (s_i + 1), \quad (\text{A5})$$

whereas, for $t \geq 2$,

$$V_{kt}^0 = \frac{1}{S+1} \sum_{i: t \leq S+1-s_i} \nu_i(t). \quad (\text{A6})$$

Since $s_i + 1 \geq 1$ and $\nu_i(2) < 1$, equation (A5) implies

$$V_{k1}^0 > V_{k2}^0.$$

For every subsequent feasible period, Lemma 1 implies that $\nu_i(t+1) < \nu_i(t)$, while the set of buyers for whom $t+1$ remains a feasible search position is a subset of the corresponding set at t . Therefore,

$$V_{k1}^0 > V_{k2}^0 > V_{k3}^0 > \dots \quad (\text{A7})$$

for periods in which the initial buyer stock generates positive visiting opportunities.

The same argument applies to matching outcomes. Let $\delta_i(t)$ denote the probability that a property occupying position t in buyer i 's remaining search sequence ultimately becomes that buyer's most preferred property. By Lemma 2,

$$\delta_i(t) > \delta_i(t+1). \quad (\text{A8})$$

Define

$$d_{ikt} = \Pr(t_{ik} = t \mid s_i, S) \delta_i(t). \quad (\text{A9})$$

Equation (A2) together with Lemma 2 implies

$$d_{ik1} > d_{ik2} > d_{ik3} > \dots$$

over the feasible positions for buyer i .

Conditional on the common search environment, suppose these buyer-specific preferred-property outcomes are independent across buyers. The probability that property k becomes the preferred property of at least one buyer in period t is then

$$D_{kt}^0 = 1 - \prod_{i \in \mathcal{B}} (1 - d_{ikt}). \quad (\text{A10})$$

Because D_{kt}^0 is strictly increasing in each d_{ikt} , it follows that

$$D_{k1}^0 > D_{k2}^0 > D_{k3}^0 > \dots$$

for periods in which the initial buyer stock generates positive matching opportunities.

Finally, under the market-clearing assumption that a property is sold whenever it attracts at least one buyer for whom it is the most preferred available property, D_{kt}^0 is also the sale probability generated by the initial buyer stock. Hence both visits and sale probabilities exhibit a first-period spike followed by a declining duration profile. $\square$

B Additional Tables

Table A1: Balance Test

Variable	Treatment		Control		Difference	
	<i>N</i>	Mean	<i>N</i>	Mean	Treat.–Control	Std. Diff.
Living Rooms	10,702	1.267	8,479	1.261	0.007	0.012
Bedrooms	10,795	2.388	8,677	2.481	-0.093***	-0.106
Bathrooms	10,676	1.321	8,343	1.385	-0.064***	-0.109
Log Floor Area	10,723	4.493	8,446	4.527	-0.035***	-0.077
Floor Level	10,768	4.664	8,601	4.309	0.356***	0.103
Log Initial List Price	10,838	14.892	8,744	14.947	-0.055***	-0.094

Notes: This table compares housing characteristics between properties in the treatment and control groups. The difference is calculated as the treatment-group mean minus the control-group mean. Statistical significance is based on two-sample tests of equality of means. The standardized difference is calculated as the difference in group means divided by the square root of the average of the two group variances. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A2: The Impact of New Listings on Visits at the Residential Complex Level

$M =$	Treatment: At Least M New Listings at Complex-Week					
	1	2	3	4	5	6
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.003 (0.031)	-0.017 (0.013)	-0.036*** (0.010)	-0.024*** (0.009)	-0.036*** (0.008)	-0.037*** (0.009)
N	31,612	357,561	927,948	1,568,800	2,164,754	2,633,024
R^2	0.329	0.168	0.148	0.141	0.137	0.135
Housing Attributes	✓	✓	✓	✓	✓	✓
Complex F.E.	✓	✓	✓	✓	✓	✓
Week F.E.	✓	✓	✓	✓	✓	✓
Neighbor $\times$ Week F.E.	✓	✓	✓	✓	✓	✓

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered at the building level. This table reports the effects of new listings on buyer visits at the residential complex level. In column M , a complex-week is classified as treated if at least M new properties are listed within the complex during that week, while complex-weeks with fewer than M new listings serve as the control group.

Table A3: The Impact of New Listings on Sales at the Residential Complex Level

$M =$	Treatment: At Least M New Listings at Complex-Week					
	1	2	3	4	5	6
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.720 (1.171)	-0.523 (0.465)	-0.275 (0.312)	-0.989*** (0.288)	-0.957*** (0.281)	-1.006*** (0.275)
N	31,612	357,561	927,948	1,568,800	2,164,754	2,633,024
R^2	0.549	0.274	0.222	0.205	0.196	0.194
Housing Attributes	✓	✓	✓	✓	✓	✓
Time-on-Market F.E.	✓	✓	✓	✓	✓	✓
Complex F.E.	✓	✓	✓	✓	✓	✓
Week F.E.	✓	✓	✓	✓	✓	✓
Neighbor $\times$ Week F.E.	✓	✓	✓	✓	✓	✓

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered at the building level. This table reports the effects of new listings at the residential complex level. In column M , a complex-week is classified as treated if at least M new properties are listed within the complex during that week, while complex-weeks with fewer than M new listings serve as the control group.

Table A4: The Impact of Cumulative New Listings on Visits and Sales

	Number of Visits			Sale Probability		
	(1)	(2)	(3)	(4)	(5)	(6)
Cumulative New Listings	-0.003*** (0.000)	-0.001*** (0.000)	-0.004*** (0.001)	-0.022*** (0.003)	-0.018*** (0.002)	-0.026*** (0.003)
<i>N</i>	2,628,275	2,628,245	2,609,218	2,628,275	2,628,245	2,609,218
<i>R</i> ²	0.130	0.136	0.177	0.048	0.051	0.101
Housing Attributes	✓	✓	✓	✓	✓	✓
Time-on-Market F.E.	✓	✓	✓	✓	✓	✓
Building F.E.	✓	✓	✓	✓	✓	✓
Week F.E.	✓	✓	✓	✓	✓	✓
Neighbor × Week F.E.		✓			✓	
Complex × Week F.E.			✓			✓

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered at the building level. *Cumulative New Listings* is defined as the total number of new listings that have entered the building from the beginning of the sample period up to and including the current week. The dependent variables are the number of visits received by the property in a given week and an indicator for whether the property is sold in that week. Control variables include floor level, floor area, and the numbers of kitchens, bedrooms, and living rooms.

Table A5: The Impact of Cumulative New Listings on Prices

	List Prices			Sale Prices		
	(1)	(2)	(3)	(4)	(5)	(6)
Cumulative New Listings	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.001)	0.001 (0.001)	-0.000 (0.003)
<i>N</i>	2,628,275	2,628,245	2,609,218	6,637	5,030	1,831
<i>R</i> ²	0.979	0.979	0.979	0.979	0.985	0.983
Housing Attributes	✓	✓	✓	✓	✓	✓
Time-on-Market F.E.	✓	✓	✓	✓	✓	✓
Building F.E.	✓	✓	✓	✓	✓	✓
Week F.E.	✓	✓	✓	✓	✓	✓
Neighbor × Week F.E.		✓			✓	
Complex × Week F.E.			✓			✓

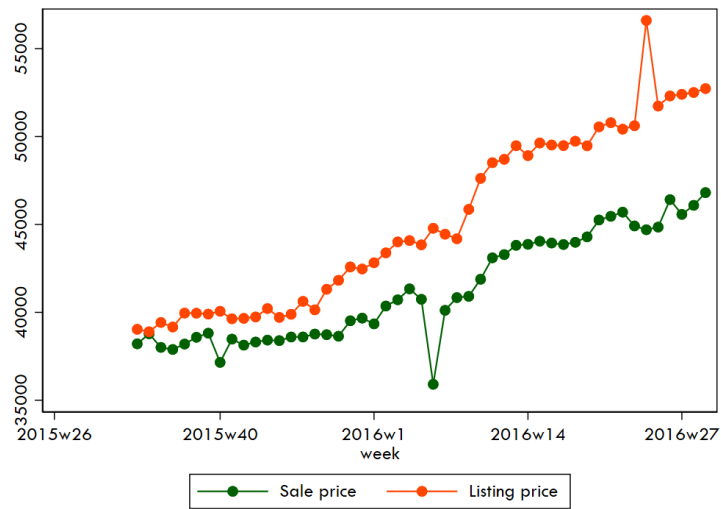
Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered at the building level. *Cumulative New Listings* is defined as the total number of new listings that have entered the building from the beginning of the sample period up to and including the current week. The dependent variables are list prices and sale prices of the property. Control variables include floor level, floor area, and the numbers of kitchens, bedrooms, and living rooms.

Table A6: The Impact of New Listings With Effects of Sales

	Number of Visits			Sale Probability		
	(1)	(2)	(3)	(4)	(5)	(6)
New Listing	-0.026*** (0.006)	-0.026*** (0.006)	-0.022*** (0.007)	-0.091** (0.040)	-0.086** (0.040)	-0.120** (0.047)
Sale	-0.061*** (0.013)	-0.052*** (0.012)	-0.049*** (0.015)	-0.158** (0.064)	-0.100 (0.065)	-0.039 (0.080)
<i>N</i>	487,200	487,170	459,273	487,200	487,170	459,273
<i>R</i> ²	0.205	0.220	0.330	0.091	0.105	0.239
Housing Attributes	✓	✓	✓	✓	✓	✓
Time-on-Market F.E.	✓	✓	✓	✓	✓	✓
Building F.E.	✓	✓	✓	✓	✓	✓
Week F.E.	✓	✓	✓	✓	✓	✓
Neighbor × Week F.E.		✓			✓	
Complex × Week F.E.			✓			✓

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered at the building level. The explained variables are the number of visits the house receives each week and whether the house is sold that week. Control variables include the floor level, area, number of kitchens, bedrooms, and living rooms of the house. Sale is an indicator equal to one if the newly listed property has already been sold by the current week, and zero otherwise.

C Additional Figures



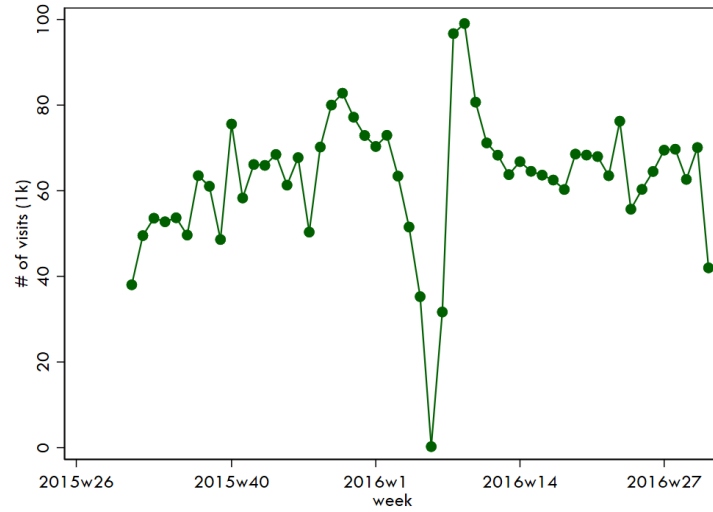
(a) Price Dynamics



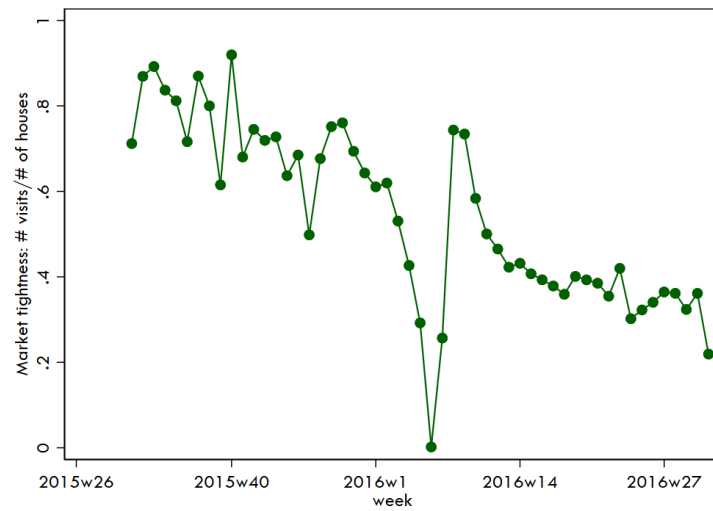
(b) New Listings and Sales

Figure A1: The price, new listing, and sales dynamics

Notes: Panel A shows the evolution of average transaction prices and list prices in Beijing over the sample period. Panel B shows the corresponding dynamics in the number of new listings and housing transactions.



(a) Number of Visits



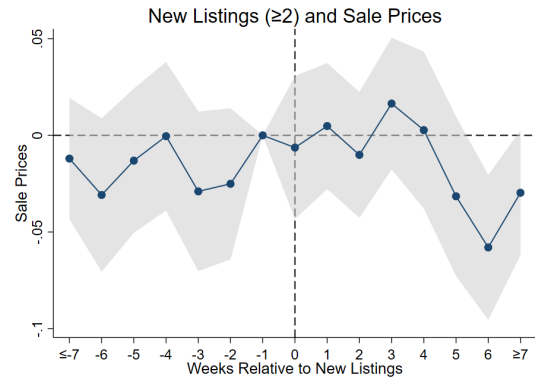
(b) Market Tightness

Figure A2: The price, new listing, and sales dynamics

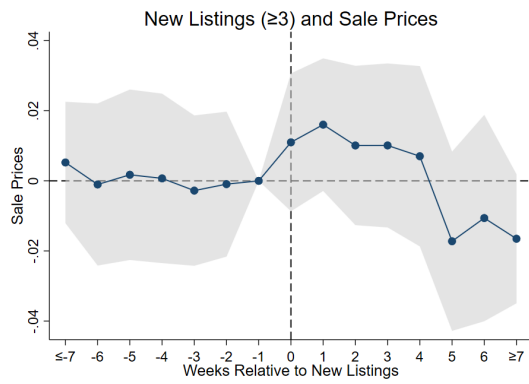
Notes: Panel A shows the evolution of the total number of buyer visits in each week over the sample period. Panel B shows the corresponding evolution of market tightness, measured as the ratio of total buyer visits to the number of active listings.



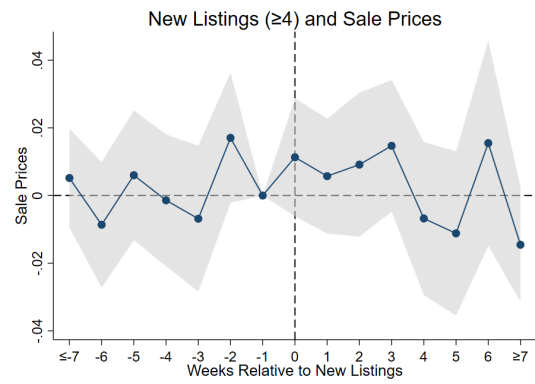
(a) At Least 1 New Listing



(b) At Least 2 New Listings



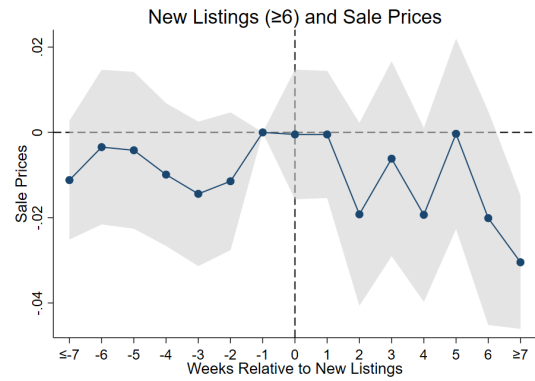
(c) At Least 3 New Listings



(d) At Least 4 New Listings



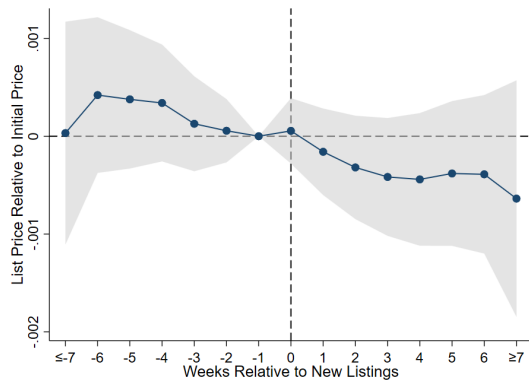
(e) At Least 5 New Listings



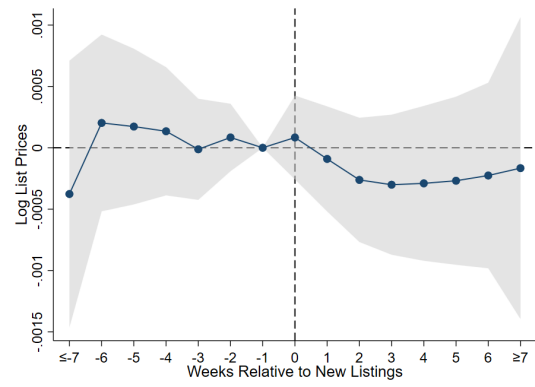
(f) At Least 6 New Listings

Figure A3: The Effects of at Least M New Listings on Sale Prices

Notes: The figure shows how sale prices of sold properties changes after new listings shock within the same apartment complex. The six panels display the results for different treatment group definitions, where the number of new listings is at least 1, at least 2, at least 3, at least 4, at least 5, and at least 6, respectively.



(a) TWFE Estimators



(b) Sun and Abraham Estimators

Figure A4: The Dynamic Effects of New Listings on List Prices

Notes: The figure shows the dynamic treatment effects of new listings shock within the same building on list prices of the existing sellers.

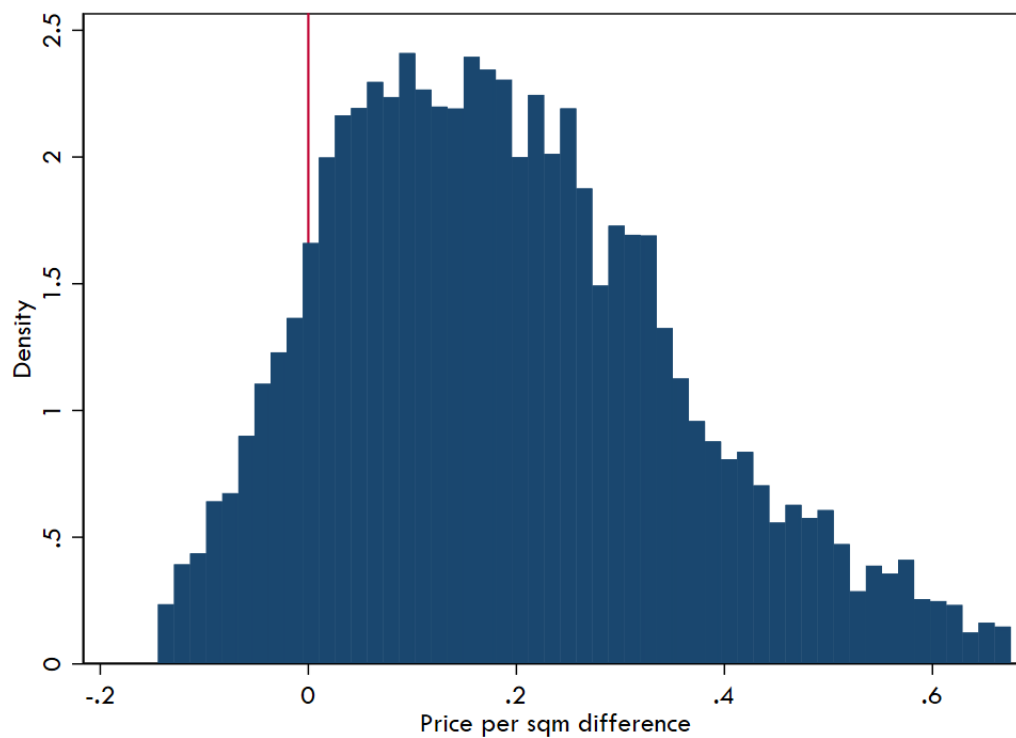


Figure A5: Histogram of the percentage price difference

Notes: This figure is a histogram of the percentage price difference between new listing houses and existing houses. This chart shows that a large number of new listings have a higher price per square meter than existing listings, up to 70%. A small number of new listings have a lower price per square meter than existing listings, up to 20%. New listings entering the market are generally more expensive primarily because prices have been rising across time for the whole market (see Figure A1).

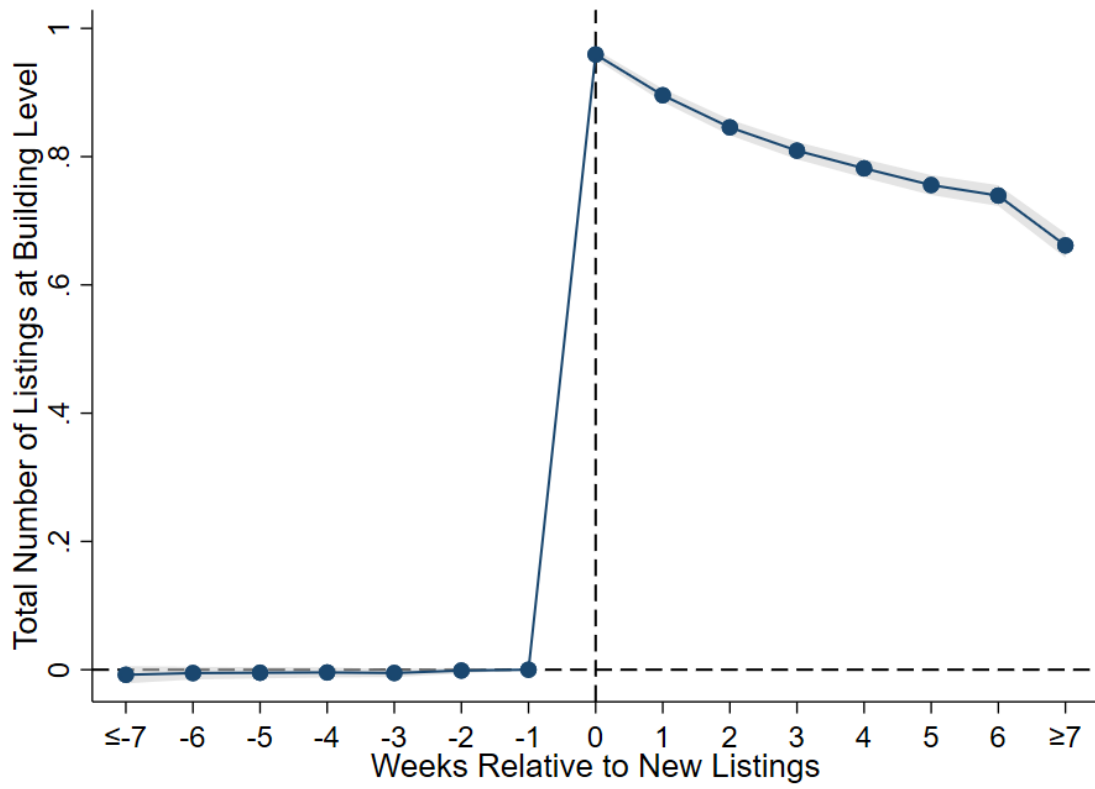
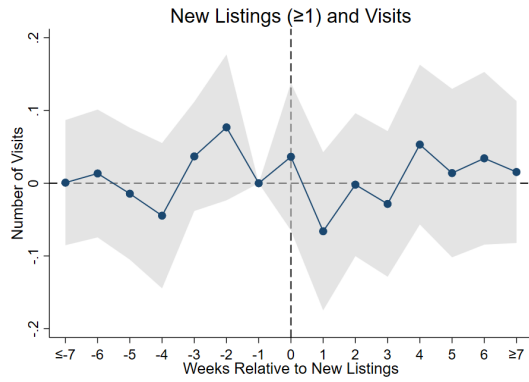


Figure A6: Number of Total Listings

Figure A7: New Listings and Total Listings at Building Level

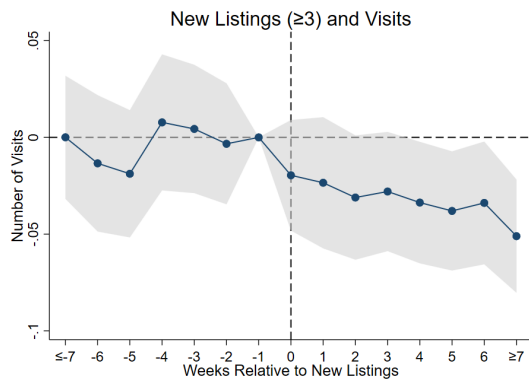
Notes: The figure shows the dynamic treatment effects of a new-listing arrival on the total number of active housing listings within the same building.



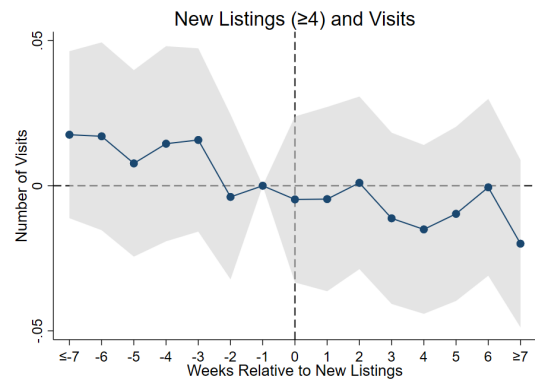
(a) At Least 1 New Listing



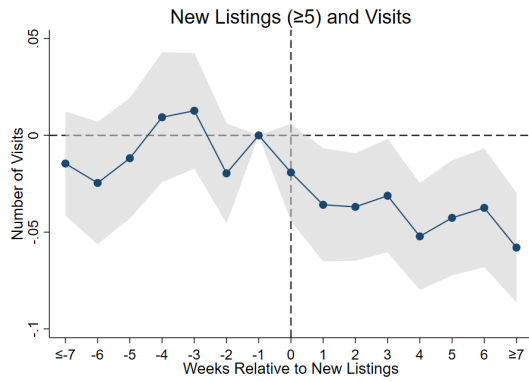
(b) At Least 2 New Listings



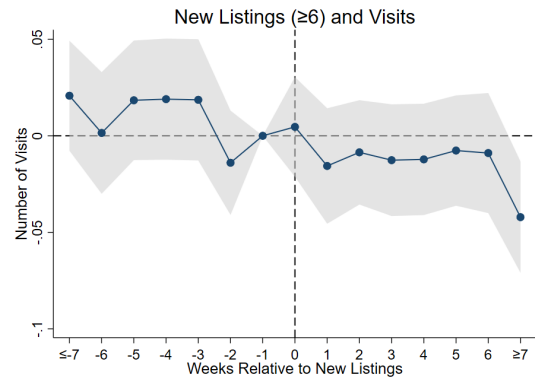
(c) At Least 3 New Listings



(d) At Least 4 New Listings



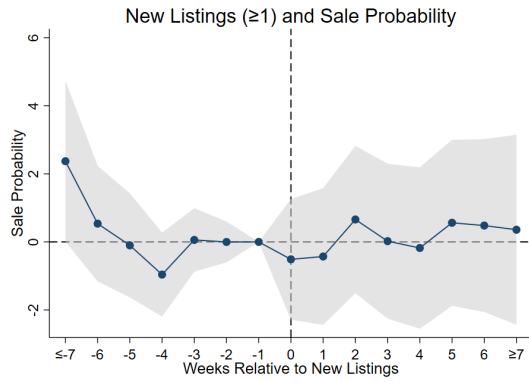
(e) At Least 5 New Listings



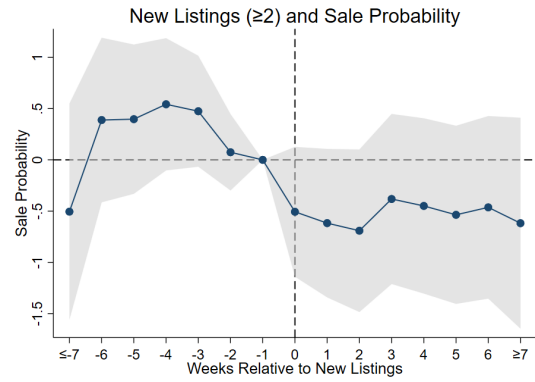
(f) At Least 6 New Listings

Figure A8: The Effects of at Least M New Listings on Visits

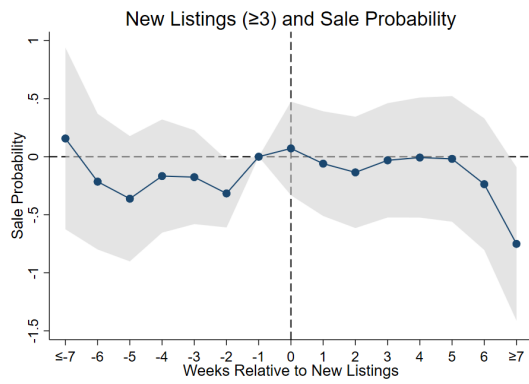
Notes: The figure shows how number of visits of the existing listings changes after new listings shock within the same apartment complex. The six panels display the results for different treatment group definitions, where the number of new listings is at least 1, at least 2, at least 3, at least 4, at least 5, and at least 6, respectively.



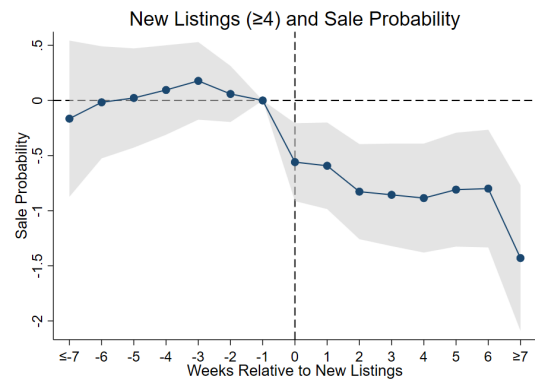
(a) At Least 1 New Listing



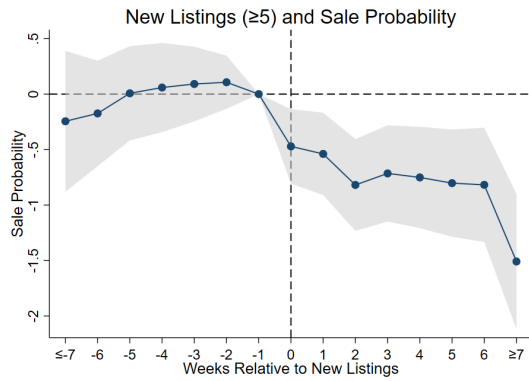
(b) At Least 2 New Listings



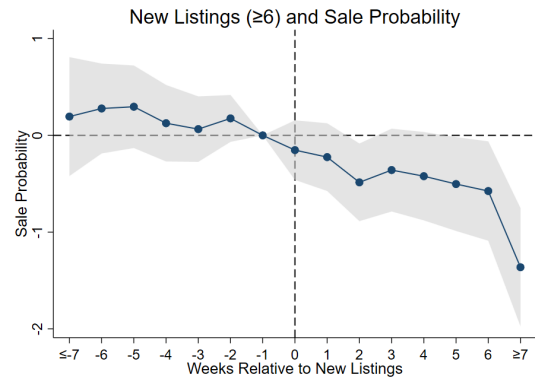
(c) At Least 3 New Listings



(d) At Least 4 New Listings



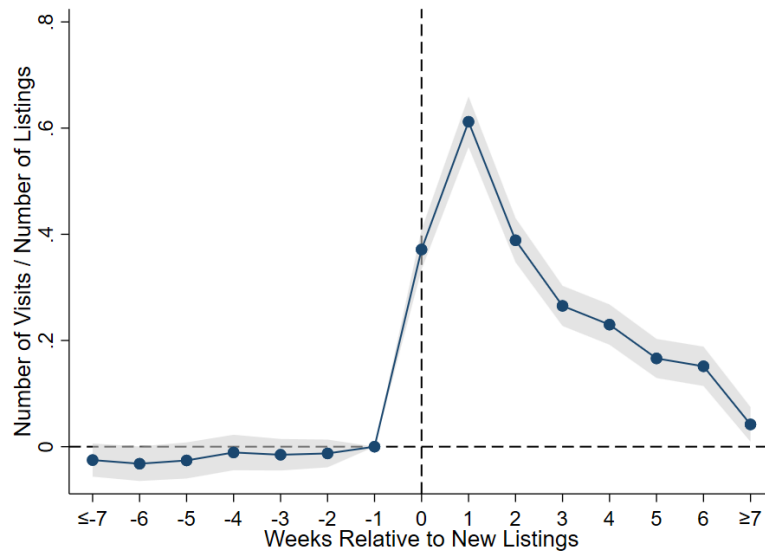
(e) At Least 5 New Listings



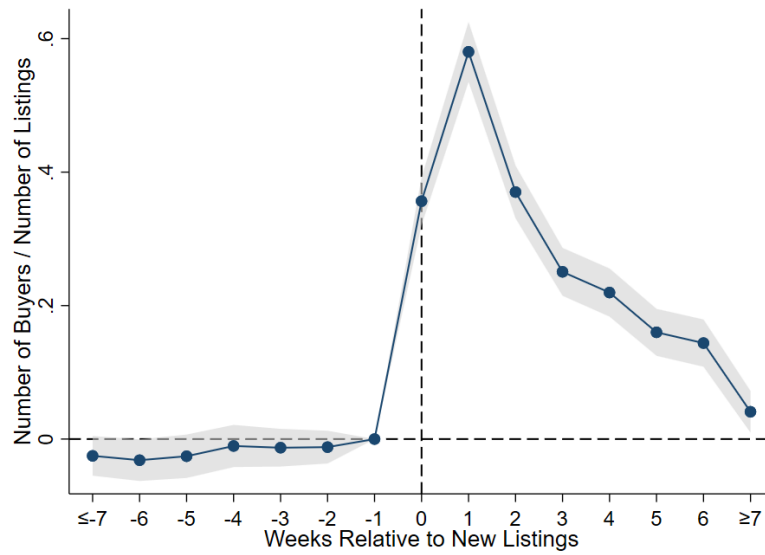
(f) At Least 6 New Listings

Figure A9: The Effects of at Least M New Listings on Sale Probability

Notes: The figure shows how transaction probability of the existing listings changes after new listings shock within the same apartment complex. The six panels display the results for different treatment group definitions, where the number of new listings is at least 1, at least 2, at least 3, at least 4, at least 5, and at least 6, respectively.



(a) Number of Visits / Number of Listings



(b) Number of Buyers / Number of Listings

Figure A10: New Listings and Visits and Market Tightness at Building Level

Notes: The figure shows the dynamic treatment effects of a new-listing arrival on market tightness within the same building. Panel A measures market tightness as the ratio of the total number of property visits in a building-week to the number of active listings in that building-week. Panel B measures market tightness as the ratio of the number of unique buyers in a building-week to the number of active listings in that building-week.