Tight Markets, High Rents: Search Technology When Housing Is Scarce

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Abstract

Standard consumer search models predict that greater information reduces prices by improving consumers' ability to compare options. We show this prediction may not hold in two-sided matching markets where both parties have a value of remaining unmatched. We develop a dynamic search model of the rental housing market to illustrate this mechanism. In partial equilibrium, we characterize how an improvement in search technology that affects only one side of the market influences equilibrium rents and other outcomes. In general equilibrium, we show that the effects of neutral technological improvements that symmetrically improve meeting rates can raise equilibrium rents, particularly in supply-constrained markets. The magnitude of this effect depends on how tight the housing market is: rent increases are larger in tight markets and attenuate as housing supply expands.

1 Introduction

Information technology has substantially changed how renters search for housing. Data from the American Housing Survey (AHS) reveal that 43% of renters found their apartments through internet platforms in 2023, up from 30% in 2015. Online platforms such as Zillow, StreetEasy, and Redfin have become prominent channels for both rental and purchase markets. We interpret these platforms as innovations in search and matching technology that change the speed at which renters and landlords meet and transact.

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These platforms allow prospective renters to browse comprehensive listings that match their preferences without the cost of physical visits. Traditional consumer search theory [Burdett and Judd, 1983, Varian, 1980, Stahl, 1989, Salop and Stiglitz, 1977, Reinganum, 1979] predicts that improved information should reduce prices, as better informed consumers can compare options more easily, forcing sellers to compete more aggressively. However, in rental markets, information technology can also speed up tenant arrivals to vacant units, intensifying competition among renters and potentially increasing rents. The empirical patterns in the AHS are consistent with a channel in which faster arrivals play an important role.

The AHS asks recent movers: *"Did you find your home on an internet site (such as Craig's List, apartment.com, realtor.com, or Zillow)?"* Figure 1 presents the rent distributions for "online" versus "offline" searchers. The probability density function (left panel) shows that while price dispersion remains similar across search methods, online searchers pay systematically higher rents on average. The empirical cumulative distribution functions (right panel) confirm this pattern: at any given rent level, online searchers face a higher probability of encountering more expensive units than offline searchers.

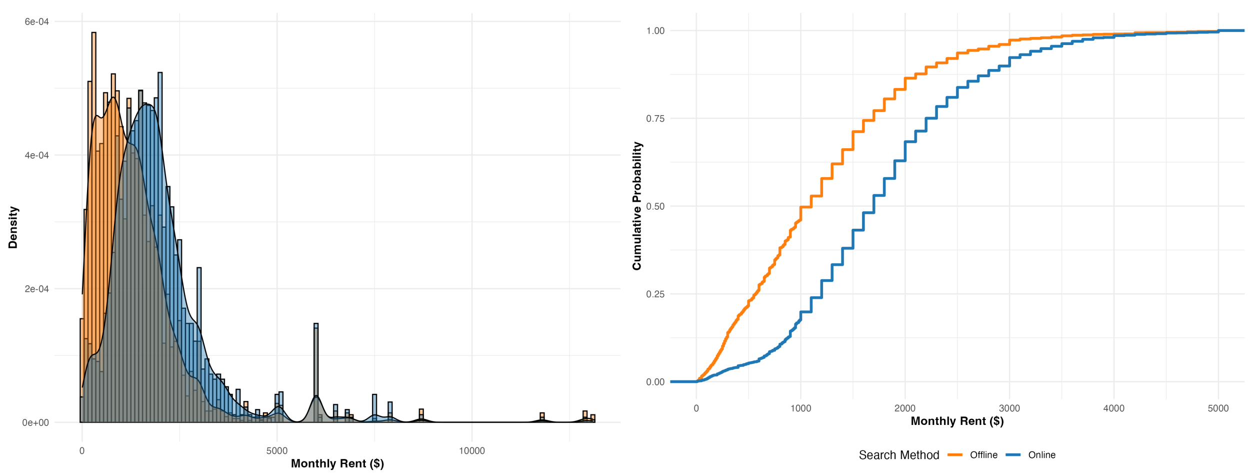

Figure 1: Distribution of rents by search method

The above distributions are unconditional, so it is possible that apartments found online are different from those found offline in ways that influence the rents independently of the technology used for discovery. We move towards accounting for this by estimating the following hedonic ordinary least squares regression using data from the 2023 AHS which is the latest available round.

$$\text{Rent}_i = \beta_0 + \beta_1 \text{Internet Search}_i + \mu_{c(i)} + \mathbf{X}_i' \beta + \varepsilon_i \quad (1)$$

where i indexes a household, Internet Search is a binary indicator that takes the value 1 if the household answered yes to the survey question described above (0 otherwise), and $\mu_{c(i)}$ are CBSA fixed effects (core-based statistical areas as defined by the Office of Management and Budget). **X** is a vector of additional covariates: total rooms, household income, physical adequacy defined by the AHS, household head age, whether the unit has an a/c, dishwasher and a fireplace, and a binary indicator for whether the unit was found through family and friends.[1]

The estimates of the regression are shown in Table 1. Column 1 omits CBSA fixed effects; columns 2 and 3 include them. The estimates in column 1 are consistent with the distributions: on average, apartments found online are about $427 more expensive compared to apartments found offline, and this difference is statistically significant. Column 2 includes the CBSA fixed effects without the additional covariates, and column 3 includes both the CBSA fixed effects and the additional covariates[2]. As we would expect, the size of the Internet Search coefficient is smaller when controlling for these observable features. However, it is still large and statistically significant at $230, given that the median rent in the data is about $1500.

[1]Ideally, we would like a more granular measure of geography such as the county, but these are not made publicly available by the AHS for privacy reasons.

[2]Only the coefficients on total rooms and income are shown in the table for conciseness.

Table 1: Hedonic regression: online search and monthly rent (AHS 2023)

	Dependent variable:		
	Monthly Rent (Dollars)		
	(1)	(2)	(3)
Internet Search	427.84***	338.67***	230.56***
	(32.80)	(31.80)	(34.91)
Total Rooms			115.39***
			(11.57)
Income Index			1.37***
			(0.10)
CBSA FE	No	Yes	Yes
Additional Controls	No	No	Yes
Observations	6,184	6,184	6,184
R^2	0.03	0.12	0.22

Note: *p<0.1; **p<0.05; ***p<0.01

Income index is the ratio of household income to the federal poverty level.

In Appendix 5, we conduct a number of robustness checks including using log rents as the dependent variable, trimming outliers in rents, conducting the analysis over time, and only within particular CBSAs. The pattern of apartments found via an internet site being more expensive relative to those that were not remains robust to these variations of equation (1).

Despite the robustness of this pattern, we cannot completely rule out omitted variable bias. Apartments that are found online could differ from those found offline in unobserved ways that affect rents. Nonetheless, it seems unlikely that selection alone accounts for the entire gap, and we view these facts as a motivating starting point for a model in which improvements in search and matching technology increase the speed of matching in rental markets.

In our model, technological improvements affect matching in the rental market by increasing meeting rates on both sides of the market. In partial equilibrium, we use this structure to isolate the effect of shifts in the renter meeting rate versus the landlord meeting rate on rent posting and acceptance behavior.

In general equilibrium, meeting rates are jointly determined by a matching function: an increase in matching efficiency raises both the rate at which renters encounter vacancies and the rate at which vacancies encounter renters, but the induced change in market tightness depends on housing supply. As a result, the effect of technology on equilibrium rents is in general ambiguous. Technology strengthens renters' outside option by making it easier to continue searching, which pushes rents down; at the same time, it increases landlords' option value of waiting by accelerating tenant arrivals, which can push rents up.

We show that which force dominates depends on how constrained the market is by available housing. In our calibration, technology raises equilibrium rents across housing supply levels, but the effect is substantially larger in tight markets (scarce housing) and attenuates as supply expands. We also characterize the implications for matching probabilities, waiting times, and welfare.

2 Related Literature

We see our results as contributing to the urban and real estate literature studying housing-market microstructure, in which prices and time on the market are jointly determined by search frictions, matching, and intermediation [Han and Strange, 2015, Genesove and Han, 2012, Albrecht et al., 2016]. Our focus is on how improvements in search and matching technology—such as online platforms that change meeting rates—affect equilibrium rents and search times, and how these effects depend on housing-market tightness.

Our results also speak to the rich theoretical literature on information and consumer search, following the seminal work of Stigler [1961]. The earlier discussed classic models often predict lower prices from an increase in ex ante information. The study most closely related to ours is Lester [2011], who show that in markets with capacity constraints, greater price transparency can lead to higher prices, depending on market size, the buyer-to-seller ratio, and the share of informed buyers. The rental market fits this structure, making these factors central to understanding how information affects prices. Our theoretical results echo this ambiguity, but in a dynamic setting where it arises from the differing option values of waiting for both renters and landlords.

Our paper also contributes to the literature on declining search frictions by focusing on the rental housing market, where technology affects both sides of the market asymmetrically. Martellini and Menzio [2020] study a labor market model in which improved search efficiency contributes to productivity growth but leaves unemployment and vacancy rates unchanged due to offsetting increases in reservation match quality. In contrast, we develop a dynamic two-sided matching model with privately known match values and endogenous rent posting. Rather than focusing on balanced growth, we show how differential improvements in meeting rates for landlords and renters affect the option value of waiting, and thereby determine whether rents and search times rise or fall with technology. Our focus on rent posting and the decision to accept or reject offered rents is also related to models of rental-market microstructure that incorporate intermediation and commissions [Niedermayer and Wang, 2018, Han and Strange, 2015].

We also contribute to the literature comparing online and offline prices across markets [Cavallo, 2017, Ellison and Ellison, 2018, 2009, Brynjolfsson and Smith, 2000, Baye et al., 2006]. Most directly related is Ellison and Ellison [2018], who find that prices are higher online for used books, rationalizing this with a model of monopoly pricing and Poisson arrivals. The landlord side of our model shares this structure, but we explicitly model technology's role in shaping renter behavior as well, which affects both matching probabilities and rent-setting incentives. More broadly, online platforms can reshape how market participants search, and how intermediaries respond [Kroft and Pope, 2014, Seamans and Zhu, 2013].

Relatedly, a growing literature examines the rise of online peer-to-peer platforms across markets, including housing (see Einav et al., 2016 for a review). In the housing context, Calder-Wang [2021] uses a structural model of New York City's housing market to show the distributional consequences of AirBnB for renters through its effect on housing utilization and rents. Our work is complementary: rather than focusing on the reallocation effects of a new rental format, we study the effects of technological innovations more broadly reshaping the search and matching process in the rental market.

Lastly, our work connects to the literature on search in housing markets (see Han and Strange, 2015 for a review). In addition to search-and-matching approaches [Genesove and Han, 2012, Albrecht et al., 2016], recent contributions such as Piazzesi et al. [2020] use data from online platforms to study micro-level search behavior, highlighting how technology enables broader or narrower searches and how this heterogeneity can affect aggregate market dynamics, including the shape of the housing market Beveridge curve.

3 A model of the rental housing market

3.1 Environment and partial equilibrium

We model a frictional search market with a unit measure of landlords and a unit measure of prospects (unmatched potential renters). Landlords and prospects are ex ante homogeneous. On meeting, the prospect draws a match-specific value for the apartment that is privately known to them. Throughout, we use r for an individual rent offer and r^m for the market rent.

Consider the dynamic problem of a prospect. With probability λ, the prospect meets a landlord. On meeting the landlord, the prospect draws a match-specific surplus $e \sim G$ and decides either to accept or reject a take-it-or-leave-it rent offer r. The matched renter faces an exogenous separation shock that arrives with probability δ.

A matched renter's value is given as:

$$U_1(r, e; r^m) = e - r + \beta \{(1-\delta)U_1(r, e; r^m) + \delta U_0(r^m)\} \tag{2}$$

An unhoused renter's value is given as:

$$U_0(r^m) = b + \beta \left\{ \lambda \int_0^{\bar{e}} \max\left[U_0(r^m), U_1(r^m, e; r^m)\right] dG(e) + (1-\lambda)U_0(r^m) \right\} \tag{3}$$

where b is the flow value of being unhoused.

The prospect's problem is akin to [McCall, 1970] and the optimal policy is an accept/reject rule characterized by a threshold surplus $\bar{e}(r; r^m)$ (suppressing its dependence on λ for notational convenience).

A vacant landlord posts a rent r before meeting prospects and does not observe the prospect's private value for the apartment. If they meet a prospect (probability γ), the probability of matching is $1 - G(\bar{e}(r; r^m))$, i.e. the probability that given rent r, the prospect's match-specific value is higher than their cut-off $\bar{e}(r; r^m)$. A landlord that posts rent r and matches with a prospect receives flow value r until the match dissolves. A renter-landlord match dissolves at the beginning of any period exogenously with probability δ. If the match dissolves, the apartment remains vacant for that period, and the landlord meets a prospect with probability γ the next period.

We can now write the value of a matched and vacant landlord recursively. The value of a matched landlord who receives rent r is given as:

$$V_1(r; r^m) = r + \beta(1-\delta)V_1(r; r^m) + \beta\delta V_0(r^m) \tag{4}$$

The value of a newly vacant apartment is:

$$V_0(r^m) = h + \beta \max_r \{\gamma \left[(1 - G(\bar{e}(r; r^m)))V_1(r; r^m) + G(\bar{e}(r; r^m))V_0(r^m)\right] + (1-\gamma)V_0(r^m)\} \tag{5}$$

Equilibrium: An equilibrium consists of value functions U_0, U_1, V_0, V_1, a policy function $\tilde{r} : [0, \bar{r}] \rightarrow \mathcal{R}$, and a market rent r_*^m such that

1. U_0, U_1, V_0, V_1 satisfy (2), (3), (4), (5).
2. $\tilde{r}$ solves the vacant landlord's problem given in (5)

3. (Consistency[3]) r^m_* is a fixed point of the $\tilde{r}$ mapping: $\tilde{r}\left(r^m_*\right) = r^m_*$.

Our partial equilibrium model of the rental market posits exogenous meeting rates λ and γ for renters and landlords respectively, that we move one at a time. The equilibrium of this model can be thought of as a 'cloning' equilibrium. In any given period, meetings occur and matches consummate as regulated by the search friction. For every match that realises, an identical searching prospect and vacant landlord enter the searchers' pool. This framework shuts down indirect effects of technology through tightness. This model, thus, enables us to isolate the direct effects of technology on the rental market.

3.2 Model mechanism and intuition

We present a discussion of the model that sets up the main intuition. We fix the market rent r^m to facilitate derivation of theoretical results; and then confirm that our intuition survives the consistency condition in numerical simulations.

When the rate at which prospects meet landlords (λ) goes up, prospects tend to get pickier. This is because, prospects are now more willing to wait to receive higher e realizations. This is reflected in that their option value to wait instead of match $U_0(r^m)$ goes up when λ goes up.

When the rate at which landlords meet prospects (γ) goes up, landlords get to make offers more frequently. Provided the option value of being able to make an offer exceeds the option value of not being able to do so, this drives their value of remaining vacant up. This can be seen in (6).

$$V_0(r^m) = h + \beta \max_r \left\{ \underbrace{\gamma\left[(1 - G(\bar{e}(r;r^m)))V_1(r;r^m) + G(\bar{e}(r;r^m))V_0(r^m)\right]}_{\text{expected value of being able to make an offer}} + (1-\gamma)V_0(r^m) \right\} \tag{6}$$

Under the assumption that the distribution of match values is uniform on $[0,1]$, we can show the following

$$\tilde{r}(r^m) = \frac{1}{2}\left(1 - (1-\beta)\left[U_0(r^m) - V_0(r^m)\right]\right)$$

[3] Let landlords be indexed by ℓ. Landlords are homogeneous, hence policy functions $\tilde{r}_\ell = \tilde{r}$. Given a market rent r^m, $r^m = \int_0^1 \tilde{r}(r^m)d\ell = \tilde{r}(r^m)$; this provides the justification for the consistency condition in point 3 of the equilibrium definition. We have not formally characterized the existence of such a fixed point. However, if the efficiency grid and rent grid have the same support, we can argue that such a fixed point should always exist. When $r^m = r_{min}$, $\tilde{r}(r^m) > r_{min}$. When $r^m = r_{max}$, $\tilde{r}(r_{max}) < r_{max}$ since the probability of matching at r_{max} is 0. Provided $\tilde{r}(r^m)$ is weakly increasing in r^m, there must be a fixed point in $[r_{min}, r_{max}]$. For our quantification, we will impose that the rent grid and efficiency grid have similar support and verify that the optimal rent policy is monotonic.

The response of rents depends on the relative change in the option values of searching for prospects and staying vacant for landlords. For instance, if the option value of staying vacant for landlords goes up while the option value of searching for tenants stays the same, the optimal take-it-or-leave-it offer goes up. An increase in the option value of waiting for the landlord intensifies buyer competition and drives rents up. An increase in the option value of searching for tenants makes tenants pickier and reduces the probability of matching at any given offer. This intensifies seller competition, as landlords compete to recover some of the lost matching probability. This drives the optimal take-it-or-leave-it down. The observed change in rents summarizes the net effect of these opposing forces.

The intuition above turns out to be quite general.

Proposition 1. *The reservation value* $\bar{e}(r; r^m, \lambda)$ *is:*

1. *increasing in* r
2. *increasing in* λ

Proof in Appendix 6.

Proposition 2. *Let* G *be twice differentiable and* $1 - G$ *be log-concave. Let* $r^*(r^m, \gamma)$ *be the optimal take-it-or-leave-it offer.* $r^*(r^m, \gamma)$ *is increasing in* γ.[4]

Proof in Appendix 6.

We think of technology as increasing both meeting rates, γ and λ. When the landlord meeting rate γ rises, the landlord can make offers more frequently and the option value of waiting while vacant increases. This strengthens buyer competition and puts upward pressure on posted rents (Proposition 2). When the prospect meeting rate λ rises, the prospect's option value of continued search increases. By Proposition 1, this raises the cutoff $\bar{e}(r; r^m, \lambda)$ for a given posted rent r, reducing the acceptance probability $1 - G(\bar{e}(r; r^m, \lambda))$. Landlords can partially offset the lower acceptance probability by cutting r, so higher λ can be interpreted as intensifying seller competition and putting downward pressure on rents.

In the quantitative results below, we also report how waiting times (time on market) respond to changes in γ and λ. We define a landlord's waiting time as the expected number of periods until a vacant unit matches with a prospect, counting the matching period itself (so a match that occurs immediately implies a realized waiting time of 1). Analogously, we define a prospect's waiting time as the expected number of periods until they match. Given a posted rent r, the per-period

[4]The normal distribution used in our calibration satisfies log-concavity of the survival function; see Bagnoli and Bergstrom [2005] for a survey of log-concave distributions.

probability that a landlord matches is $\gamma\left(1-G(\bar{e}(r;r^m,\lambda))\right)$, while the per-period probability that a prospect matches is $\lambda\left(1-G(\bar{e}(r;r^m,\lambda))\right)$. Therefore,

$$
\begin{aligned}
time_l &= \frac{1}{\gamma\left(1-G(\bar{e}(r;r^m,\lambda))\right)}\\
time_p &= \frac{1}{\lambda\left(1-G(\bar{e}(r;r^m,\lambda))\right)}
\end{aligned}
$$

The result that the expected waiting time for an event that occurs each period with probability p equals $\frac{1}{p}$ follows from the geometric distribution[5]

3.2.1 Parametrization

Table 2: Baseline parameters

Parameter	Value	Description	Source
e	$\mathcal{N}(0, 0.4^2)$	Prospect idiosyncratic value	AHS rent residuals
b	10^{-3}	Flow value for an unmatched searcher	Normalization
h	10^{-3}	Flow value of a vacant unit	Normalization
δ	0.2	Separation rate	ACS 2023 (5-year avg tenure)
β	0.96	Discount factor	Standard

Table 2 summarizes the baseline parameter values used in the quantitative exercises. The model is parsimonious, and our goal is to choose parameters that deliver plausible discounting, turnover, and cross-sectional dispersion in match values.

We interpret one model period as one year. We set the discount factor to $\beta = 0.96$ and calibrate the exogenous separation rate to $\delta = 0.2$ to match the average renter tenure of approximately 5 years observed in the 2023 ACS Public Use Microdata Sample, which implies $\delta = 1/5 = 0.2$ under geometric separation. We normalize the flow value of being unmatched for renters (b) and the flow value of a vacant unit for landlords (h) to 0.0001 (0.1% of mean rent). This normalization keeps outside options meaningfully below typical transaction values so that matching probabilities are positive for a broad range of match realizations; it affects levels but not comparative statics in our exercises.

[5] Let $T \in \{1, 2, \dots\}$ be the (inclusive) waiting time until success and p the per-period success probability. Then

$$
\begin{aligned}
&\mathbb{E}[T] = p \cdot 1 + (1-p)\cdot(1+\mathbb{E}[T]),\\
\Rightarrow\ &\mathbb{E}[T] = \frac{1}{p}.
\end{aligned}
$$

Match values are drawn from a normal distribution, $e \sim \mathcal{N}(\mu, \sigma^2)$, normalized so that mean rent equals 1. We set $(\mu, \sigma) = (0, 0.4)$ to discipline the magnitude of match-specific heterogeneity using the dispersion of residualized rents in the AHS. Specifically, we run a hedonic regression of rent on observable characteristics (rooms, building age, CBSA fixed effects, and amenities) and search mode for renters, excluding the top and bottom 5% of rents to remove outliers exactly matching our robustness check from 1. The standard deviation of residuals, normalized by mean rent, yields $\sigma = 0.4$. This implies that match-specific values create rent differences of approximately $\pm 40\%$ of average rent within a market.

3.2.2 Comparative statics

We quantify the intuition from the theoretical discussion using numerical comparative statics in the cloning equilibrium. We vary γ and λ one at a time, holding all other parameters fixed. Figures 2–3 report the responses of key objects. Panels are organized as follows: row 1 shows equilibrium rent, the matching probability (i.e., acceptance conditional on a meeting), and the landlord vacancy value V_0; row 2 shows the tenant search value U_0, the expected time-to-fill for a vacant unit (apartment wait time), and the expected time-to-match for a tenant (tenant wait time).

Figure 2 increases the landlord meeting rate γ, holding the tenant meeting rate λ fixed. Panel (1,1) shows equilibrium rents rising: when landlords can make offers more frequently, the option value of waiting increases and landlords optimally post higher take-it-or-leave-it rents. Panel (1,3) confirms the mechanism, showing V_0 increasing in γ. Panel (1,2) shows the response of acceptance conditional on meeting. While higher rents mechanically reduce acceptance, the induced increase in the market rent lowers the gains from continued search; in this calibration, acceptance rises on net. On the tenant side, Panel (2,1) shows that U_0 falls: higher rents reduce the continuation value of searching even when meetings are unchanged. Consistent with higher acceptance, apartment wait times fall (Panel (2,2)). Tenant wait times also fall (Panel (2,3)): with λ fixed, the acceptance response is the dominant force.

Figure 3 instead increases the tenant meeting rate λ, holding γ fixed. Panel (1,2) shows acceptance conditional on meeting falling: when tenants expect to see more apartments, their option value of waiting rises and they become more selective. Landlords respond by cutting posted rents (Panel (1,1)), but in this calibration the rent reduction does not fully offset the increase in selectivity, so acceptance declines overall. The landlord vacancy value V_0 falls (Panel (1,3)), reflecting longer expected times-to-fill. Panel (2,1) shows the corresponding increase in the tenant search value U_0. Apartment wait times rise (Panel (2,2)) as vacancies take longer to fill. Tenant wait times are theoretically ambiguous because meetings arrive faster but acceptance is lower; in this calibration, Panel (2,3) shows that the increase in meeting frequency dominates and tenants match sooner on average.

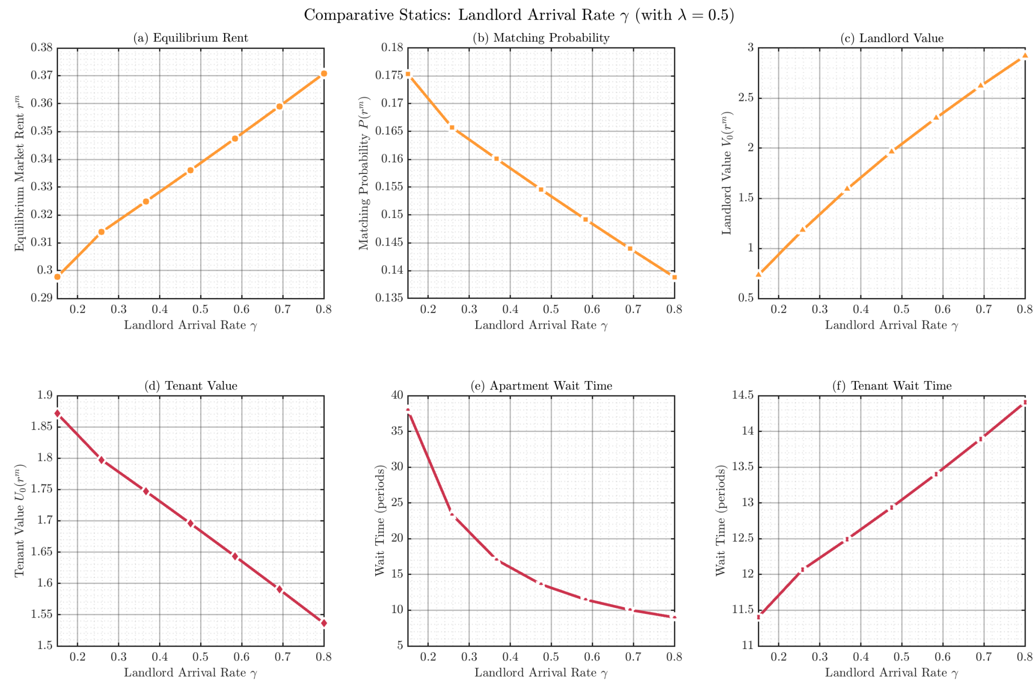

Figure 2: Increasing the landlord meeting rate

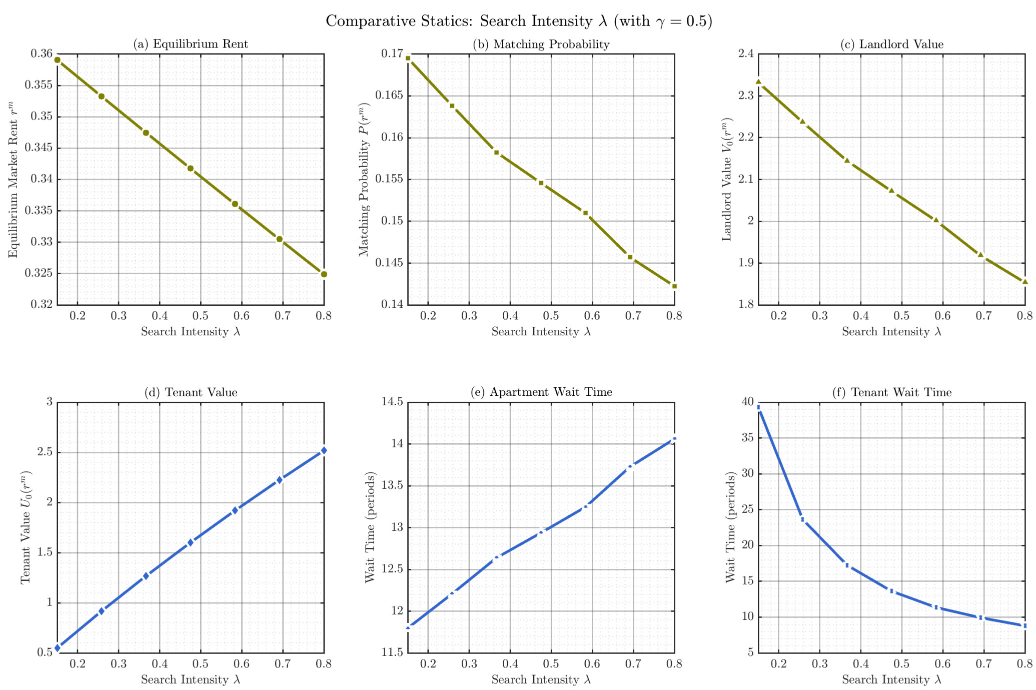

Figure 3: Increasing the prospect meeting rate

3.3 General equilibrium

The meeting rates γ (for landlords) and λ (for prospects) are endogenized through a matching function $\mathcal{M}(s,v)$; s is the measure of searchers, and v is the measure of vacancies. We use a standard Cobb-Douglas matching function with constant returns to scale, so that $\mathcal{M}(s,v) = \kappa s^{\alpha} v^{1-\alpha}$, and define market tightness $\theta = \frac{s}{v}$. κ is the technological parameter. Under this definition, we can derive the rate at which a searcher meets a vacant apartment ($p(\theta)$) and the rate at which a vacant apartment meets a searcher ($q(\theta)$).

$$p(\theta) = \kappa\theta^{\alpha-1} \equiv \lambda; \qquad q(\theta) = \kappa\theta^{\alpha} \equiv \gamma$$

Stationarity: We normalize the measure of households to 1 and the measure of apartments to H. A household is either matched or searching for an apartment. We characterize a stationary equilibrium using the measure of searchers. The flow equation for the measure of searchers is given by:

$$s_{t+1} = (1-\lambda)s_t + \lambda G(\bar{e}(r^m(\theta)))s_t + \delta(1-s_t)$$

where $\bar{e}$ denotes the cutoff efficiency level. That is, searchers tomorrow are the sum of searchers today who did not meet an apartment $(1-\lambda)s_t$, searchers who met an apartment but did not match $\lambda G(\bar{e}(r^m(\theta)))s_t$, and the matched households who separate $\delta(1-s_t)$ [6].

In a stationary equilibrium, the measure of searchers is unchanging from period to period and so we drop the time subscript and solve for $s(\theta)$:

$$s(\theta) = \frac{\delta}{\lambda + \delta - \lambda G(\bar{e}(r^m(\theta)))} \tag{7}$$

From our definition of market tightness, $s = \theta v$. Given our defined measures of apartments, households, and searchers, the measure of vacancies v is given by $H - (1-s) = H - 1 + s$ (total apartments minus occupied apartments). Combining the expression for tightness with this expression for vacancies, we recover another expression for $s(\theta)$ as follows:

$$s(\theta) = \frac{(H-1)\theta}{1-\theta} \tag{8}$$

We can recover the equilibrium tightness by combining (7) and (8) to give the following non-linear equation in θ:

$$\frac{(H-1)\theta}{1-\theta} = \frac{\delta}{\lambda + \delta - \lambda G(\bar{e}(r^m(\theta)))} \tag{9}$$

[6] we have made the dependence of the matching probabilities on the market tightness explicit here

Notice that for the measure of searchers to be positive, either (i) $H > 1$ and $\theta < 1$ or (ii) $H < 1$ and $\theta > 1$ are required. We show in Appendix 6.3 that, in equilibrium, one of these must hold. [7]

Equilibrium: An equilibrium consists of value functions U_0, U_1, V_0, V_1, a policy function $\tilde{r} : [0, \bar{r}] \to \mathcal{R}$, a market rent r_*^m and a market tightness θ_* such that:

1. U_0, U_1, V_0, V_1 satisfy (2), (3), (4), (5).
2. $\tilde{r}$ solves the vacant landlord's problem given in (5)
3. (Consistency) r_*^m is a fixed point of the $\tilde{r}$ mapping: $\tilde{r}\left(r_*^m\right) = r_*^m$
4. (Stationarity) Market tightness θ_* satisfies (9)

3.3.1 Comparative statics

In line with our PE exercise, we fix all other parameters and illustrate how equilibrium outcomes respond to a technology improvement. Figure 4 presents a central general-equilibrium result. It plots how equilibrium rents respond to increases in matching-function efficiency across different levels of housing supply. When housing is scarce (tight markets), both the level and the sensitivity of rents to a technology shock are larger: technological improvements raise rents more under tighter supply. As housing supply increases, the rent response attenuates. In our calibration, rents rise with technology at all supply levels, but the increase ranges from approximately 9% in the tightest market to 6% in the loosest.

Figure 5 reports the responses of other equilibrium objects to increases in matching efficiency, holding housing supply fixed at $H = 1.1$[8]. Panel (1,1) shows that the present discounted value of a vacant landlord, V_0, rises with κ, reflecting that higher meeting rates increase the landlord's outside option. Panel (2,1) shows a similar upward response for the unmatched prospect value, U_0. Because equilibrium rents increase in this parametrization, the value of being matched for landlords, V_1 (panel (1,2)), also rises.

Although matching probabilities decline (see Figure 7), waiting times fall for both landlords and renters (panels (1,3) and (2,3)), indicating that faster meeting rates more than offset lower acceptance probabilities. Matched renters are, on average, better off despite higher rents because the matches that occur have higher idiosyncratic values.

[7] In our comparative statics, we focus on the case $H > 1$, which corresponds to an environment with enough housing units to accommodate the unit mass of households. We view this as the empirically relevant case for our application. In the Appendix, we also report a robustness check for the case $H < 1$ (excess demand); the resulting comparative statics are qualitatively similar to those in our tightest $H > 1$ calibration.

[8] The Appendix reports results at other housing supply levels; the core patterns discussed here are robust, except in parameterizations where equilibrium rents decline, which we discuss briefly in the Appendix.

Overall, these representative-agent exercises show that improved matching technology can raise aggregate welfare even when rents increase. We emphasize that our framework abstracts from heterogeneity; distributional effects could lead some groups to gain and others to lose, which we leave for future work.

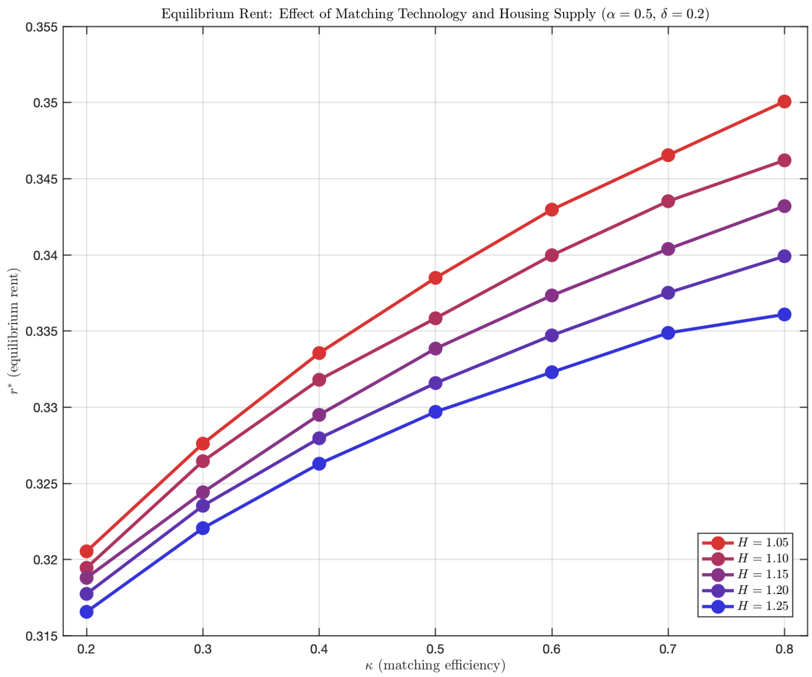

Figure 4: Equilibrium rent response to matching efficiency. Rents increase with technology at all supply levels, but the effect is stronger in tight markets. Red lines indicate tight housing markets (low H); blue lines indicate loose markets (high H).

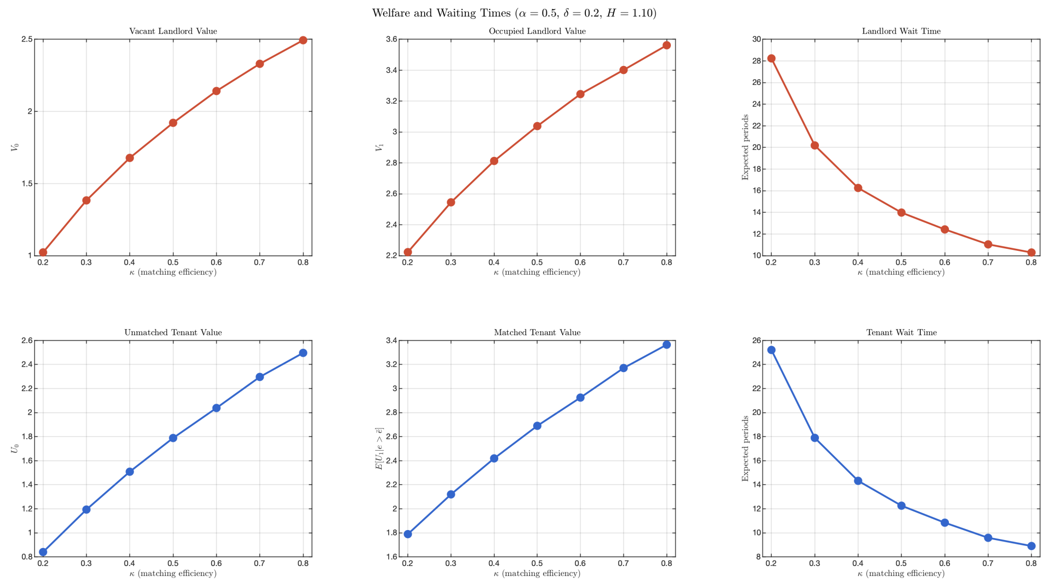

Figure 5: Welfare and waiting time responses to matching efficiency at $H = 1.10$

3.3.2 Discussion of results on rents

To understand why rents rise more in tighter housing markets, we return to the landlord's first-order condition, which yields the equilibrium rent as

$$r = (1 - \beta)V_0 + \frac{1 - G(\bar{e})}{g(\bar{e})}. \tag{10}$$

where g is the probability density function associated with G. The rent decomposes into two distinct components: a *vacancy value* term, $(1 - \beta)V_0$, capturing the flow value of the landlord's outside option; and a *markup* term, given by the inverse hazard rate at the acceptance margin. Our numerical solutions confirm that this decomposition holds almost exactly (Appendix Figure 8), validating the analytical characterization.

Figure 6 illustrates how these components respond to improvements in matching technology across three housing supply levels. The two panels reveal opposing forces at work. Panel (a) shows that the vacancy value rises with technology: as landlords can make offers more frequently, the option value of staying vacant increases. This effect is stronger in tight markets (H=1.05, relatively scarce housing) where competition among renters is more intense. Panel (b) shows that the markup declines with technology: as tenants become more selective in response to faster arrival rates, the acceptance probability $1 - G(\bar{e})$ falls, compressing the inverse hazard rate.

The net effect on rents depends on which component dominates. In tight markets (H=1.05), the vacancy value effect dominates and rents increase by approximately 9% as κ increases from

0.2 to 0.8. In looser markets (H=1.25, relatively abundant housing), the opposing forces are more balanced: rents still rise, but only by about 6%. The attenuation reflects that in looser markets, tenant selectivity erodes more of the landlord's gains from improved meeting rates.

This decomposition clarifies the economic intuition. Technology strengthens the landlord's bargaining position by improving their outside option, but it simultaneously weakens their pricing power by making tenants pickier. Housing supply determines the balance: when housing is scarce, landlords can more fully exploit their improved outside option; when housing is abundant, tenant selectivity partially offsets these gains, though in our calibration the vacancy value effect still dominates.

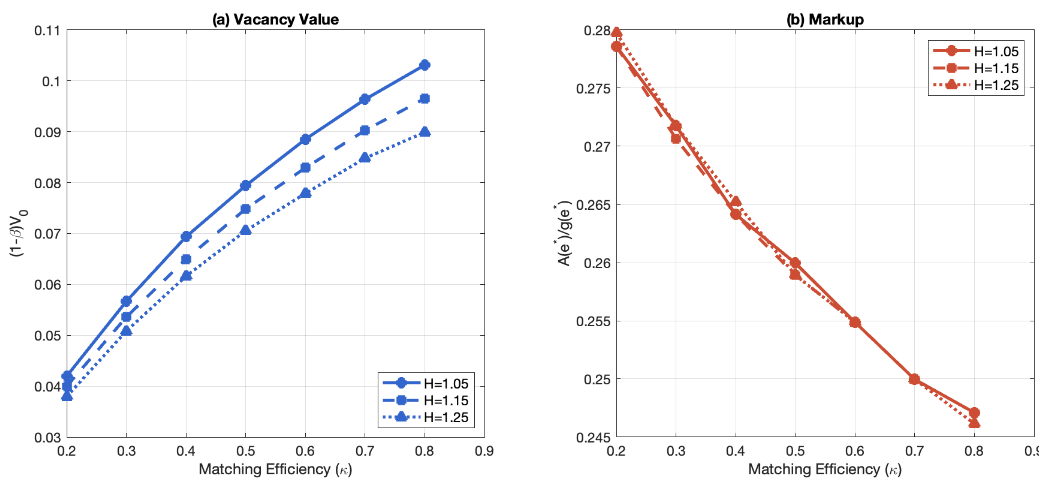

Figure 6: Rent decomposition into vacancy value and markup components

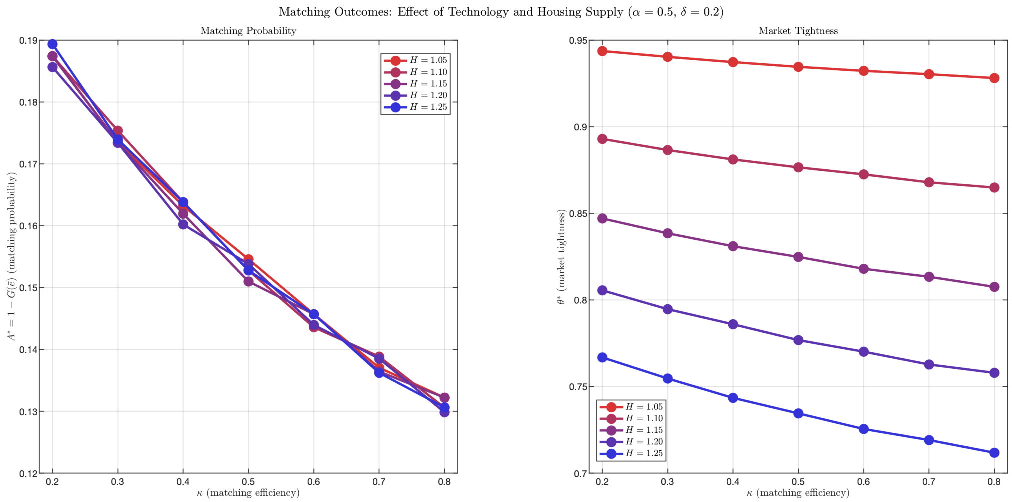

Figure 7: Matching outcomes by matching efficiency and housing supply. Left panel: matching probability $A^* = 1 - G(\bar{e})$ decreases with technology as tenants become more selective. Right panel: market tightness θ^* decreases with technology capturing declining search frictions. Red lines indicate tight markets (low H); blue lines indicate loose markets (high H).

4 Conclusion

We have developed a two-sided model of frictional rental housing search in which landlords and renters have option values: landlords value remaining vacant, and renters value continuing to search. We use the model to study how improvements in search technology affect equilibrium outcomes. In general equilibrium, faster meeting rates simultaneously make tenants more selective and raise the value of vacancy for landlords, generating two opposing forces on rents. Higher vacancy values push rents up because landlords require greater compensation to match, while increased selectivity pushes rents down by reducing acceptance probabilities and compressing rental markups. We find that in tighter housing markets the vacancy value effect dominates and rents increase substantially; in looser markets the markup channel partially offsets the vacancy value gains, attenuating but not reversing the rent increase in our calibration. The equilibrium can feature higher rents together with shorter waiting times, because higher meeting rates more than offset lower acceptance probabilities. It can also feature higher aggregate welfare, driven by shorter waits and higher-quality matches.

Our framework generates predictions consistent with the possibility that resolving search frictions can increase prices. This offers a potential mechanism behind the empirical pattern that rents are higher for households that report finding housing through online platforms. We do not address selection into online versus offline search, and we abstract from renter and apartment heterogeneity that would be essential for distributional analysis. We also take housing supply as exogenous. We view these extensions as natural avenues for future work. On the empirical front, a calibrated version of the model can be brought to data on how technology shocks shift time-on-market, acceptance rates, and the slope of the rent response across markets with different supply constraints, allowing us to quantify the effects of technological improvements in rental housing markets.

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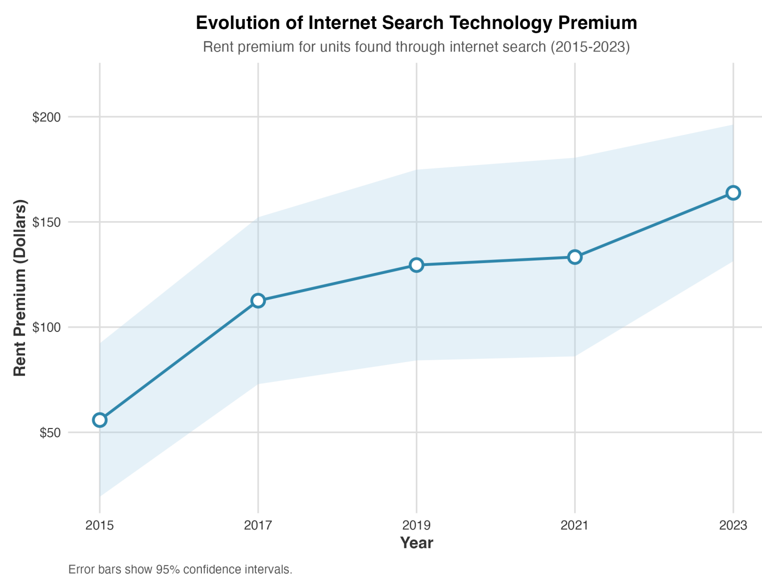
5 Appendix: Empirical

5.1 Analyzing other survey years

The figure below shows the coefficient of the Internet Search variable from equation (1) for all AHS survey years dating back to 2015 which is the first time the survey question pertaining to the method through which apartments are found was asked.



5.2 Normalizing rents to a log scale

Table 3 below estimates 1 using the log transformed rents.

Table 3: Hedonic regression: online search and log monthly rent (AHS 2023)

	Dependent variable:
	Log Monthly Rent
Internet Search	0.14^{***}
	(0.01)
Total Rooms	0.06^{***}
	(0.004)
Income Index	0.001^{***}
	(0.0000)
CBSA FE	Yes
Additional Controls	Yes
Observations	5,566
R^2	0.43
Note:	*p<0.1; **p<0.05; ***p<0.01

5.3 Accounting for outliers

Table 4 below estimates equation 1 dropping the bottom and top 5% of rents.

Table 4

	Dependent variable:
	Log Monthly Rent
Internet Search	163.82***
	(16.55)
Total Rooms	90.25***
	(5.56)
Income Index	1.01***
	(0.05)
CBSA FE	Yes
Additional Controls	Yes
Observations	5,566
R^2	0.45
Note:	*p<0.1; **p<0.05; ***p<0.01
	Income index is the ratio of household income to the federal poverty level.

5.4 Accounting for geographic differences

To ensure that our results are not being driven by high-rent and high internet-usage in metro areas, we run the regression separately non-metro areas. Table 5 below reports the results.

Table 5

	Dependent variable:
	Log Monthly Rent Non-Metro
Internet Search	0.16**
	(0.07)
Total Rooms	0.07**
	(0.03)
Income Index	0.001***
	(0.0002)
Additional Controls	Yes
Observations	357
R^2	0.32

Note: *p<0.1; **p<0.05; ***p<0.01

Income index is the ratio of household income to the federal poverty level.

6 Appendix: Theory

6.1 Proof of Proposition 1

The reservation surplus is characterized by the equation

$$U_1(r, e(r; r^m), r^m) = U_0(r^m) \tag{11}$$

We can express $U_1(r, e; r^m) = \frac{e-r}{1-\beta}$ and $U_0(r^m) = \frac{e(r^m;r^m)-r^m}{1-\beta}$.

Given that $U_1(r, e; r^m)$ is strictly increasing in e and $U_0(r^m)$ is constant in e, we know that there exists a unique $e(r; r^m)$. Now, $U_1(r, e; r^m)$ is unaffected by changes λ. We argue that $\frac{dU_0(r^m)}{d\lambda} > 0$, which then implies that $\frac{de(r;r^m)}{d\lambda} > 0$.

$$U_0(r^m) = h + \beta \left\{ \lambda \int_0^{\bar{e}} \max\left[U_0(r^m), U_1(r, e; r^m)\right] dG(e) + (1-\lambda) U_0(r^m) \right\}$$

Let $\int_0^{\bar{e}} \max\left[U_0(r^m), U_1(r, e; r^m)\right] dG(e) = \Phi$. Then,

$$U_0(r^m) = h + \beta\lambda\Phi + \beta(1-\lambda)U_0(r^m)$$

$$\frac{dU_0(r^m)}{d\lambda} = \beta\lambda\frac{d\Phi}{d\lambda} + \beta\Phi + \beta(1-\lambda)\frac{dU_0(r^m)}{d\lambda} - \beta U_0(r^m)$$

$$\frac{dU_0(r^m)}{d\lambda}(1-\beta(1-\lambda)) = \beta\lambda\frac{d\Phi}{d\lambda} + \beta\Phi - \beta U_0(r^m) \tag{12}$$

Lemma 2 calculates $\frac{d\Phi}{d\lambda} = \frac{dU_0(r^m)}{d\lambda}G(e(r^m;r^m,\lambda))$. Substituting into (2),

$$\frac{dU_0(r^m)}{d\lambda}(1-\beta(1-\lambda)) = \beta\left(\Phi - U_0(r^m)\right) + \beta\lambda\frac{dU_0(r^m)}{d\lambda}G(e(r^m;r^m,\lambda))$$

$$\frac{dU_0(r^m)}{d\lambda} = \frac{\beta\left(\Phi - U_0(r^m)\right)}{1-\beta+\beta\lambda\left(1-G(e(r^m;r^m,\lambda))\right)}$$

$\frac{dU_0(r^m)}{d\lambda} > 0$ follows from the fact that $\Phi = \int_0^{\bar{e}} \max\left[U_0(r^m), U_1(r^m,e;r^m)\right] dG(e) > \int_0^{\bar{e}} U_0(r^m)dG(e) = U_0(r^m)$. Consequently, $\frac{de(r;r^m)}{d\lambda} > 0$.

Lemma 1

Let $\int_0^{\bar{e}} \max\left[U_0(r^m), U_1(r^m,e;r^m)\right] dG(e) = \Phi$; $\frac{d\Phi}{d\lambda} = \frac{dU_0(r^m)}{d\lambda}G(e(r^m;r^m,\lambda))$.

Proof.

$$\begin{aligned}
\Phi &= \int_0^{e(r^m;r^m,\lambda)} U_0(r^m)dG(e) + \int_{e(r^m;r^m,\lambda)}^{\bar{e}} U_1(r^m,e;r^m)dG(e) \\
&= \int_0^{e(r^m;r^m,\lambda)} \frac{e(r^m;r^m,\lambda)-r}{1-\beta}dG(e) + \int_{e(r^m;r^m,\lambda)}^{\bar{e}} \frac{e-r^m}{1-\beta}dG(e)
\end{aligned}$$

Differentiating wrt λ and using Liebnitz's rule,

$$\begin{aligned}
\frac{d\Phi}{d\lambda} &= \int_0^{e(r^m;r^m,\lambda)} \frac{\partial}{\partial\lambda}U_0(r^m)g(e)de + U_0(r^m)g(e(r^m;r^m,\lambda))\frac{de(r^m;r^m,\lambda)}{d\lambda} - U_0(r^m)g(0)\frac{d}{d\lambda}(0) \\
&+ \int_{e(r^m;r^m,\lambda)}^{\bar{e}} \frac{\partial}{\partial\lambda}U_1(r^m,e;r^m)g(e)de + U_1(r^m,\bar{e};r^m)g(\bar{e})\frac{d}{d\lambda}(\bar{e}) \\
&- U_1(r^m,e(r^m;r^m,\lambda);r^m)g(e(r^m;r^m,\lambda))\frac{de(r^m;r^m,\lambda)}{d\lambda} \\
&= \frac{dU_0(r^m)}{d\lambda}G(e(r^m;r^m,\lambda))
\end{aligned}$$

where we use the (11). □

The fact that $e(r; r^m)$ is increasing in r is immediate from the (11):

$$\begin{aligned}\frac{e(r; r^m) - r}{1-\beta} &= U_0(r^m) \\ e(r; r^m) &= (1-\beta)U_0(r^m) + r \\ \frac{de(r; r^m)}{dr} &= 1\end{aligned}$$

We omit the proof that $e(r; r^m)$ is decreasing in r^m.

6.2 Proof of Proposition 2

We take r^m to be fixed. To economize on notation, we will write V_0 for $V_0(r^m)$ and $V_1(r)$ for $V_1(r; r^m)$. Consequently, we will understand that r^* stands for $r^*(r^m)$.

Lemma

Let G be a twice differentiable distribution function and $1 - G$ be log-concave. Let r^* be the optimal posted rent. Then,

$$sign\left(\frac{dr^*}{d\gamma}\right) = sign\left(\frac{dV_0}{d\gamma}\right)$$

Proof. Using the first order conditions of the rent-posting problem,

$$\max_r \{\gamma\left[(1 - G(r))V_1(r) + G(r)V_0\right] + (1-\gamma)V_0\}$$

We obtain

$$-G'(r^*)\gamma V_1(r^*) + \gamma(1 - G(r^*))V_1'(r^*) + \gamma G'(r^*)V_0 = 0$$

where we use the Envelope theorem in setting $\frac{dV_0}{dr} = 0$. Rearranging yields,

$$\frac{1 - G(r^*)}{G'(r^*)} = \frac{V_1(r^*) - V_0}{V_1'(r^*)}$$

Substituting for $V_1(r^*)$

$$\begin{aligned}\frac{1 - G(r^*)}{G'(r^*)} &= \frac{\frac{r^* + \beta\delta V_0}{1-\beta(1-\delta)} - V_0}{\frac{1}{1-\beta(1-\delta)}} \\ &= r^* + \beta\delta V_0 - V_0(1 - \beta(1-\delta))\end{aligned}$$

Differentiating wrt γ,

$$\frac{G'(r^*)\left[-G'(r^*)\frac{dr^*}{d\gamma}\right] - (1-G(r^*))G''(r^*)\frac{dr^*}{d\gamma}}{(G'(r^*))^2} = \frac{dr^*}{d\gamma} + \beta\delta\frac{dV_0}{d\gamma} - (1-\beta(1-\delta))\frac{dV_0}{d\gamma}$$

$$\frac{dV_0}{d\gamma}(\beta\delta - (1-\beta(1-\delta))) + \frac{dr^*}{d\gamma} = -\frac{dr^*}{d\gamma} - \frac{(1-G(r^*))G''(r^*)}{(G'(r^*))^2}$$

$$\frac{dV_0}{d\gamma}(\beta - 1) = \frac{dr^*}{d\gamma}\left[-2 - \frac{(1-G(r^*))G''(r^*)}{(G'(r^*))^2}\right]$$

$$\frac{dr^*}{d\gamma} = \frac{dV_0}{d\gamma}\left[\frac{\beta - 1}{-2 - \frac{(1-G(r^*))G''(r^*)}{(G'(r^*))}}\right]$$

To obtain the result then we need that $-2 < \frac{1-G(r^*)}{G'(r^*)}\frac{G''(r^*)}{G'(r^*)}$.

When the survival function $1 - G(r)$ is log concave, the above condition holds and we have that

$sign\left(\frac{dr^*}{d\gamma}\right) = sign\left(\frac{dV_0}{d\gamma}\right)$

□

Proposition 3. *Let r^* be the optimal posted rent. Then,*

$$\frac{dr^*}{d\gamma} > 0$$

Proof. We prove that $\frac{dV_0}{d\gamma} > 0$ and use Lemma 1 to conclude

$$\begin{aligned} V_0 &= b + \beta\gamma((1-G(r(\gamma)))V_1(r(\gamma))) + \beta\gamma G(r(\gamma))V_0 + \beta(1-\gamma)V_0 \\ \frac{dV_0}{d\gamma} &= \beta\Big[(1-G(r(\gamma)))V_1(r(\gamma)) \\ &\quad - \gamma G'(r(\gamma))r'(\gamma)V_1(r(\gamma)) \\ &\quad + \gamma(1-G(r(\gamma)))V_1'(r(\gamma))r'(\gamma)\Big] \end{aligned}$$

Using the Envelope theorem:

$$\frac{dV_0}{d\gamma} = \beta(1-G(r(\gamma)))V_1(r(\gamma)) + \beta G(r(\gamma))V_0 + \beta\gamma G(r(\gamma))\frac{dV_0}{d\gamma} - \beta V_0 + \beta(1-\gamma)\frac{dV_0}{d\gamma}$$

$$\frac{dV_0}{d\gamma}[1-\beta\gamma G(r(\gamma)) - \beta(1-\gamma)] = \beta G(r(\gamma))V_0 - \beta V_0 + \beta(1-G(r(\gamma)))V_1(r(\gamma))$$

$$\frac{dV_0}{d\gamma} = \frac{\beta}{1-\beta\gamma G(r(\gamma)) - \beta(1-\gamma)}[G(r(\gamma))V_0 - V_0 + (1-G(r(\gamma)))V_1(r(\gamma))]$$

$$\frac{dV_0}{d\gamma} = \frac{\beta}{1-\beta\gamma G(r(\gamma)) - \beta(1-\gamma)} \times [G(r(\gamma))V_0 - V_0 + (1-G(r(\gamma)))V_1(r(\gamma))]$$

We want to show that :

$$G(r(\gamma))V_0 - V_0 + (1-G(r(\gamma)))V_1(r(\gamma)) \geq 0$$

$$V_0(G(r(\gamma)) - 1) + (1-G(r(\gamma)))V_1(r(\gamma)) \geq 0$$

$$V_0 G(r(\gamma)) + (1-G(r(\gamma)))V_1(r(\gamma)) \geq V_0$$

For the above to be true, we need that $V_1(r(\gamma)) \geq V_0$.

$$V_1(r(\gamma)) \geq V_0$$

$$\frac{r(\gamma) + \beta\delta V_0}{1-\beta(1-\delta)} \geq V_0$$

$$r(\gamma) + \beta\delta V_0 \geq V_0 - V_0\beta(1-\delta)$$

$$r(\gamma) \geq V_0(1-\beta)$$

which is the condition that the annuitized value of remaining vacant forever should be at most the optimal posted rent; which must be true. □

6.3 Proof of tightness condition

From the definition of tightness, we have that $s = \theta v$. Given our defined measures of apartments, households, and searchers, the measure of vacancies v is given by $H - (1-s) = H - 1 + s$ (total apartments minus occupied apartments). Combining the expression for tightness with this expression for vacancies, we recover another expression for $s(\theta)$ as follows:

$$s(\theta) = \frac{(H-1)\theta}{1-\theta} \tag{13}$$

For the measure of searchers to be positive, either (i) $H > 1$ and $\theta < 1$ or (ii) $H < 1$ and $\theta > 1$ are required. We now show that, in equilibrium, one of these must hold. From the stationarity condition, we have that:

$$s(\theta) = \frac{\delta}{\lambda + \delta - \lambda G(\bar{e}(r^m(\theta)))} \tag{14}$$

Equating (13) and (14), we have that:

$$\frac{(H-1)\theta}{1-\theta} = \frac{\delta}{\lambda + \delta - \lambda G(\bar{e}(r^m(\theta)))} \tag{15}$$

Rearranging (15), we have that:

$$(H-1)\theta(\lambda + \delta - \lambda G(\bar{e}(r^m(\theta)))) = \delta(1-\theta) \tag{16}$$

Suppose that $H > 1$ and $\theta > 1$; then, the LHS of (16) is positive and the RHS is negative; a contradiction. Suppose that $H < 1$ and $\theta < 1$; then, the LHS of (16) is negative and the RHS is positive; a contradiction. Hence, in equilibrium, either (i) $H > 1$ and $\theta < 1$ or (ii) $H < 1$ and $\theta > 1$ must hold.

6.4 Degenerate example

Suppose the distribution of idiosyncratic taste shocks is degenerate; and hence is fixed $e = \hat{e}$. Let $\hat{e} > b$ be the prospect's value. Let r^m be the market rent. Given $\hat{e}$ and r^m, let $\tilde{r}$ be given by: $U_0(r^m) = U_1(\tilde{r}, \hat{e}; r^m)$. $\tilde{r}$ is the highest rent that the prospect is willing to pay. For any $r \leq \tilde{r}$, matching probability is 1, and for any $r > \tilde{r}$, matching probability is 0. Hence, the landlord posts $\tilde{r}$ if $V_1(\tilde{r}; r^m) > V_0(r^m)$; otherwise posts $r > \tilde{r}$.

Suppose $U_0(r^m) > U_1(r^m, \hat{e}; r^m)$; then $U_0(r^m) = \frac{h}{1-\beta}$ and $U_1(r, \hat{e}, r^m) = \frac{1}{1-\beta(1-\delta)}\left(\hat{e} - r + \frac{\delta h}{1-\beta}\right)$. $\tilde{r}$, then, is $\tilde{r} = \hat{e} - h(1-\delta)$. When the market rent is so high that the prospect never matches, the rent that makes the prospect indifferent between matching and not today is a discount on the value of matching; if the flow value of the outside option is large, the discount is large. If match destruction is impossible, it is exactly the gap between the match value and the flow value of remaining unmatched.

Suppose $U_0(r^m) < U_1(r^m, \hat{e}; r^m)$; then $U_0(r^m) = \frac{h(1-\beta(1-\delta)) + \beta\lambda(\hat{e} - r^m)}{\lambda(1-\beta)}$; and $\tilde{r} = \hat{e} - \frac{(1-\delta)(h(1-\beta(1-\delta)) + \beta\lambda(\hat{e} - r^m))}{\lambda}$. When the market rent is a large discount relative to the value, the rent that makes the prospect indifferent is also a large discount relative to the value. The smaller the meeting rate, the smaller is the size of this discount.

Suppose given $\tilde{r}$, it is the case that $V_1(\tilde{r}, r^m) > V_0(r^m)$. Then the landlord must post $\tilde{r}$, optimally. Consistency then requires that $r^m = \tilde{r}$ and so $U_0(r^m) = U_1(r^m, \hat{e}; r^m)$. Since in our environment, the renter who in equilibrium is indifferent between matching and not always breaks the tie in favor of matching, the market rent is identified as a solution to the equation $r^m =$

$\hat{e} - \frac{(1-\delta)(h(1-\beta(1-\delta))+\beta\lambda(\hat{e}-r^m))}{\lambda}$; which solves to return:

$$\begin{aligned} r^m &= \frac{\lambda\hat{e} - h(1-\delta)(1-\beta(1-\delta)) - (1-\delta)\beta\lambda\hat{e}}{\lambda - (1-\delta)\beta\lambda} \\ &= \frac{\lambda\hat{e}(1-\beta(1-\delta)) - h(1-\delta)(1-\beta(1-\delta))}{\lambda - (1-\delta)\beta\lambda} \\ &= \frac{\lambda\hat{e} - h(1-\delta)}{\lambda} \qquad (17) \\ &= \hat{e} - \frac{h(1-\delta)}{\lambda} \qquad (18) \end{aligned}$$

As the meeting rate goes up and we move to the competitive limit, the market rent collapses to $\hat{e}$, which is intuitive. On the equilibrium path, the prospect is indifferent between matching and not, and breaks the tie in favor of matching. If given $\tilde{r}$, $V_1(\tilde{r}, r^m) < V_0(r^m)$, then any rent $\hat{r} > \tilde{r}$ is optimal. Consistency requires that $r^m = \hat{r}$; and so, it must be that on the equilibrium path, the prospect never matches.

7 Appendix: Quantitative results

7.1 Validation of the Rent Decomposition

Figure 8 confirms that the equilibrium rent in our numerical solutions satisfies the first-order condition (10) almost exactly. Each point represents an equilibrium computed for a different parameter combination; the tight clustering along the 45-degree line indicates that the decomposition $r = (1-\beta)V_0 + \frac{1-G(\bar{e})}{g(\bar{e})}$ holds with an R^2 of 0.987 and a mean absolute error of less than 0.01. This provides strong numerical validation for our analytical characterization of equilibrium rents.

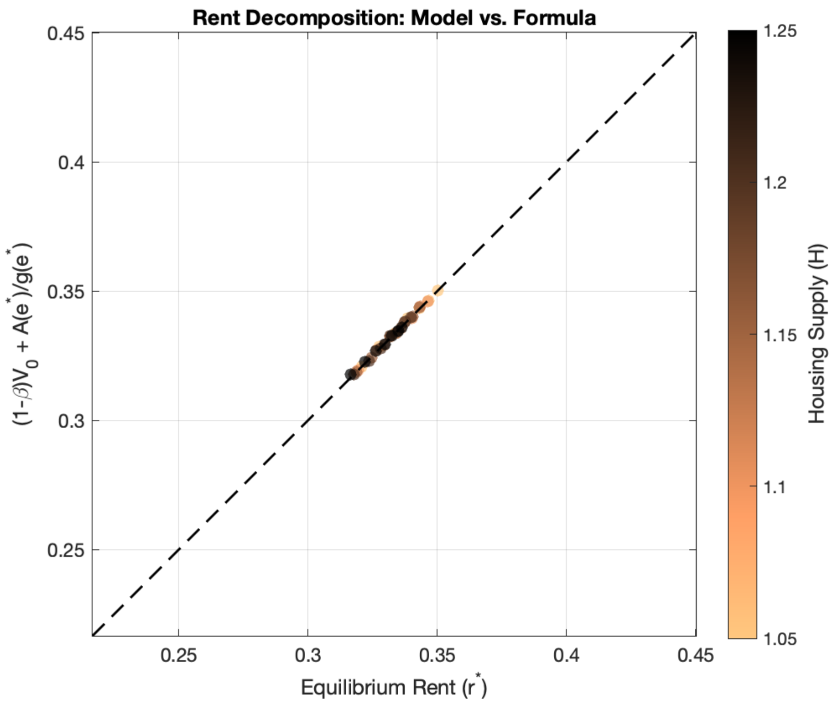


Figure 8: Rent decomposition: numerical equilibria vs. analytical formula

7.2 Different elasticities of matching technology

The baseline results use a Cobb-Douglas matching function with equal elasticity ($\alpha = 0.5$). Figure 9 explores robustness to the matching function elasticity, varying $\alpha \in \{0.1, 0.3, 0.5, 0.7\}$. Lower values of α imply that increases in matching efficiency κ translate more strongly into higher landlord meeting rates γ; higher values of α favor tenant meeting rates λ.

The left panel shows that rents rise with technology across all values of α at $H = 1.10$. The right panel shows that the percentage rent increase is larger when α is small (landlord-favoring), consistent with the intuition that the landlord meeting channel is the dominant force behind rent increases. Even when the matching function strongly favors tenants ($\alpha = 0.7$), rents still increase with technology in our calibration, though by a smaller amount.

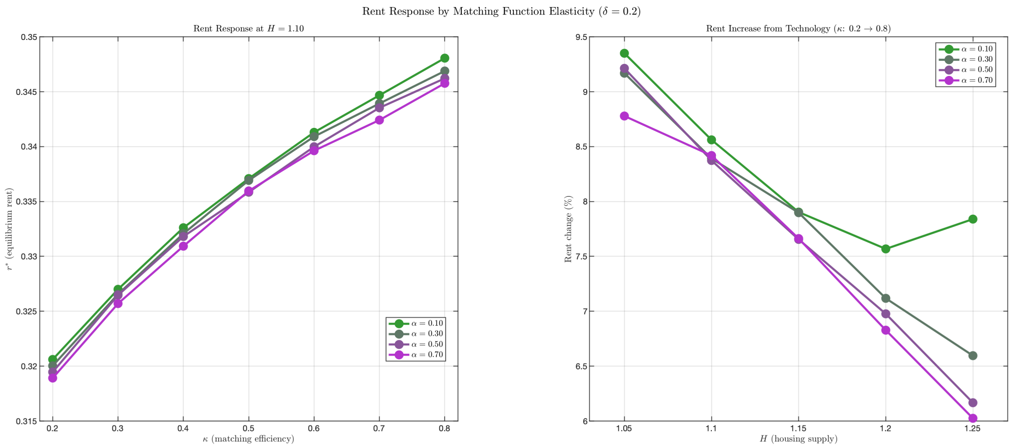


Figure 9: Rent response by matching function elasticity. Left panel: rent vs κ at $H = 1.10$ for different α. Right panel: percentage rent increase from $\kappa = 0.2$ to 0.8 across housing supply levels. Lower α (green) favors landlord meetings; higher α (purple) favors tenant meetings.