Technology and search in rental markets

Olalekan Bello [*1] and Arnav Deshpande[2]

[1]ob708@nyu.edu
[2]ad6790@nyu.edu

August 25, 2025

Abstract

Standard models of consumer search predict that greater ex-ante information should reduce prices by improving consumers' ability to compare options. However, data from the American Housing Survey show that renters who find their apartments online tend to pay higher rents than those using offline methods, even for observably similar units. To explain this fact, we develop a two-sided dynamic search and matching model of the rental market. In our framework, internet search technology accelerates the rate at which renters locate vacant units, raising their option value of waiting. At the same time, it enables landlords to attract prospective tenants more quickly, increasing their option value of holding out for better offers. When the landlord-side effect dominates, improvements in search technology can lead to higher equilibrium rents even as renter search becomes more efficient.

1 Introduction

Information technology has fundamentally transformed 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 the dominant channels for both rental and purchase markets.

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

*We thank Guido Menzio, Venky Venkateswaran, Abdoulaye Ndiaye and participants at the NYU IO Mini day for helpful comments.
We do not have financial support or conflicts of interest to disclose.

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, improvements in information technology could also enable faster arrivals of prospective renters to apartments which could drive competition between renters and drive up prices. Empirical evidence from the AHS suggests that the effect of the increase in arrival rates dominates that of improved information for renters.

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.

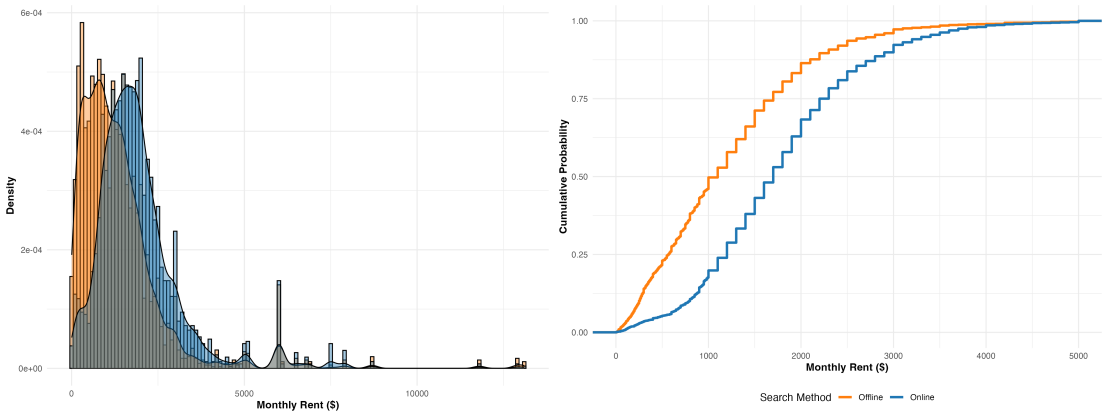


Figure 1: Distribution of rents by search method

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.

$$\text{Rent}_i = \beta_0 + \beta_1 \text{Internet Search}_i + \beta_2 \text{CBSA13}_i + \mathbf{X}'\beta + \varepsilon_i \tag{1}$$

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), CBSA13 are fixed effects for core-based statistical areas defined by the Office of Management and Budget in 2013. **X** are additional covariates we control for which are: 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 below. Column 1 does not include the CBSA13 fixed effects while column 2 does. The estimates in column 1 are consistent with the distributions, and we see that on average, apartments found online are about $563 more expensive compared to apartments found offline. This difference is also 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 all these observable features. However, it is still quite large and significant at $211, given that the median rent in the data is about $1500.

Table 1

	Dependent variable:		
	Monthly Rent (Dollars)		
	(1)	(2)	(3)
Internet Search	563.31***	414.01***	211.36***
	(34.63)	(33.26)	(36.04)
Total Rooms			131.16***
			(11.85)
Income Index			1.76***
			(0.10)
CBSA FE	No	Yes	Yes
Additional Controls	No	No	Yes
Observations	6,184	6,184	6,184
R^2	0.04	0.16	0.27

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

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

[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

In appendix A, we conduct a number of robustness checks including using log rents as the dependent variable, trimming the outliers in the rents, conducting the analysis over time and only within particular CBSAs. The pattern of the 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 the potential for omitted variable bias. The apartments that select into listing on an internet site could be different from those that do not in ways that our observable controls do not account for. Nonetheless, it would be hard to imagine that the matching technology does not play an important role and this difference is entirely driven by selection. While we do not have perfectly conclusive evidence to believe that the difference in rents is being driven entirely by the effect of technology, we see the evidence we do have as a sufficient starting point to explore a model where rents for apartments found online are higher due to the speed of matching the internet enables.

In our model, technological improvements affect matching in the rental market through two distinct channels: the rate at which prospective renters encounter available apartments and the rate at which potential tenants arrive to compete for any given vacant unit. We interpret the first channel as expanding renters' effective search scope, enabling them to observe a broader pool of available apartments, while the second channel increases the flow of potential tenants competing for each individual apartment.

An increase in renters' meeting rates creates downward pressure on equilibrium rents by strengthening their outside option. When prospective renters can more easily find alternative apartments, their value of remaining unmatched increases. Anticipating this improved outside option, landlords must reduce rents to maintain their attractiveness and secure tenants. Conversely, an increase in tenant arrival rates generates upward pressure on rents by enhancing landlords' option value of waiting. With more prospective renters arriving each period, landlords can afford to be more selective, holding out for tenants with higher valuations who are willing to pay premium rents.

We illustrate these dynamics in Section 4 and demonstrate that these opposing forces can result in net rent increases even when renters' search technology improves, provided that landlords simultaneously gain access to larger pools of potential tenants. This occurs because landlords' enhanced pricing power from increased tenant flows can dominate the competitive pressure from renters' improved search capabilities. We also discuss the implications of this for wait times and welfare.

2 Related Literature

We see our results as contributing to the rich theoretical literature on information and consumer search, following the seminal work of Stigler [1961]. Building on this are the earlier discussed classic models predicting 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 buyers and sellers.

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.

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.

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). 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 nar-

rower 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 Market

We model a frictional search market with a unit measure of landlords and a unit measure of 'prospect' (potential renter). 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.

Consider the dynamic problem of a prospect. With probability λ, the prospect meets a landlord. On meeting the landlord, the prospect draws a i.i.d match-specific surplus $s \sim G$ 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. We use r for the rent offer, and r^m for the market rent, which we think of as an aggregate state that we will determine in equilibrium.

We state the problem of the matched and prospective renter recursively.

A matched renter's value is given as:

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

A prospective (searching) renter's value is given as:

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

where h is the flow value of search (their outside option). We think of the searching prospect as someone who currently lives outside of the housing market being modeled. Consequently, the flow value of search is to be thought of as the value of staying outside the market.

The prospect's problem is akin to [McCall, 1970] and the optimal policy is an accept/ reject rule characterized by a threshold surplus $s(r; r^m)$.

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 $1 - G(s(r; r^m))$, i.e. the probability that given rent r, the prospect's match-specific value is higher than their cut-off $s(r; r^m)$. 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:

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

Equilibrium: An equilibrium consists of value functions U_0, U_1, V_0, V_1 a policy function $\tilde{r} : [0, \bar{r}] \to \mathcal{R}$ 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) r_*^m is a fixed point of the $\tilde{r}$ mapping: $\tilde{r}\left(r_*^m\right) = r_*^m$.

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 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.

We present two theoretical results that set up the main intuition in our model. In doing this, we take the market wage r^m to be fixed. In numerical simulations, we will demonstrate that our intuition is robust to the consistency requirement in the equilibrium definition.

Proposition 1. *The reservation value $s(r; r^m, \lambda)$ is:*

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

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.*

We think of technology as increasing γ and λ. When the arrival rate for the landlord, γ, goes up, the landlord's option value of waiting increases. This can be thought of as intensifying buyer competition, putting upward pressure on the rent (Proposition 2). When the arrival rate for the prospect, λ, goes up, the prospect's option value of waiting increases. An increase in λ increases

the cut-off $s(r; r^m, \lambda)$, for a given r, reducing the probability of matching (Proposition 1). The landlord can recover the loss in matching probability for a given r by reducing r; thus an increase in λ can be thought of as intensifying seller competition, putting downward pressure on the rent (Proposition 2).

In our quantitative results in the following section, we would also discuss how a measure of time-on-market or waiting time changes as γ and λ change. We define waiting time for the landlord as the expected number of periods it takes a vacant apartment to match with a tenant; including the period in which the match consummates. Consequently, if the landlord matches in this period, their realized waiting time is 1 period. Similarly, we also define waiting time for the prospect. The expressions for waiting time are stated below.

$$time_l = \frac{1}{\gamma(1 - G(s(r; r^m)))}$$
$$time_o = \frac{1}{\lambda(1 - G(s(r; r^m)))}$$

The probability of a match for a landlord is the probability that the landlord meets a tenant times the probability that the tenant has an efficiency value high enough, given the posted rent, to match. The result that the expected wait time of an event with probability p is $\frac{1}{p}$ is standard[3]

4 Comparative statics

We perform two experiments. In the first experiment, we raise the rate at which prospects arrive at apartments γ, and in the second, we raise the rate at which prospects learn about places, λ. In both experiments, we use the parametrization detailed in Table 2. Results are robust to alternative parametrizations.

[3]Let T be the waiting time and p be the success probability. Then

$$\mathbb{E}(T) = p.1 + (1 - p).(\mathbb{E}(T) + 1)$$
$$\mathbb{E}(T) = \frac{1}{p}$$

Table 2: Simulation parameters

Parameter	Value	Description
s	$\mathcal{N}(5, 3^2)$	Tenant efficiency distribution
r	$[0, 10]$	Rent range
h	1	Flow value of search
b	1	Flow value of remaining vacant
δ	0.1	Separation rate
β	0.95	Discount factor

In performing these experiments, we solve the model for the equilibrium rent, imposing the consistency condition. We provide an example of the rent policy in Figure 7 in the appendix. We also verify our propositions by fixing an r^m and checking how the rent policy responds to changes in λ and γ for a given r^m. Results are qualitatively the same.

4.1 Effects of changes in γ

Figure 2 presents results from raising the rate at which prospects arrive at apartments. Increasing γ increases the landlord's option value of waiting for a prospect who would be willing to pay a high rent (cell (1,3)). Thus, raising meeting rates for the landlord acts to intensify competition among prospects, putting upward pressure on the optimal take-it-or-leave-it rent offer (cell (1,1)). As γ goes up, the equilibrium market rent increases as well. While an increase in r increases $s(r; r^m)$, an increase in r^m reduces $s(r; r^m)$. This is because, when r goes up, the prospect's value from matching goes down and so they must be compensated with a higher match efficiency to be willing to match. On the other hand, when r^m goes up, the value of continued search goes down for the prospect and this acts to reduce the efficiency cut-off at any rent offer r. The net effect of these two forces in our quantification is a decrease in $s(r; r^m)$, and that drives an increase in the matching probability (cell (1,2)).

As the matching probability goes up, the waiting time for the tenant (the expected number of periods until and including the period in which the match consummates) unambiguously goes down (cell (2,2)). Similarly, as the meeting rate increases and the matching probability also increases, the waiting time for the landlord unambiguously goes down (cell (2,3)). Finally, as rents go up, the value of continued search for the prospective renter goes down (cell (2,1)); since every match that consummates produces a smaller current surplus and fewer matches consummate.

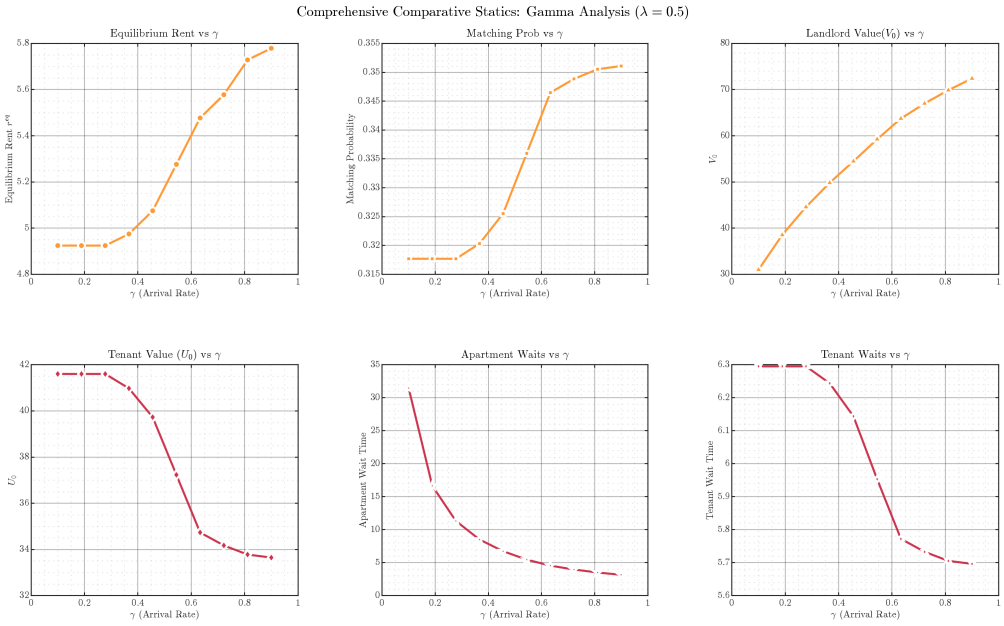


Figure 2: Increasing meeting rate for landlords

4.2 Effects of changes in λ

Figure 3 presents results from raising the rate at which prospects meet apartments. Increasing λ raises the option value of waiting for an apartment that would produce high match-specific utility for the prospect (cell (2,1)). At any given offer r and market rent r^m, this raises the cut-off efficiency below which prospects reject and search. This causes the matching probability to diminish. The landlord recovers this erosion in the matching probability by lowering their optimal take-it-or-leave-it rent offer (cell (1,1)). Thus, raising meeting rates for prospects acts to intensify competition amongst landlords. As rents go down, the option value of remaining vacant also goes down (cell (1,3)). While the landlord recovers the matching probability by reducing their rent offer, in our quantification, the net result is still a reduction in the matching probability (cell (1,2)).

As the matching probability goes down, the the apartment waiting time unambiguously increases (cell (2,2)). Effects on the tenant's waiting time are ambiguous: an increase in the arrival rate of apartments puts downward pressure on the tenant's expected waiting time, while a decrease in the matching probability conditional on meeting puts upward pressure on the expected waiting time. In our quantification, the increase in the meeting rate dominates and the expected waiting time for the tenant decreases (cell (2,3)). Finally, as rents go down, the tenant can extract more surplus from any efficiency level; further the frequency of arrivals is also higher. Both these effects increase the prospect's value of continued search (cell (2,1)).

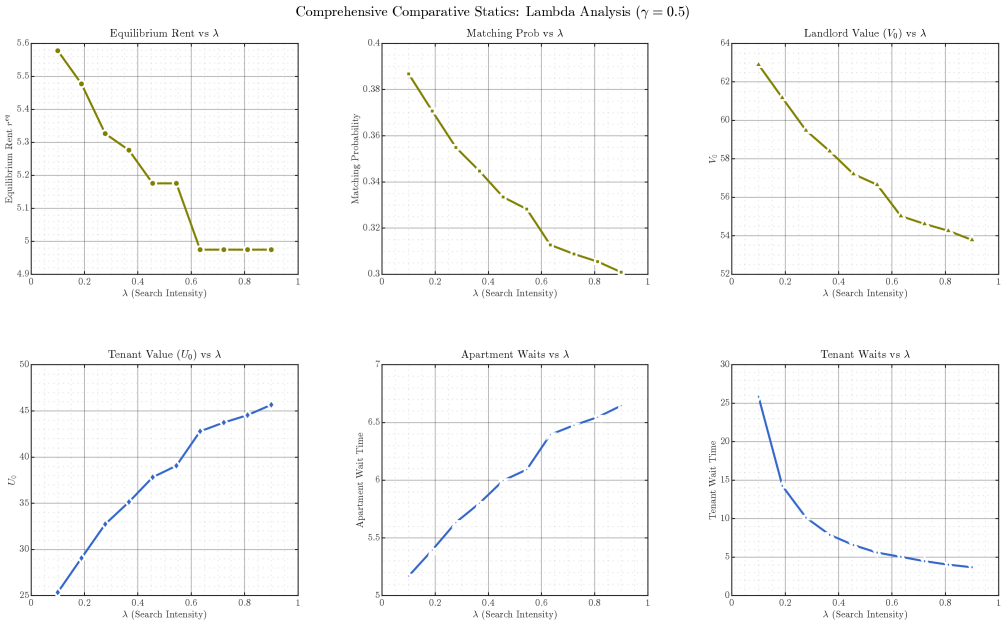


Figure 3: Increasing meeting rate for prospect

4.3 Welfare

We measure welfare using four distinct measures: (i) matched renter welfare $\mathbb{E}[U_1(s; r, r^m)|s \geq s^*(r; r^m)]$, the expected utility of renters conditional on matching; (ii) unmatched renter welfare $U_0(r^m)$, the value of search; (iii) matched landlord welfare $V_1(r; r^m)$, the flow value from a filled unit; and (iv) unmatched landlord welfare $V_0(r^m)$, the option value of a vacant unit. This decomposition reveals how search market changes create winners and losers even within agent types, highlighting that aggregate welfare measures may mask important distributional consequences.

Results are presented Figure 4 and Figure 5. When the arrival rate for landlords increases Figure 4, higher arrival rates strengthen landlords' bargaining position by improving their outside option of remaining vacant. The equilibrium rent r^m rises, which increases the flow payoff for matched landlords through higher rental income while also improving the option value of vacant units. On the renter side, matched renters experience reduced surplus from all efficiency levels above the cutoff, lowering the value of being matched. Similarly, searching renters anticipate lower expected matching surplus, reducing the value of continued search.

An increase in the arrival rate of apartments (Figure 5) creates symmetric but opposite effects: higher apartment arrival rates strengthen renters' bargaining position by improving their outside option of continued search. This drives equilibrium rents downward, creating a mirror image where renters benefit and landlords lose across both matching states.

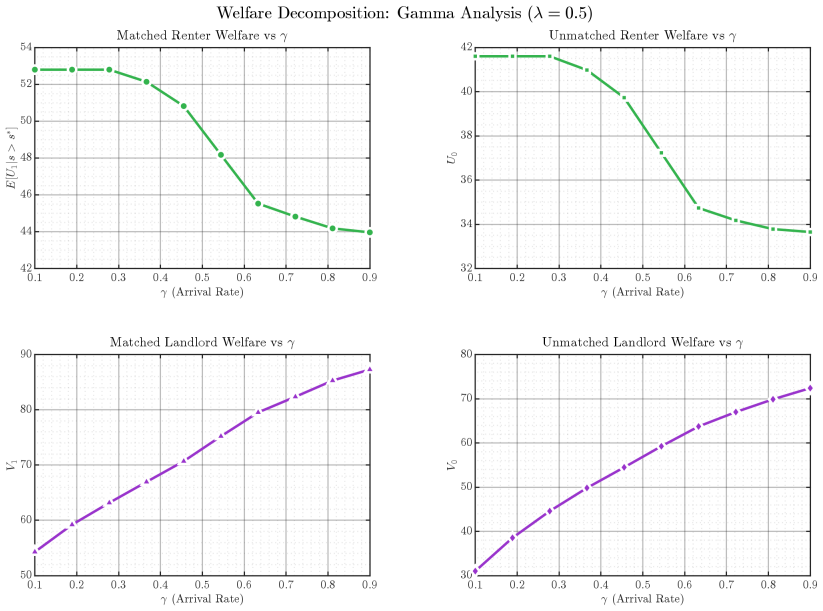


Figure 4: Welfare response to γ

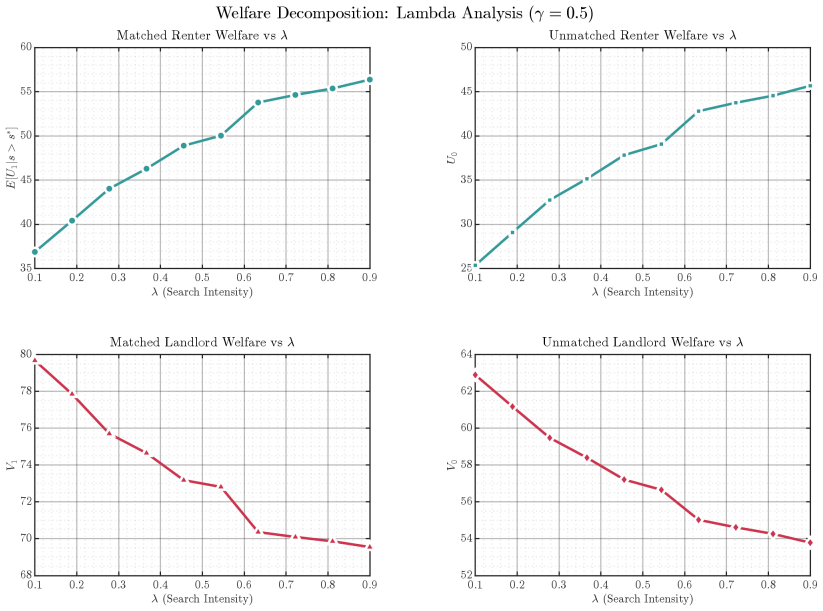


Figure 5: Welfare response to λ

4.4 Discussion

The above analysis leads to a number of important findings that we highlight and discuss in this section.

First, the findings documented in Section 4.1 indicate that the effects of search technologies on the rental housing market depend critically on which side of the market benefits more from technological improvements. Technology that primarily helps landlords find tenants (higher γ) strengthens the outside option for landlords, while technology that helps tenants find apartments (higher λ) strengthens the outside option of renters. These effects depend on how technology affects buyer relative to seller competition in the rental market. Figure 6 reveals that equilibrium rents increase when γ rises faster than λ, while rents decrease when λ rises faster than γ.

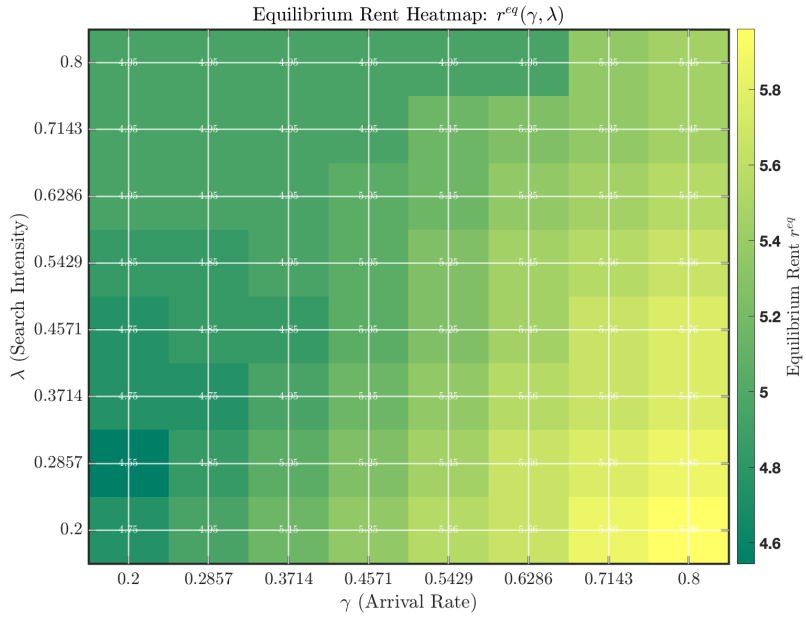


Figure 6: Net effect of technology

Second, search technologies do not uniformly reduce waiting times for prospects and apartments. Improvements in γ, the arrival rate for landlords, reduce waiting times for both landlords and prospects. Improvements in λ reduce waiting times for prospects, but increase waiting times for landlords. This yields a novel empirical test of how technology affects market sides differentially. If new rental platforms primarily reduce waiting times for renters but increase waiting times for landlords, this suggests effect on λ dominates that of γ. Conversely, if both sides experience reduced waiting times, this indicates technology primarily enhances γ.

Third, technological improvements do not uniformly improve welfare for landlords and renters.

Our welfare decomposition reveals that technological improvements create winners and losers even within agent types. For instance, when γ increases, both matched and unmatched landlords benefit, while both matched and unmatched renters lose. This suggests that the distributional consequences of rental market technology extend beyond simple landlord-versus-renter effects to more nuanced patterns based on matching status.

Our current analysis abstracts from important factors that could modify these results. We assume fixed measures of landlords and renters, abstracting from entry and exit decisions that might respond to technological changes. We also maintain the assumption of a single rental market, ignoring potential heterogeneity in housing quality, location, or other attributes that could create market segmentation. Additionally, our welfare analysis focuses on the direct effects of search technology on matching and rent determination, without considering potential changes in housing quality or other dimensions of the rental relationship. Nevertheless, our core mechanism of asymmetric shifts in the outside options for both sides of the rental market provides a useful framework for analyzing the effects of technological improvements.

5 Conclusion

Housing affordability is a pressing issue in the United States, and understanding the role of technology in this crisis is critical for designing effective policies to address it. We developed a model to examine how advancements in information technology influence the rents set by landlords. Our model demonstrates that optimal posted rents can increase as technology improves, depending on the balance between its effects on buyer competition and seller competition. Specifically, if technological improvements disproportionately intensify renter competition relative to landlord competition, landlords may have an incentive to raise rents. Conversely, if seller competition intensifies, it could exert downward pressure on rents.

References

Michael R. Baye, John Morgan, and Patrick Scholten. Information, search, and price dispersion. In Terence Hendershott, editor, Handbook on Economics and Information Systems, pages 323–376. Elsevier, Amsterdam, 2006.

Erik Brynjolfsson and Michael D. Smith. Frictionless commerce? a comparison of internet and conventional retailers. Management Science, 46(4):563–585, 2000. ISSN 00251909, 15265501. URL http://www.jstor.org/stable/2661602.

Kenneth Burdett and Kenneth L. Judd. Equilibrium price dispersion. Econometrica, 51(4):955–969, 1983. ISSN 00129682, 14680262. URL http://www.jstor.org/stable/1912045.

Sophie Calder-Wang. The distributional impact of the sharing economy on the housing market. SSRN Working Paper, https://ssrn.com/abstract=3908062, 2021. Accessed July 2021.

Alberto Cavallo. Are online and offline prices similar? evidence from large multi-channel retailers. American Economic Review, 107(1):283–303, January 2017. doi: 10.1257/aer.20160542. URL https://www.aeaweb.org/articles?id=10.1257/aer.20160542.

Liran Einav, Chiara Farronato, and Jonathan Levin. Peer-to-peer markets. Annual Review of Economics, 8(Volume 8, 2016):615–635, 2016. ISSN 1941-1391. doi: https://doi.org/10.1146/annurev-economics-080315-015334. URL https://www.annualreviews.org/content/journals/10.1146/annurev-economics-080315-015334.

Glenn Ellison and Sara Fisher Ellison. Search, obfuscation, and price elasticities on the internet. Econometrica, 77(2):427–452, 2009. doi: https://doi.org/10.3982/ECTA5708. URL https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA5708.

Glenn Ellison and Sara Fisher Ellison. Match quality, search, and the internet market for used books. Working Paper 24197, National Bureau of Economic Research, January 2018. URL http://www.nber.org/papers/w24197.

Lu Han and William C. Strange. Chapter 13 - the microstructure of housing markets: Search, bargaining, and brokerage. In Gilles Duranton, J. Vernon Henderson, and William C. Strange, editors, Handbook of Regional and Urban Economics, volume 5 of Handbook of Regional and Urban Economics, pages 813–886. Elsevier, 2015. doi: https://doi.org/10.1016/B978-0-444-59531-7.00013-2. URL https://www.sciencedirect.com/science/article/pii/B9780444595317000132.

Benjamin Lester. Information and prices with capacity constraints. American Economic Review, 101(4):1591–1600, June 2011. doi: 10.1257/aer.101.4.1591. URL https://www.aeaweb.org/articles?id=10.1257/aer.101.4.1591.

Paolo Martellini and Guido Menzio. Declining search frictions, unemployment, and growth. Journal of Political Economy, 128(12):4387–4437, 2020. doi: 10.1086/710975. URL https://doi.org/10.1086/710975.

J. J. McCall. Economics of information and job search. The Quarterly Journal of Economics, 84(1):113–126, 1970. ISSN 00335533, 15314650. URL http://www.jstor.org/stable/1879403.

Monika Piazzesi, Martin Schneider, and Johannes Stroebel. Segmented housing search. American Economic Review, 110(3):720–59, March 2020. doi: 10.1257/aer.20141772. URL https://www.aeaweb.org/articles?id=10.1257/aer.20141772.

Jennifer F. Reinganum. A simple model of equilibrium price dispersion. Journal of Political Economy, 87(4):851–858, 1979. ISSN 00223808, 1537534X. URL http://www.jstor.org/stable/1831011.

Steven Salop and Joseph Stiglitz. Bargains and ripoffs: A model of monopolistically competitive price dispersion. The Review of Economic Studies, 44(3):493–510, 10 1977. ISSN 0034-6527. doi: 10.2307/2296903. URL https://doi.org/10.2307/2296903.

Dale O. Stahl. Oligopolistic pricing with sequential consumer search. The American Economic Review, 79(4):700–712, 1989. ISSN 00028282. URL http://www.jstor.org/stable/1827927.

George J. Stigler. The economics of information. Journal of Political Economy, 69(3):213–225, 1961. ISSN 00223808, 1537534X. URL http://www.jstor.org/stable/1829263.

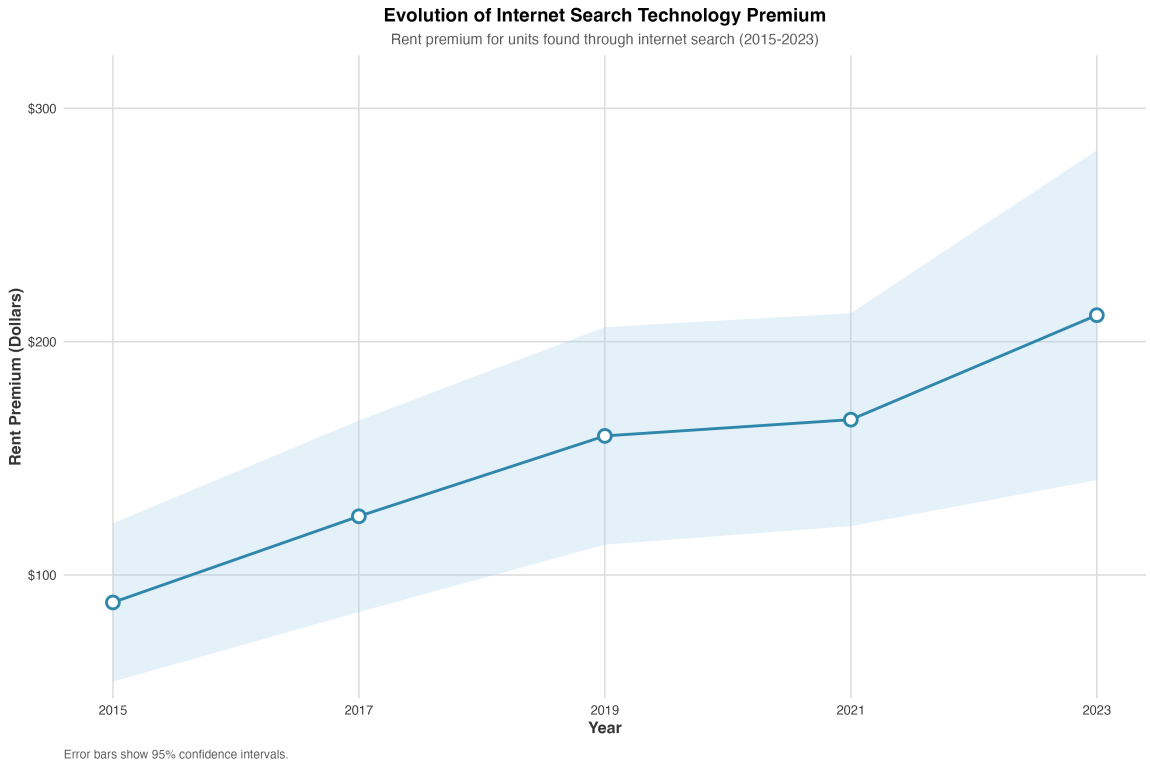
Hal R. Varian. A model of sales. The American Economic Review, 70(4):651–659, 1980. ISSN 00028282. URL http://www.jstor.org/stable/1803562.

6 Appendix

6.1 Robustness checks

6.1.1 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.



6.1.2 Normalizing rents to a log scale

Table 3 below estimates equation (1) using the log transformed rents.

Table 3

	Dependent variable:		
	Log Monthly Rent		
	(1)	(2)	(3)
Internet Search	0.53***	0.42***	0.19***
	(0.02)	(0.02)	(0.02)
Total Rooms			0.07***
			(0.01)
Income Index			0.002***
			(0.0001)
CBSA FE	No	Yes	Yes
Additional Controls	No	No	Yes
Observations	6,184	6,184	6,184
R^2	0.08	0.21	0.38

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

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

6.1.3 Accounting for outliers

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

Table 4

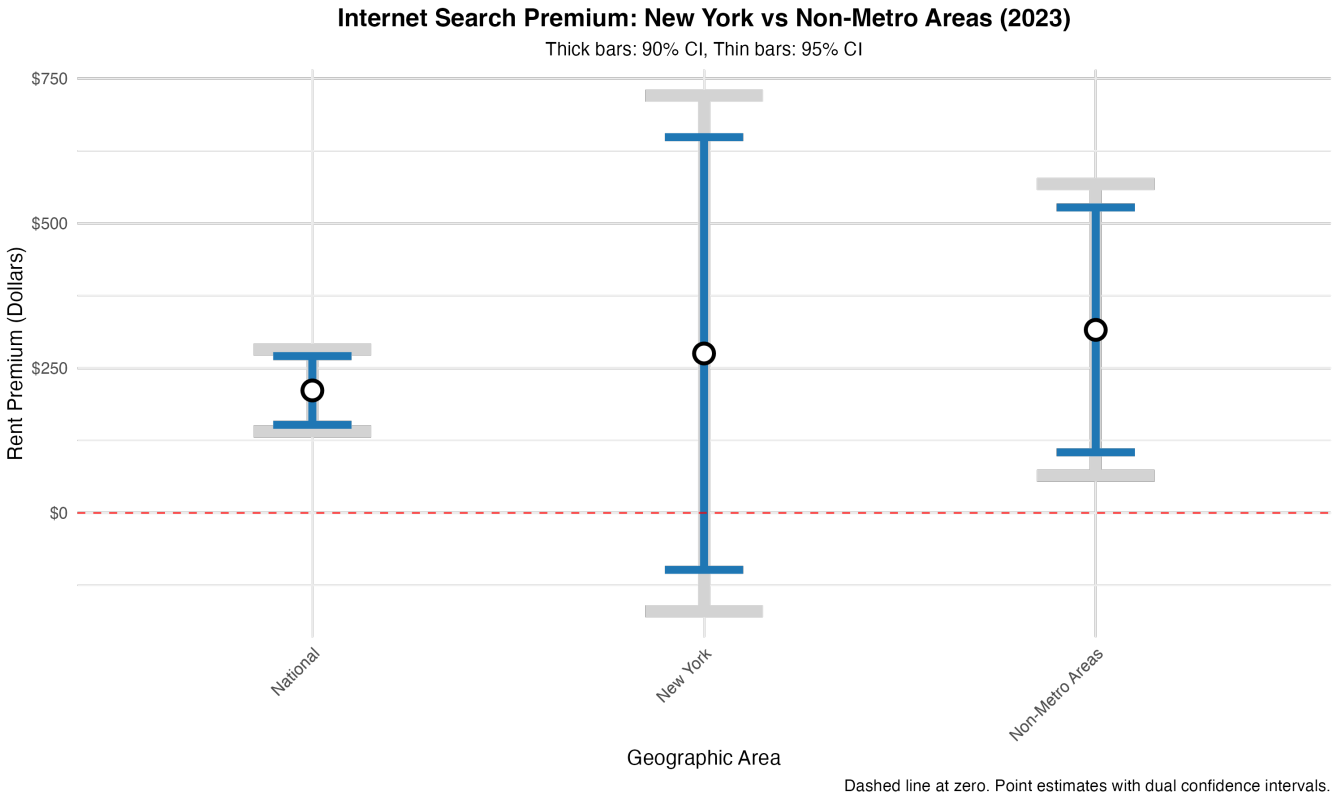
	Dependent variable:	
	Monthly Rent (Dollars)	
	Full Sample	Trimmed (5%-95%)
	(1)	(2)
Internet Search	211.36***	160.38***
	(36.04)	(17.35)
Total Rooms	131.16***	101.36***
	(11.85)	(5.79)
Income Index	1.76***	1.18***
	(0.10)	(0.05)
CBSA FE	Yes	Yes
Additional Controls	Yes	Yes
Observations	6,184	5,566
R^2	0.27	0.52

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

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

6.1.4 Accounting for potential geographic differences

The figure below presents estimates of the Internet search coefficient from equation 1, separately for the New York Metro area and for non-metro areas. While the rent gap between online and offline listings persists in both regions, the estimates are no longer statistically significant at the 95% level due to the smaller sample size. For this reason, we highlight the 90% confidence interval in the figure



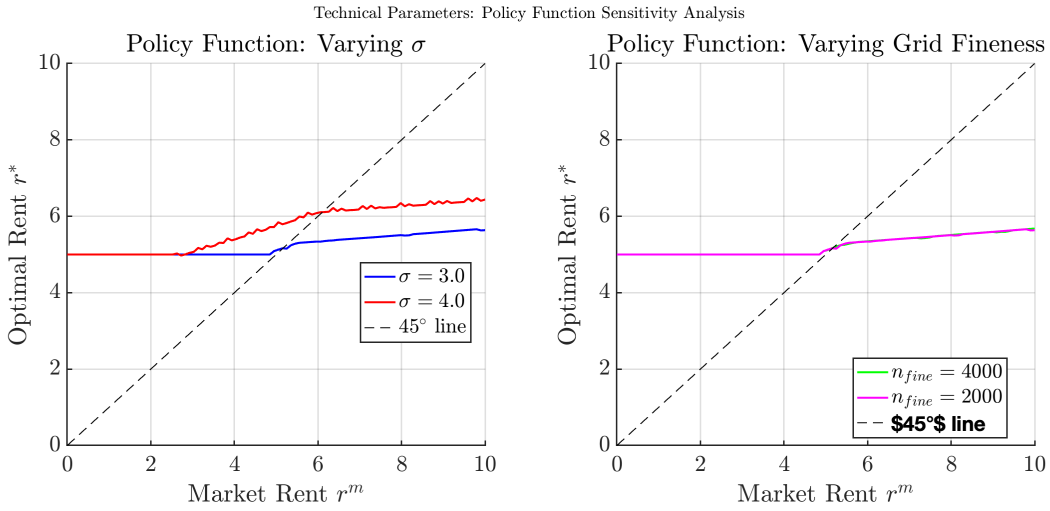


Figure 7: Net effect of technology

7 Appendix: Theory

7.1 Proof of Proposition 1

The reservation surplus is characterized by the equation

$$U_1(r, s(r; r^m), r^m) = U_0(r^m) \tag{6}$$

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

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

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

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

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

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

$$\frac{dU_0(r^m)}{d\lambda}(1 - \beta(1-\lambda)) = \beta\lambda \frac{d\Phi}{d\lambda} + \beta\Phi - \beta U_0(r^m) \tag{7}$$

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

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

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

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

Lemma 1

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

Proof.

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

Differentiating wrt λ and using Liebnitz's rule,

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

where we use the (6). □

The fact that $s(r; r^m)$ is increasing in r is immediate from the (6):

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

The proof that $s(r; r^m)$ is decreasing in r^m is still being worked.

7.2 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 F be a twice differentiable distribution function and $1 - F$ 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,

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

We obtain

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

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

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

Substituting for $V_1(r^*)$

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

Differentiating wrt γ,

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

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

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

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

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

When the survival function $1 - F(r)$ 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

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

Using the Envelope theorem:

$$\begin{aligned}
\frac{dV_0}{d\gamma} &= \beta(1 - F(r(\gamma))V_1(r(\gamma)) + \beta F(r(\gamma))V_0 + \beta\gamma F(r(\gamma))\frac{dV_0}{d\gamma} - \beta V_0 + \beta(1-\gamma)\frac{dV_0}{d\gamma} \\
\frac{dV_0}{d\gamma}\left[1 - \beta\gamma F(r(\gamma)) - \beta(1-\gamma)\right] &= \beta F(r(\gamma))V_0 - \beta V_0 + \beta(1 - F(r(\gamma)))V_1(r(\gamma)) \\
\frac{dV_0}{d\gamma} &= \frac{\beta}{1 - \beta\gamma F(r(\gamma)) - \beta(1-\gamma)}\left[F(r(\gamma))V_0 - V_0 + (1 - F(r(\gamma)))V_1(r(\gamma))\right] \\
\frac{dV_0}{d\gamma} &= \underbrace{\frac{\beta}{1 - \beta(1 - \gamma(1 - (F(r(\gamma)))}}_{>0}\left[F(r(\gamma))V_0 - V_0 + (1 - F(r(\gamma)))V_1(r(\gamma))\right]
\end{aligned}$$

We want to show that :

$$\begin{aligned}
F(r(\gamma))V_0 - V_0 + (1 - F(r(\gamma)))V_1(r(\gamma)) &\geq 0 \\
V_0(F(r(\gamma)) - 1) + (1 - F(r(\gamma)))V_1(r(\gamma)) &\geq 0 \\
V_0F(r(\gamma)) + (1 - F(r(\gamma))V_1(r(\gamma)) &\geq V_0
\end{aligned}$$

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

$$\begin{aligned}
V_1(r(\gamma)) &\geq V_0 \\
\frac{r(\gamma) + \beta\delta V_0}{1 - \beta(1-\delta)} &\geq V_0 \\
r(\gamma) + \beta\delta V_0 &\geq V_0 - V_0\beta(1-\delta) \\
r(\gamma) &\geq V_0(1-\beta)
\end{aligned}$$

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