Technology and search in rental housing markets

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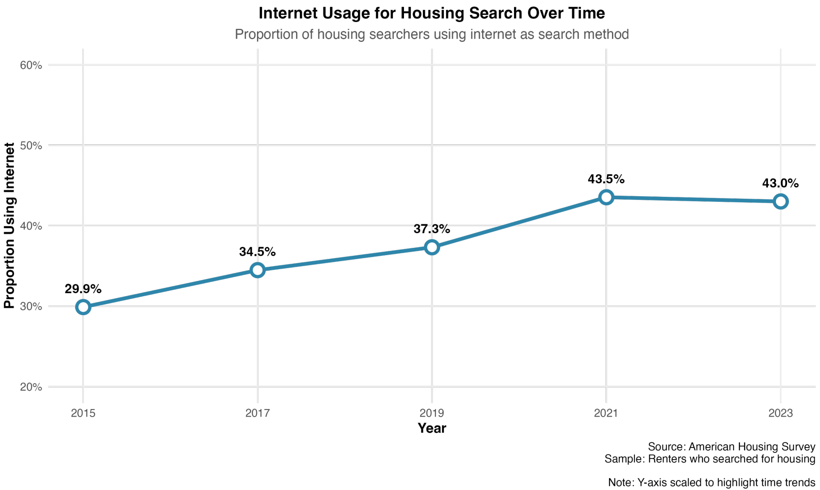
Motivation

- Search technologies (Zillow, Streeteasy) have changed how people search for housing
- Renters are now aware of a broader pool of apartments → competition between landlords
- Landlords have more potential renters arrive for their apartment → competition between renters
- **What is the effect of technological improvements in the market for rental housing?**

Internet and apartment search



Survey question: **Did you find your home on an internet site (such as Craig's List, apartment.com, realtor.com, or Zillow)?**

What we do

- Build a simple frictional search model of the rental housing market
- Partial equilibrium experiments where search technologies improve meeting rates for one side
- General equilibrium experiment where search technologies improve efficiency of the matching technology
- Ideas for empirical motivation/quantification

▸ literature

Model

Overview

- The market consists of a measure H of homogeneous landlords and a measure 1 of heterogeneous ‘prospects’
- Prospects arrive at an apartment and draw an idiosyncratic value that is privately known to the prospect
- Landlords make a take-it-or-leave-it rent offer
- Given the offer and idiosyncratic value, prospects either accept and match or reject and search

Renter's dynamic problem

- Prospect meets a vacant apartment with probability λ, draws idiosynratic value $e \sim G$
- Takes the rent offer r and the market rent r^m as given
- Decides whether to accept and match or reject and search
- Housed prospect loses apartment with probability δ at the beginning of every period
- A searching renter's flow value is b

Renter's dynamic problem

- A matched renter's value is given as:

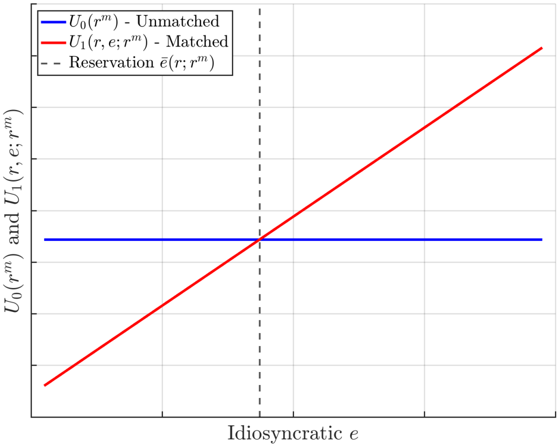
$$U_1(r, e; r^m) = e - r + \beta \{(1 - \delta) U_1(r, e; r^m) + \delta U_0(r^m)\} \tag{1}$$

- A searching renter's value is given as:

$$U_0(r^m) = b + \beta \left\{ \lambda \int_0^{\bar{e}} \max \left[U_0(r^m), U_1(r^m, e; r^m) \right] dG(e) + (1 - \lambda) U_0(r^m) \right\} \tag{2}$$

Renter's accept-reject policy

- The unique reservation value, $e(r; r^m)$, is characterized by: $U_1(r, e; r^m) = U_0(r^m)$.



- Rent $r \Rightarrow$ cutoff $e(r; r^m) \Rightarrow$ matching probability $1 - G(e(r; r^m))$

Landlord's dynamic problem

- Landlord meets prospect with probability γ, makes a take-it-or-leave-it offer r
- Matching probabilities are given by $1 - G(e(r; r^m))$ recovered from the prospect's problem
- Matched landlord becomes vacant at the beginning of the period with prob δ
- Landlord's flow value from vacant apartment is h

Landlord's dynamic problem

- Value of a matched landlord

$$V_1(r; r^m) = r + \beta(1-\delta)V_1(r; r^m) + \beta\delta V_0(r^m) \tag{3}$$

- Value of a newly vacant landlord

$$V_0(r^m) = h + \beta \max_r \left\{ \underbrace{\gamma\left[(1 - G(e(r; r^m)))V_1(r; r^m) + G(e(r; r^m))V_0(r^m)\right]}_{\text{expected value of being able to make an offer}} + (1-\gamma)V_0(r^m) \right\} \tag{4}$$

(Partial) Equilibrium

A (partial) equilibrium consists of a 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 (1), (2), (3), (4).

2. $\tilde{r}$ solves the vacant landlord's problem given in (4)

3. (Consistency) r_*^m is a fixed point of the $\tilde{r}$ mapping: $\tilde{r}\left(r_*^m\right) = r_*^m$ ▸ policy.

Option values to wait mechanism

Result: Holding the market rent r^m fixed, we show that

1. $\gamma \uparrow \implies$ the option value of being vacant for the landlord $(V_0(r^m)) \uparrow$

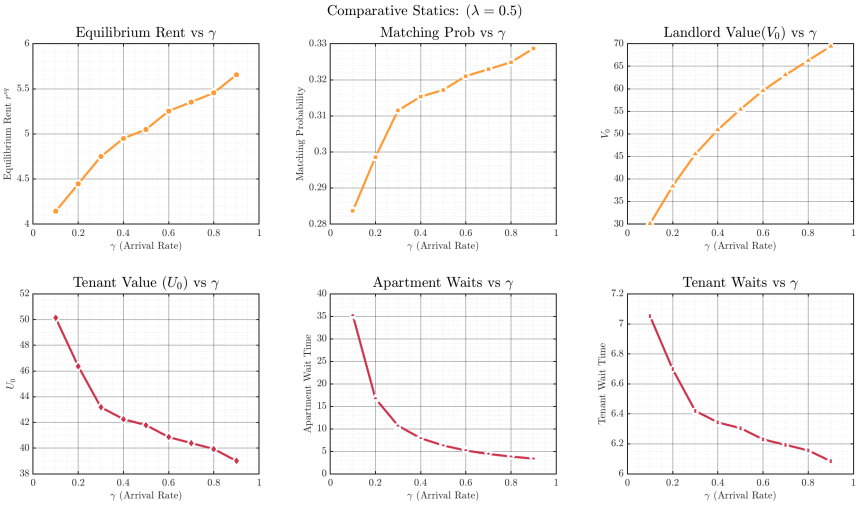
2. $\lambda \uparrow \implies$ the option value of searching for the prospect $(U_0(r^m)) \uparrow$

3. Suppose $e \sim U[0, 1]$:

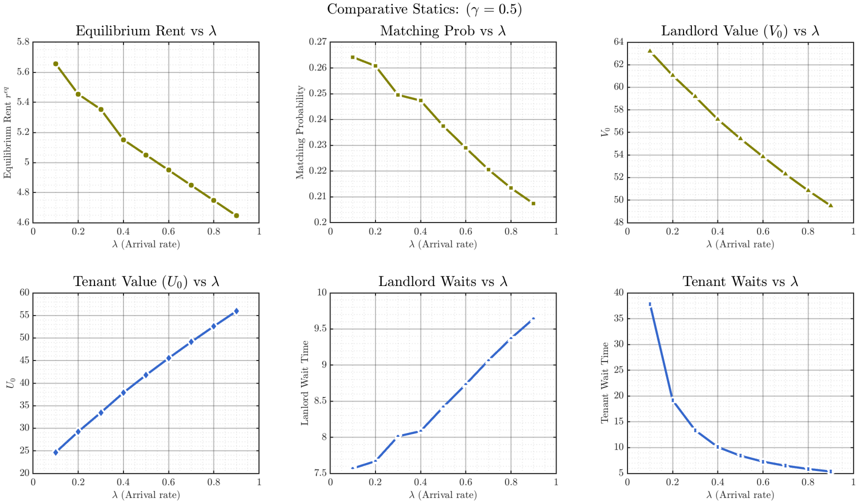
$$\tilde{r}(r^m) = \frac{1}{2} \left(1 - (1 - \beta) \left[U_0(r^m) - V_0(r^m)\right]\right)$$

▸ proof

γ (renter arrival) goes up



λ (apartment arrival) goes up



General Equilibrium

Endogenous meeting rates

- Cobb-Douglas matching function

$$\mathcal{M}(s, v) = \kappa s^{\alpha} v^{1-\alpha}$$

- Market tightness

$$\theta = \frac{s}{v}$$

- Matching probabilities

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

Stationarity

Normalize the measure of households to 1 and the measure of apartments to $H > 1$

- The measure of searchers evolves according to:

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

- In a stationary equilibrium:

$$s(\theta) = \frac{\delta}{\lambda + \delta - \lambda G(\bar{e}(r^m(\theta)))} \tag{5}$$

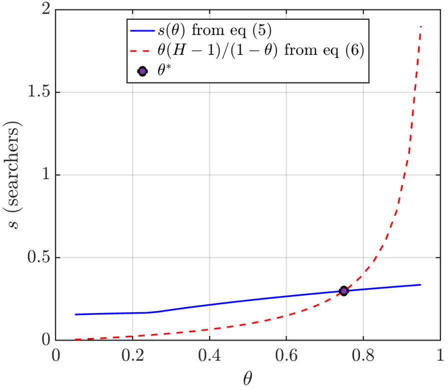
- One-to-one matching and market clearing implies that:

$$s(\theta) = \frac{(H-1)\theta}{1-\theta} \tag{6}$$

Equilibrium tightness

- The equilibrium tightness is characterized by:

$$\frac{(H-1)\theta}{1-\theta} = \frac{\delta}{\lambda + \delta - \lambda G(\bar{e}(r^m(\theta); r^m(\theta)))} \Rightarrow \theta_* \tag{7}$$



Stationary 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:

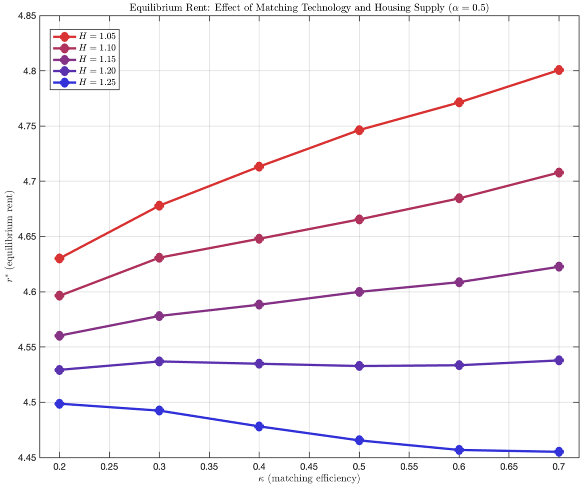
1. U_0, U_1, V_0, V_1 satisfy (1), (2), (3), (4).
2. $\tilde{r}$ solves the vacant landlord's problem given in (4).
3. (Consistency) r_*^m is a fixed point of the $\tilde{r}$ mapping: $\tilde{r}\left(r_*^m\right) = r_*^m$
4. (Stationarity) Market tightness θ_* satisfies (7)

Quantitative results

Parametrization

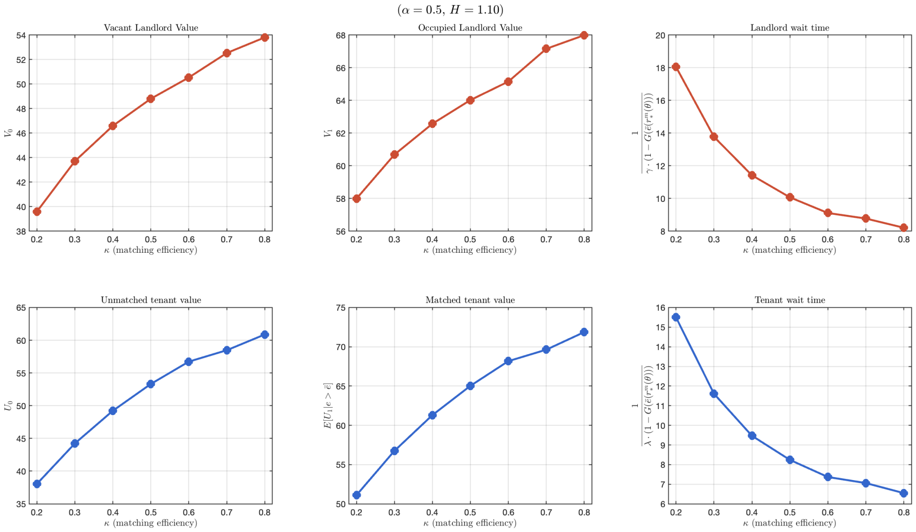
Parameter	Value	Description
e	$\mathcal{N}(5, 3^2)$	Prospect idiosyncratic value
h	1	Flow value for vacant landlord
b	1	Flow value for searcher
δ	0.1	Separation rate
β	0.95	Discount factor

Rents and Housing supply



▸ excessdemand ▸ elasticity

Values and Wait times

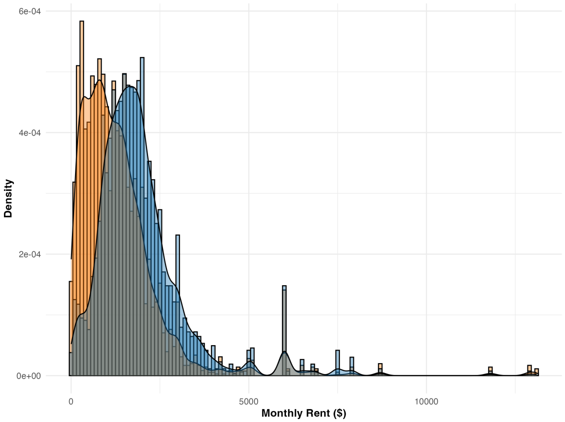


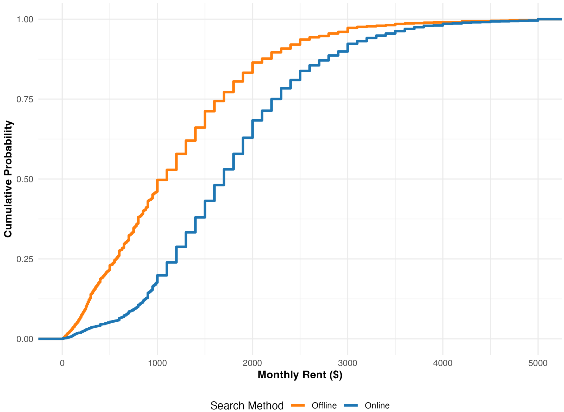
Summary

- In partial equilibrium
  - Improved tenant meeting ($\lambda \uparrow$) raises tenant outside option U_0 and lowers rents
  - Improved landlord meeting ($\gamma \uparrow$) raises landlord outside option V_0 and increases rents
  - Effects on wait times for both sides are ambiguous
- In general equilibrium
  - Direction and response of prices to higher matching efficieny ($\kappa \uparrow$) depend on housing supply
  - The value of waiting is higher for both sides of the market
  - Wait times are lower for both sides of the market

Preliminary empirics

Online vs offline apartments





▸ regression

Craigslist experiment

- Craigslist is a platform for users to post ads about jobs, housing, services, personals, etc.
- Craigslist rolled out in different cities at different times starting 1995
- This variation has been exploited in the empirical literature to explore various outcomes including:
  - job and rental vacancies (Kroft and Pope, 2014)
  - wages and migration (Balgova, 2024)
  - firm entry (Seamans and Zhu, 2013)

Our idea: Validate model prediction of stronger rent response to technology improvements in tighter housing markets by interacting Craigslist rollout with Saiz elasticities

Conclusion

- We develop a model illustrating the effect of declining search frictions on rents in the housing market
- We show that the price response depends on the relative housing supply
- Faster and better matching leads to overall higher welfare despite higher prices

Conclusion

- We develop a model illustrating the effect of declining search frictions on rents in the housing market
- We show that the price response depends on the relative housing supply
- Faster and better matching leads to overall higher welfare despite higher prices

Next steps

- Want to quantify how much of the increase in rental prices can be attributed to lower search frictions
- Preliminary empirics suggest that comparable apartments found online are $\sim$$200 more expensive
- Interact staggered roll-out of Craigslist with Saiz elasticities of housing supply

Thank you!

Path to Estimation

Estimation Strategy: Overview

- Goal: Estimate preference parameters (μ, σ) and matching function (κ, α)
- Challenge: These parameters are not directly observed
- Solution: Use individual search outcomes and market-level data
- **This is a simplified illustrative example**

What We Observe

- **Individual-level data:**
  - Rent paid r_i
  - Search duration: $Y_i = 1$ if searched > 1 month
- **Market-level data:**
  - Vacancy rate v
  - Housing supply H (apartments per household)
- **Fixed parameters:**
  - Discount factor $\beta = 0.95$
  - Separation rate $\delta = 0.10$

Simple Example: Single Market

- Consider one market with vacancy rate $v = 0.07$, housing supply $H = 1.05$
- From stationarity: $(H - 1) = v - s$ where s is searcher share
  - Implies: $s = v - (H - 1) = 0.02$
- From flow equilibrium: $\lambda \bar{a} = \frac{\delta(1-s)}{s}$
  - Product $\lambda \bar{a}$ is identified from market data
  - But λ (meeting rate) and $\bar{a}$ (acceptance rate) are separately unidentified

Identification via Search Duration

- Individual i matches with probability: $p_i = \lambda \times a_i$
- Where acceptance probability: $a_i = 1 - \Phi\left(\frac{e_i^* - \mu}{\sigma}\right)$
- Cutoff: $e_i^* = r_i + (1 - \beta)U_0$
- **Key insight:** How search duration varies with rent identifies (μ, σ)
  - Higher rent $\rightarrow$ higher cutoff $\rightarrow$ lower acceptance $\rightarrow$ longer search
  - The sensitivity reveals preference distribution

Maximum Likelihood Estimation

- For each individual i, compute:
  1. Cutoff: $e_i^*(r_i; \mu, \sigma)$
  2. Acceptance: $a_i(\mu, \sigma) = 1 - \Phi\left(\frac{e_i^* - \mu}{\sigma}\right)$
  3. Match probability: $p_i = \lambda \bar{a} \times \frac{a_i}{\bar{a}}$
  4. Long search probability: $q_i = (1 - p_i)^m$

- Likelihood: $\mathcal{L}(\mu, \sigma) = \prod_{i=1}^{N} q_i^{Y_i}(1 - q_i)^{1 - Y_i}$

- Maximize over (μ, σ) treating $\lambda \bar{a}$ as known from market data

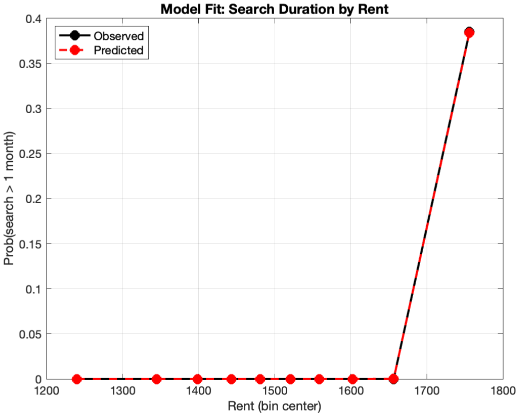
Simulation Results: Model Fit

True vs Estimated:

- μ: 1400 vs 1264
- σ: 200 vs 248
- Y_i: 3.85% vs 3.84%

Sample:

- $N = 2000$ renters



Observed vs predicted search duration by rent decile

Extensions to Multi-Market Estimation

- **Cross-metro variation** allows separate identification of λ from $\bar{a}$:
    - Different vacancy rates $\rightarrow$ different λ across metros
    - Preferences (μ, σ) constant across metros
- **Additional data** strengthen identification:
    - Number of apartment visits
    - Time-to-match distribution
- Estimate matching function (κ, α) and metro-specific housing supply H_m

Next Steps

- Implement full structural estimator with:
  - Multiple metros
  - Rich micro data (AHS, ACS)
  - Matching function parameters
- Counterfactuals:
  - Effect of Craigslist expansion on rents and welfare
  - Heterogeneous effects by housing supply elasticity
- **This simplified example demonstrates feasibility**

Appendix

Literature

- **Search Theory**
  - Stigler (1961); Burdett and Judd (1983); Varian (1980); Salop and Stiglitz (1977); Lester (2011); Martellini and Menzio (2020)
- **Online Markets & Platform Economics**
  - Ellison and Ellison (2018), Brown and Goolsbee (2002); Cavallo (2017); Brynjolfsson and Smith (2000); Ellison and Ellison (2009)
  - Calder-Wang (2021); Einav et al. (2016)
- **Housing Search**
  - Genesove and Han (2012); Han and Strange (2015); Piazzesi et al. (2020); Moszkowski and Stackman (2024)

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Proof of result 1

Using the envelope theorem,

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

For the sign to be positive, we need

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

which is true provided

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

which is true provided

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

i.e. the annuitized value of remaining vacant forever should be at most the optimal posted rent back

Proof of result 2

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

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

$$\frac{dU_0(r^m)}{d\lambda}(1-\beta(1-\lambda)) = \beta\lambda\frac{d\Phi}{d\lambda} + \beta\Phi - \beta U_0(r^m) \tag{8}$$

We calculate $\frac{d\Phi}{d\lambda} = \frac{dU_0(r^m)}{d\lambda}G(s(r^m;r^m,\lambda))$. Substituting into (8),

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

$\frac{dU_0(r^m)}{d\lambda} > 0$ 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, $\frac{ds(r;r^m)}{d\lambda} > 0$.

Proof of result 3

The landlord's first order condition for the rental offer yields,

$$\frac{1 - G(s(r; r^m))}{G'(s(r; r^m))} = r + \beta\delta V_0(r^m) - V_0(r^m)(1 - \beta(1 - \delta)) \tag{9}$$

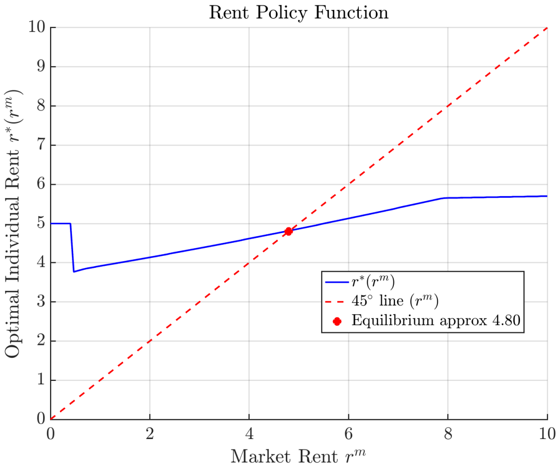
The tenant's indifference condition at the threshold yields,

$$s(r; r^m) = (1 - \beta)U_0(r^m) + r \tag{10}$$

Assuming G is uniform and combining the two,

$$\tilde{r}(r^m) = \frac{1}{2}\left(1 - (1 - \beta)\left[U_0(r^m) - V_0(r^m)\right]\right) \tag{11}$$

Landlord policy function



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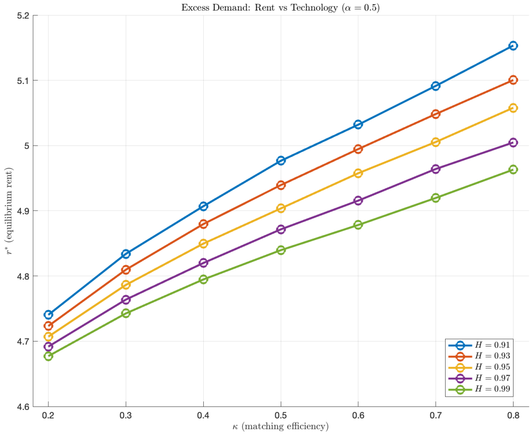
Housing supply H < 1



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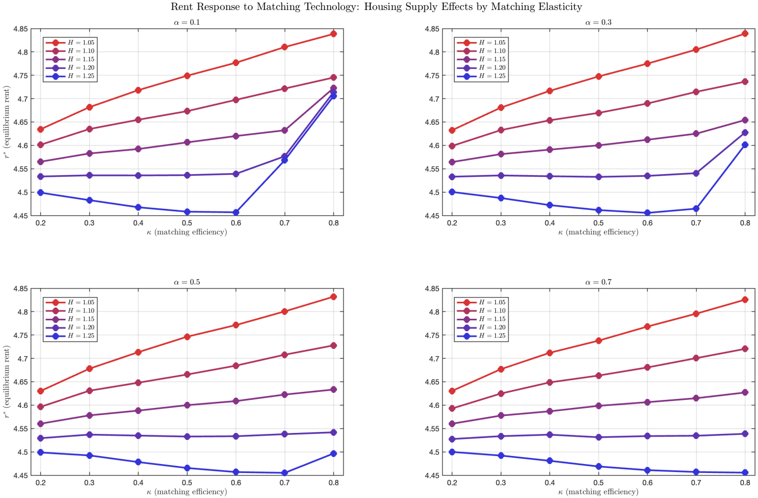
Varying matching function elasticities



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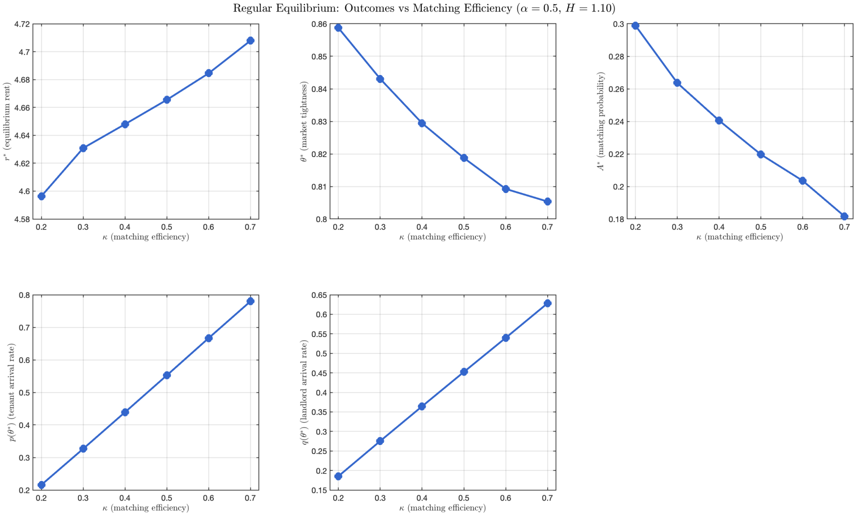
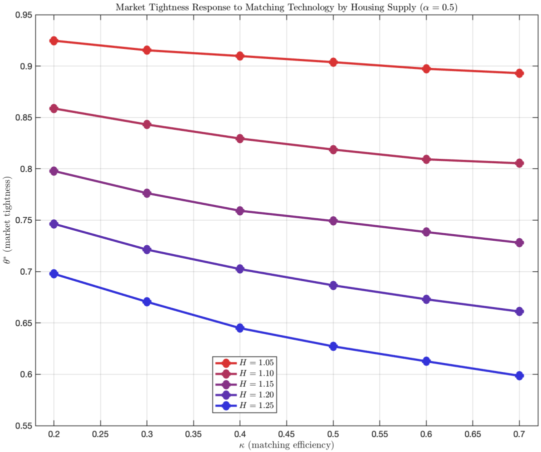
Matching probabilities and market tightness



Market tightness by housing supply



Rents are on average higher for apartments found online

Table

	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.

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