

# An Agent-Based Simulation of Rental Housing Markets

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## Abstract

We simulate a closed rental housing market with search and matching frictions, in which both landlord and tenant agents are imperfectly informed of the characteristics of the market. Landlords, who observe a random sample of market offered rents, decide what rent to post based on the expected effect of the rent on the time-on-the-market (TOM) required to find a tenant. Tenants are heterogeneous in income. Each tenant observes their idiosyncratic preference for a random offer and decides whether to accept the offer or continue searching, based on their imperfect knowledge of the offered rent distribution.

The steady state to which the simulation evolves shows price dispersion, nonzero search times and vacancies. We further assess the effects of increasing information on either side of the market. Tenants' information level has a positive effect on their welfare. Conversely, landlords are better off when they have less information. In that case they underestimate the TOM and so the steady-state of the market moves to higher rents. However, when landlords with different levels of information are present on the market, the better informed are consistently better off.

The model allows the analysis of the dynamics. It is observed that dynamic shocks to the discount rate can provoke overshoots in rent adjustments due in part to landlords use of outdated information in their rent posting decision.

# 1 Introduction

In the urban rental housing market two categories of agents meet. The first category consists of landlords who post rents. The second category consists of tenants who choose among offers. These markets are imperfect as can be seen by the existence of vacancies, price dispersion and nonzero search times for all agents. One source of imperfection is that both categories of agents are imperfectly informed about the characteristics of the market, and acquiring information is costly. Take for instance the tenants. Visiting more residences gives them more information but is costly and so tenants may accept an offer quickly to avoid further search costs. Moreover the market state (rents, apartments on the market etc) changes over time, making previously acquired information less useful or even misleading. Likewise, the landlords observe times-on-the-market required to find a tenant for a given rent but this observation does not give them perfect information about the preferences of the tenants and the state of the market.

These imperfections in comparison to the theoretical perfectly competitive market are referred to as frictions and more particularly as search frictions. The impact of frictions has been extensively studied in search-matching models of the labor market. A survey of search theoretic models of the labor market by Rogerson et al. (2005) presents the various approaches to modeling the main search related frictions: how agents meet and how wages are determined. Search models have been less systematically used in the existing housing market literature, although existing contributions provide a major understanding of several features of housing markets.

The first major contribution to the housing market literature based on this pre-existing labor market literature is that of Wheaton (1990). He created a model of the owner-occupier market in which buyers are also sellers and the cost of search effort and its efficiency are defined by an exogenous matching function. This model was later extended to a spatial rental market by Desgranges and Wasmer (2000) who studied notably a tax on vacancies. The 'thin' nature of the housing rental market due to the heterogeneity of housing and tenants' idiosyncratic tastes has been used to explain vacancies by Arnott (1989). The existence of vacancies is shown to have a social function as it expands the choice set of tenants. Further theoretical models of the housing market are discussed in Section 2.2. All of these static analytical models contain strong simplifying assumptions which ignore important aspects of the housing market. Among these assumptions are the 'law of one price', the absence of heterogeneities and perfect information on the state of the market. Certain of these assumptions are relaxed in the models mentioned above but never all together in a general equilibrium model.

The contribution of the present paper is to propose a multi-agent model as a basis for relaxing many of the assumptions of analytical models in order to obtain a more realistic dynamic model of housing markets. The evolution of rents is influenced by many factors including interest rates, conditions of credit, land supply and zoning, the economic environment, incomes, demographics etc. All of

these factors cannot be easily integrated into a single model. Here, we attempt to determine the generic effects that result from the fundamental market structure of heterogeneous agents searching with imperfect information. Our aim is to build a model close enough to the existing search literature for its results to be comparable, while allowing the extension of these existing models in different directions.

We develop a simulation model of a closed urban housing market focusing on the role of information. van der Vlist et al. (2002) proposed a general equilibrium search model of the housing market with rent-setting landlords who know the acceptance probability of any rent offer and with searching tenants who optimize their behaviors based on the trade-off between the expected benefit of searching and random rent offers. Our agents behave following the same rule. However, our model departs from van der Vlist's hypotheses in the first place by allowing the quantity of information available to landlords and tenants to vary. In particular, landlord agents do not know the acceptance probability of all tenants searching on the market. Following important results found in the literature (e.g. Clayton et al. (2008)), the rate at which information arrives affects the quality of landlord's estimation of the market state. The discrepancy in the results which ensues from these differences with the analytical models is highlighted. In particular, we examine changes in the steady state configuration due to alterations in the level of information available to agents. Our model also allows to model the dynamics following macroeconomic shocks such as an abrupt changes in the discount rate.

The major results concern the different influences of the level of information on both sides of the market. Increasing tenants' information benefits tenants by decreasing rents and hence increasing their welfare. It is however notable that this positive effect saturates at low levels of information. Landlords are penalized when they are better informed, as when they are less well-informed underestimations of the TOM move the market to higher rents which are accepted by the tenants. However, when landlords are heterogeneous in information, the better informed are better off. The role of information in the market's reaction to a shock in the discount rate is examined. 'Errors' in landlords initial reactions to changing market conditions resulting from their backward looking accumulation of market signals over time can be seen.

Section 2 presents related theoretical, empirical and simulation literature. In Section 3 the model is presented. The comparative static results are presented in Section 4 along with the results of simulations with an exogenous shock to the discount rate. A comparison of these results with the literature is discussed in Section 5. Section 6 concludes. The appendices present the comparative statics due to changes in tenant's information levels and also graphs from sensitivity tests with variations in the other model parameters.

## 2 Related literature

### 2.1 Empirical literature

We review here the empirical work on the main phenomena related to frictions in the housing market: agent's information, vacancies, time on the market and price setting, and price dispersion.

Blanck and Winnock (1953) made a major contribution to the understanding of vacancies' role in determining urban housing price dynamics. They showed that price dynamics appear to be led by changes in the vacancy rate. A more thorough analysis was performed by Rosen and Smith (1983) who provided evidence, in a cross city analysis, of the existence of natural vacancy rates that are crucial in determining the strong correlations between fluctuations in the vacancy rate and the evolution of rents. Numerous authors report similar results including Gabriel and Nothhaft (1988) in the rental housing market, Shilling et al. (1987), Grenadier (1995) in the office rental market and Hwang and Quigley (2006) in the purchasing housing market.

The role of information in the evolution of housing markets has received much attention. Fisher et al. (2003) studied the correlations in prices and liquidity changes over the housing market cycle. It is well known that when prices rise liquidity is high and when prices fall liquidity is low. They attributed this to the differing rates at which agents update their beliefs. For example, when liquidity is low, there are few market signals for sellers to follow, causing them to be slow to update their beliefs. Clayton et al. (2008) examined a number of possible explanations of the correlations in price and liquidity changes, and found evidence supporting sellers slow rate for updating their beliefs.

The price setting behavior and the relation between prices and selling times has been closely studied, primarily in the residential purchasing market. (Yavas and Yang, 1995, Knight, 2002, Anglin et al., 2003) have shown that in the selling market a house with a higher asking price generally takes longer to sell, particularly in thick markets. This has been confirmed in the rental market for single family housing by Allen et al. (2009). Merlo and Ortalo-Magne (2004) have also looked at posted price changes and found that when reductions in asking price occur, they are generally substantial rather than incremental. Cheng et al. (2009) review rents studies of the relationship between asking price and TOM in housing markets, they conclude that there is convincing evidence that a negative relationship exists.

### 2.2 Theoretical literature

As a benchmark to the analysis of housing markets, it is worth recalling briefly the two parallel paths followed in search-matching models of the labor market, which accounts for a large part of the search literature in economics. On one hand, models aimed at analyzing varying unemployment rates have focused on the matching function and search behaviors on the part of workers (Pissarides, 1990, Mortensen and Pissarides, 1994). On the other hand, models aiming to

explain the observed dispersion of wages have highlighted the behaviors of wage posting firms that benefit from the existence of frictions to offer wages below the Walrasian wage (Burdett and Mortensen, 1989, 1998, Mortensen, 1990). Mortensen (2000) builds a model merging the two approaches. He underlines the contribution of doing so: by allowing for a general equilibrium in which the wage distribution and the unemployment rate interact, this model allows the study of the welfare effect of a minimum wage or of an unemployment subsidy policy.

Literature on search on the housing market, although less systematically developed, followed two similar strands. Wheaton (1990) and Desgranges and Wasmer (2000) are interested in explaining the existence of vacancies and consider a matching function with a Nash bargaining on rents. Arnott (1989) proposed a rent-posting model with no search costs on the part of the tenants but with idiosyncratic tastes that give some monopoly power to the sellers. Read (1993, 1997) developed two search models of the rental market with rent-setting landlords. Both papers are partial equilibrium model with tenants engaged in non-sequential search. They provide insightful results regarding the role of imperfect information on rent dispersion and existence of vacancies. Read (1993) considers tenants with heterogeneous search intensities but identical exogenous reservation rents. In Read (1997), searchers all visit more than one housing but differ by their reservation rent. A distribution of rents arises as the outcome of landlords having some monopoly power due to imperfectly informed tenants. Vacancies are the consequence of the possibility of profit exhaustion through free entry of landlords. In these models, there is a strong asymmetry between tenants and landlords: whereas tenants base their acceptance on a limited number of offers, landlords compute their expected profit knowing perfectly tenants behavior.

van der Vlist et al. (2002) extend this analysis by considering a more general search model in which both landlords and tenants optimize their behavior taking the market state into account. Indeed, tenants receive rent offers that they trade-off against the benefit they have if they continue searching. However, the model does not account for heterogeneities in tastes, search costs or housing characteristics.

Due to their analytical resolution, these models are limited as to the heterogeneities that can be taken into account. More important, all of these models are static approaches of which only the steady-state can be analyzed, although dynamics are very important in real estate markets. As noted by Arnott (1989) *"It will be of interest to examine how the behavior of the market differs when it is either growing or contracting, or when it is subject to anticipated or unanticipated shocks and policy changes."* (Arnott, 1989, p. 23) One contribution in this direction is Cheng et al. (2009), who studies the effects of changing market conditions on sale prices and TOM in the presence of heterogeneously constrained sellers.

## 2.3 Simulation literature

The difficulty of studying out-of-equilibrium dynamics in analytical search models with price dispersion has been underlined by Postel-Vinay and Robin (2006). Agent-based modeling has considerable advantages over analytical approaches when modeling dynamic processes and heterogeneities among agents. In such models, the agents themselves, their behaviors and their possible interactions are defined initially and the simulation evolves independently in rounds of interactions. The results of the simulation are the sequence of decisions taken by agents and their outcome can be analyzed using standard empirical methods. Aspects of the model specification can be altered and the corresponding changes in the outcome analyzed. In this way, according to Bradburd et al. (2006) "...agent-based modeling permits formation of testable hypotheses about the likely impacts of comparable changes in actual markets or systems".

A notable and very detailed multi-agent model of the 1970's French labor market was constructed by Ballot (2002). As to the housing market, Bradburd et al. (2005, 2006) use agent-based simulations to relax the assumption of a single price with random matching and Nash bargaining in two rental housing models. These static models examine the distributional effects of rent controls (Bradburd et al., 2006) and 'access discrimination' (Bradburd et al., 2005), modeled as a reduced matching probability. Those analyses however do not model search behavior.

## 3 Model

In our rental housing search model, *homogeneous* landlords post rents and make take-it-or-leave-it offers to the tenants, who are *heterogeneous* in income. These landlords face a trade-off between setting a higher rent and finding a tenant more quickly. Their optimizing behavior is based on their knowledge of the market state, both in terms of rent offers and corresponding times-on-the-market. They withdraw from the market if their expected benefit from participation is negative.

Tenants are supposed to observe a sample of the offer distribution and to visit one randomly chosen residence each iteration. They accept offers based on an optimizing behavior that trade-offs a quicker match, and therefore reduced search costs, against a lower rent. Tenants must decide their reservation utility  $U_{res}$ , that is the minimum utility they are willing to accept from a residence. This reservation utility is chosen to determine whether a residence they have viewed is better in expectation than the outside opportunity, which is to continue searching with the associated costs. Each iteration, housed tenants have an exogenous probability  $1/X$  to leave their apartment and become searchers.

We see in the top part of Figure 1 the timing of the tenant agents' reservation utility decision and its consequences. At each iteration (time zero), every tenant agent decides their reservation utility  $U_{res}$ , which determines their search time  $T(U_{res})$  in expectation. While searching they experience a (negative) utility

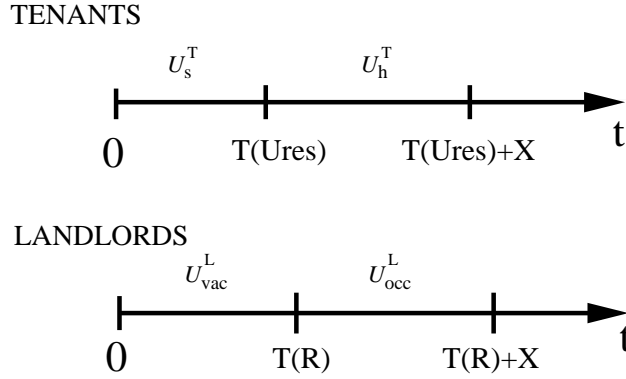


Figure 1: Tenants' and landlords' timing of decisions and their utilities. When landlords revise the rent of vacant residences the procedure is repeated.

flow  $U_s^T$ .  $U_{res}$ , by determining the acceptable offers, also determines in expectation their utility flow once housed  $U_h^T$ . The expected duration of residence of tenants  $X$  is an exogenous constant, and hence  $T(U_{res}) + X$  is the total time over which tenant agents optimize their expected utility; this is a reasonable approximation for the rental market, see de Una-Alvarez et al. (2008).

The bottom part of Figure 1 shows the timing of the landlords rent posting decision and its consequences. Landlords choose their posted rent  $R$  at time zero, which determines their expected time-on-the-market  $T(R)$  and clearly their utility flow once their residence is occupied. Landlords obtain the utility flow  $U_{vac}^L$  while their residence is vacant, and the utility flow  $U_{occ}^L$  once their residence is occupied. Note that if landlords review the posted rent of a vacant apartment, the moment of decision is taken once more to be time zero.

In the following, we outline more specifically the proposed agent behaviors, the simulation procedure as well as the dimensions of heterogeneity and the parameters whose influence on simulation outcomes shall be explored.

### 3.1 Tenants

We now describe in detail how tenant agents trade-off between, on one hand, minimizing the cost of searching and on the other hand, maximizing the eventual utility obtained from housing. Tenants decide their reservation utility  $U_{res}$  and obtain  $U_h$  from the market, after experiencing a negative utility  $U_s^T$  while searching.

Tenant agents' have a separable utility function whose housing part differs depending on their situation on the housing market. When housed, the agent's instantaneous utility flow from 'housing' is given by:

$$U_h^T = Y - R + \eta \geq 0 \tag{1}$$

where  $U_h^T$  is the instantaneous utility flow,  $Y$  is housing budget,  $R$  is the

rent paid and  $\eta$  is the idiosyncratic preference of an agent for an apartment, discovered by the agent once the apartment is visited.  $\eta \sim N(0, \sigma)$ , where  $\sigma$  is the variance of the normally distributed idiosyncratic preferences.  $\sigma$  is expressed as a percentage of the housing budget, as shown in Table 3.3.3 in Section 3.3.3. The introduction of stochastic idiosyncratic preferences adds an important element of heterogeneity to the model. A positive effect of including heterogeneities was remarked in Kirman (1992).<sup>1</sup>

While searching, the agent's instantaneous utility flow from 'housing' is given by:

$$U_s^T = Y - C_T < 0 \tag{2}$$

where  $C_T$  is the monetarised cost of searching, including both actual costs (temporary accommodation costs, transport costs, lost earnings and estate agency fees) and non-monetary inconveniences.<sup>2</sup> It is homogeneous across tenant agents.

Each tenant is fully described by his *housing budget*  $Y$ . In this simple model, this represents the maximum price she is willing to pay to rent an apartment (assuming neutral idiosyncratic preferences) and is a fixed percentage of income. It is uniformly distributed among fifty groups of tenants in the range [100,198].

Tenant agents have heterogeneous incomes which translate into heterogeneous housing budgets for the purpose of this model. Unhoused tenant agents search every iteration. A searching agent sees one randomly chosen apartment from the distribution of offers, which is referred to as undirected search in the search literature. Upon visiting an apartment, agents have to decide whether to accept it or keep searching. This will depend upon their idiosyncratic preference for the apartment, the posted rent, their housing budget and the cost of search. It also depends on their outside opportunity, that is the value they have while continuing searching, which they assess - imperfectly - based on their knowledge of a percentage  $S_T$  of the full distribution of offers.

$U_{res}$  is optimized to yield the maximum utility per unit time over the expected period of search and residence. Tenant agents idiosyncratic preferences are supposed not to play any role in this decision. The expected benefit per unit time for a given reservation utility is given by

$$B_T(U_{res}) = \frac{U_s^T}{X + T(U_{res})} \int_0^{T(U_{res})} \exp(rt) dt +$$

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<sup>1</sup>This is the result of heterogeneous agents changing their behaviours in different ways. If all agents are homogeneous then they shall adopt the same behaviours and abrupt system level changes will follow from any synchronised change in individual behaviour.

<sup>2</sup>Note that this negative utility can be interpreted as causing either reduced consumption of the composite good (all non-housing expenses) to cover temporary accommodation costs or that  $U_s^T$  represents a non-monetary disutility, or a combination of both.

$$\frac{E[U_h^T]}{X + T(U_{res})} \int_{T(U_{res})}^{T(U_{res})+X} \exp(rt) dt \quad (3)$$

where  $U_s^T$  is the utility flow experienced while searching,  $X$  is the expected duration of residence,  $T(U_{res})$  is the expected search time,  $r$  is the discount rate and  $E[U_h^T]$  is the expected utility flow per iteration once housed if the chosen reservation utility is  $U_{res}$ . Equation (3) is rewritten:

$$B_T(U_{res}) = \frac{U_s^T}{X + T(U_{res})} [1 - \exp(-rT(U_{res}))] + \frac{E[U_h^T]}{X + T(U_{res})} [\exp(-rT(U_{res})) * (1 - \exp(-rX))]. \quad (4)$$

The first line in Equations (3) & (4) are the total expected discounted search cost divided by the full expected duration of search and residency. The second line is the discounted total expected utility flow during residency divided by the full expected duration of search and residency. Equation (3) is similar to that used by Igarashi (1991) for the expected discounted housing costs of a searcher. This equation differs from it however, as here we take the expected benefit per unit time. Also, for the sake of simplicity, we do not explicitly include in the agents' optimization the discounted expected benefit upon re-entering the market after the tenant eventually leaves the residence. This choice does not impact the qualitative results of the model in a context where agents assume the market state to be constant.

The expected probability of accepting the residence visited in any given iteration is simply the number of residences the agent is prepared to accept divided by the total number of residences, both quantities being taken from the offers that the agent sees. As this is a Poisson process, the expected search time  $T(U_{res})$  in iterations is equal to the inverse of the probability of accepting a residence at each iteration. The expected utility flow per iteration once housed  $E[U_h^T]$ , is given by the average utility of residences which are expected to yield utilities larger than  $U_{res}$ :

$$E[U_h^T] = \frac{\sum U_h^T * \phi(U(U_{res}))}{\sum \phi(U(U_{res}))}, \quad (5)$$

where  $\phi(U(a)) = 1$  if  $U > a$  and  $\phi(U(a)) = 0$  if  $U \leq a$ . The sums are over all offers seen by the agent in this iteration. Idiosyncratic preferences for these housings are supposed not to be known by the agent.

Observe that the probability of accepting an apartment increases when the outside opportunity is less promising and that the accuracy of the appreciation of this option depends on the number of offers seen. Once a residence is rejected it cannot be revisited, unless it remains vacant and is randomly reselected.

All tenant agents participate in the housing market and searching tenant agents recalculate their reservation utility each iteration. When offered rents would improve their utility, but this utility is still negative, tenants cannot accept the housing. These tenants are considered as having a zero utility in the computation of the average tenant welfare.

### 3.2 Landlords

Landlords' have three possible states, having a tenant, on the market and off the market. The corresponding utilities are,  $U_{occ}^L = R - C_L$  the rent minus the maintenance cost,  $U_{vac}^L = -C_L$  the cost of a vacancy, and 0 their outside opportunity, that is the utility they can expect if they withdraw from the market.

Landlords' decision variable is what rent to post. In making this decision, they are assumed to trade-off speed of sale with rent procured. Landlords calculate their most advantageous rent, that is the rent that in expectation provides the highest benefit per iteration, given that contracts are for fixed rents and have an exogenous probability  $1/X$  of being terminated each iteration.

The function that gives this expected benefit is  $B_L(R)$  :

$$B_L(R) = \frac{-C_L}{X + T(R)} \int_0^{T(R)} e^{-rt} dt + \frac{R - C_L}{X + T(R)} \int_{T(R)}^{X+T(R)} e^{-rt} dt \quad (6)$$

where  $r$  is the discount rate,  $X$  is the exogenous expected time a tenant will stay in the apartment,  $C_L$  is the maintenance cost per iteration and  $T(R)$  is the expected time-on-the-market, whose calculation is described below.

Equation 6 is rewritten:

$$B_L(R) = \frac{-C_L}{X + T(R)} [1 - \exp(-rT(R))] + \frac{R - C_L}{X + T(R)} [\exp(-rT(R)) * (1 - \exp(-rX))]. \quad (7)$$

The first line in Equations (6) & (7) is the total expected discounted costs incurred while searching for a tenant, divided by the full expected time-on-the-market and residency duration. The second term is the total expected discounted utility flow during occupancy, divided by the full expected time-on-the-market and residency duration. Note that the overall time over which the profit is determined varies with  $T(R)$ . Average landlord welfare is the average utility over all landlords.

A landlord is fully described by their identical maintenance costs  $C_L$  (default value 100, see Table 3.3.3). The off-market cost associated with ownership is

normalized to zero<sup>3</sup> and hence a landlord is never willing to post a rent below  $C_L$ . Landlords may withdraw from the market if they do not expect to benefit from participation.

### Expected time on the market

Landlords can be assumed to be generally aware of the distribution of prices for similar rented accommodation and to have a somewhat vaguer idea of the time required to sell an apartment, as this is harder to observe. In their trade-off between TOM and expected rent flows, landlords need information on the relationship between both of these elements. Landlords are assumed to have access to information on a certain percentage of residences on the market over the last  $F$  iterations. Concretely, they know for these residences for how many iterations they were on the market at their most recent market price, within the last  $F$  iterations. They also know whether or not they have been rented, as shown in Figure 2.

The above procedure generates two histograms, one of the cumulative times on the market within each rent interval (of size  $R_I$ , see Table 3.3.3) and another of the number of sales within each interval. This allows landlords to calculate the probability per iteration of finding a tenant for a range of price intervals, making the implicit assumption that the probability to sell was constant over the last  $F$  iterations. This probability is simply the number of agreed rents divided by the cumulative times on the market. A constant hazard is assumed, which means that the landlords assume an exponential probability distribution for the time-on-the-market for a constant rent, see Kiefer (1988).

The landlords calculate the expected TOM within each rent interval from the data and estimate the best least-squares fit of the exponential function for the expected TOM  $T(R)$  as a function of the rent  $R$ ,<sup>4</sup>

$$T(R) = \alpha \exp(\beta R) \tag{8}$$

where  $\alpha$  and  $\beta$  are fit parameters.

In the simulations, to avoid errors by landlords that would lengthen search times for tenant agents, the chosen rent cannot be more than  $I_{max}\%$  above the highest accepted rent seen. The percentage of rent increases equal to the maximum allowed is near 2% for the default value of  $I_{max} = 10$ , see Figure 20-*Right* in Appendix A.

Furthermore, in order for landlords to always have enough information to perceive the basic relation between time-on-the-market and posted rents, a minimum number of recent sales in memory is imposed and its default value set to 100.

<sup>3</sup>This is equivalent to assuming that the expected utility flow in another activity, or ‘outside opportunity’ is equal to zero.

<sup>4</sup>Each point  $T(R) = \omega$  is given a weight equal to the natural logarithm of the number of rentals  $N(R)$  in the rent interval centered on  $R$ , plus one, that is  $weight = \ln(N(R) + 1)$ . This weighting as opposed to a linear weighting gives greater importance to rarer information (higher agreed rents) and hence leads to a reduction in posted rents.

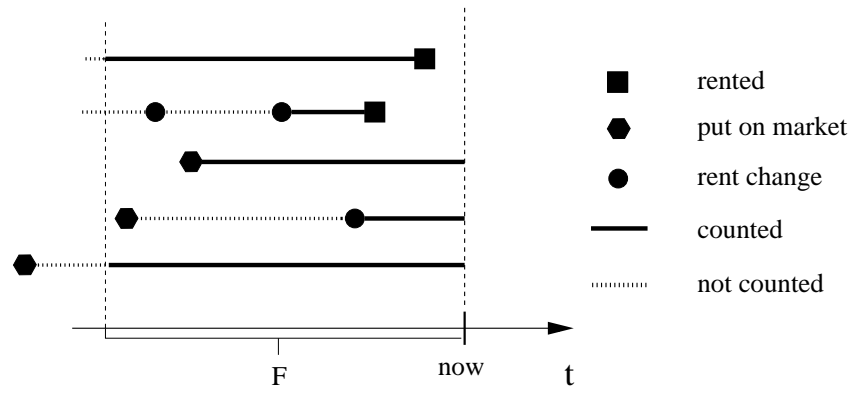


Figure 2: The periods of time-on-the-market known to landlords.

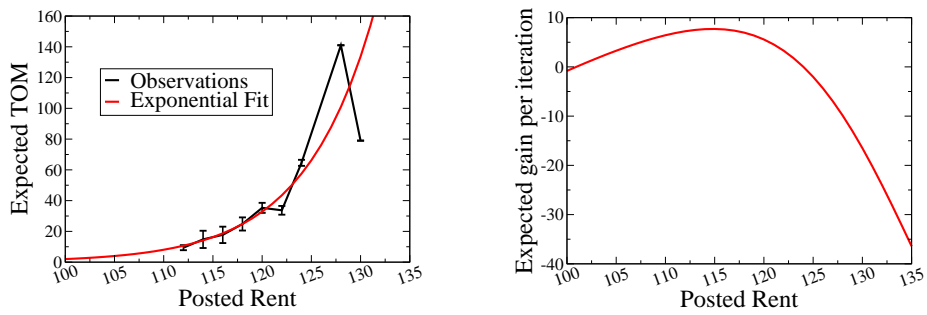


Figure 3: *Left*: Example of an estimated relation (red line) between asking rent and TOM per rental. The size of the ‘error bars’ is the statistical weight given to each point in the least-squares fit of the exponential. *Right*: The corresponding expected profits.

To sum up, landlords require a two dimensional information in order to trade-off TOM against expected rent. For this information to be useable in their decision making, it is summarized by means of a statistical fit. We believe that it is an elegant way to simulate the trade-off between speed of sale and rent procured made by real landlords who have imperfect information on the market.

### Rent revision

When a residence remains on the market at the end of an iteration, landlords review their chosen rent with probability  $1/F$ .<sup>5</sup> They repeat the procedure described above and choose the rent that they believe will bring the maximum profit.

### Withdrawing and returning to the market

If the expected profit estimated for a residence is negative, the residence is withdrawn from the market. Landlords who have withdrawn residences from the market review the market situation with probability  $1/F$  every iteration, and return to the market if the expected profit is positive.

## 3.3 Simulation procedure

### 3.3.1 Main phase

After an initialization phase described in the next section, our model repeats the following steps until a steady state is reached:

- Searchers visit a randomly chosen apartment, and accept or reject it.
- A portion of landlords ( $1/F$ ) whose apartments remain vacant decide if they shall change their rent or withdraw from the market.
- A portion of landlords ( $1/F$ ) who have withdrawn from the market decide if they shall return.
- A certain fraction ( $1/X$ ) of tenants, randomly chosen, leave.
- Landlords of newly empty apartments choose their asking rents.
- The next iteration begins.

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<sup>5</sup>In order to keep the number of parameters in the model as small as possible, we choose here the same parameter as for the number of sale times seen by landlords. This means that landlords change their decisions on average every  $F$  iterations, which is the same time over which they consider information on the market state to remain relevant.

Table 1: Parameters of the Model

Symbol	Meaning	Default Value of Parameters
<u>Landlords' parameters</u>		
$S_L$	% of sales seen	20%
$F$	Timescale rent changes (and memory) (iterations)	15
$I_{max}$	Maximum rent increase	10%
$C_L$	Maintenance cost	100
<u>Tenants' parameters</u>		
$X$	Expected length of residence (iterations)	240
$\sigma$	Idiosyncrasy of tenants preferences (% $Y$ )	5
$S_T$	Percentage of offers seen	5%
$C_T$	Search costs	200
$Y$	Housing budget	[100-198]
<u>General parameters</u>		
$r$	Discount rate (default 3% annual rate)	0.0005
$size$	Town size	10000
$Z$	Number of initializing iterations	10
$R_I$	Estimation rent interval size	2

### 3.3.2 Initialization

In order that landlords have some information on the market so that they can set rents, we use the following initialization procedure. Ten thousand landlords and tenants are created. The landlords all have an occupancy maintenance cost  $C_L$  of 100 and an initial asking rent randomly chosen in the interval 100-120. The tenant agents have a uniform distribution of housing budgets between 100 and 198 in 50 discrete groups.

Over the first  $Z$  iterations, tenant agents see five apartments and select the lowest asking rent if it offers the agent a positive utility. This preference for lower rent residences initializes the market in such a way that the information available to landlords indicates that higher rents mean longer waiting times. Landlords do not review their rents during the initialization phase. After the  $Z$  initialization iterations are complete, the mechanism described in Section 3.3 is implemented, in which searchers see only one residence per iteration.

### 3.3.3 Parameters

In Table 3.3.3 the parameters of the model are listed, along with their default values. These values are used in all simulations presented, unless stated otherwise. The parameters listed in Table 3.3.3 along with the distribution of the housing budgets of tenants defines a simulation run.

The default value of  $X$ , the expected length of residence, which can reasonably be assumed as being of the order of 4 years (see de Una-Alvarez et al. (2008)), means that five iterations corresponds to one month and hence 60 iterations represents a year. Hence landlords' knowledge of recent rentals,  $F$ , stretches three months into the past and they change their rent in expectation every three months. The default discount rate is equivalent to an annual rate of 3%. It should be noted that these are simply default values. The effects of varying the parameters on the steady state configuration are discussed below and in the Appendix.

## 4 Results

### 4.1 Base Case

We present simulation results for a 'city' with an inelastic supply of ten thousand apartments owned by ten thousand different landlords and ten thousand tenant agents wishing to be accommodated. All the parameters values are the default values presented in Table 3.3.3.

As can be seen in Figure 4-*Left*, the basic model converges for any initialization to a reasonable steady-state with a positive vacancy rate, rent dispersion and nonzero search times. The vacancy rate is about 15%, and the percentage of landlords who have withdrawn from the market is negligible. The number of unhoused tenants is equal to the difference between the 'Population', shown in figures throughout this section, and the total number of tenant agents, which is ten thousand. The number of landlords searching for tenants is equal to the difference between the 'Population' plus the number of landlords 'Off the market' and the total number of landlords, which is again ten thousand.

The dispersion in both accepted and posted rents can be seen in Figure 5-*Left*. The curves are the cumulated distributions of rents set and accepted over 15 iterations. In Figure 5-*Right* we can see that, as expected, lower rents are more likely to be accepted. Figure 5-*Left* shows that most landlords offer rents close to the 'going rate'. The few who ask higher rents are less likely to find tenants. As in existing analytical models, the heterogeneity of tenants' incomes and the presence of market frictions (undirected search with a unitary arrival rate of offers) contribute to the dispersion of rents. Additional factors contributing to the dispersion of prices are the idiosyncratic preferences of tenants and stochastic information effects: agents observe different samples of market signals and therefore take different decisions. This is particularly true for low levels of information and for landlords, as will be discussed in Section 4.3.1.

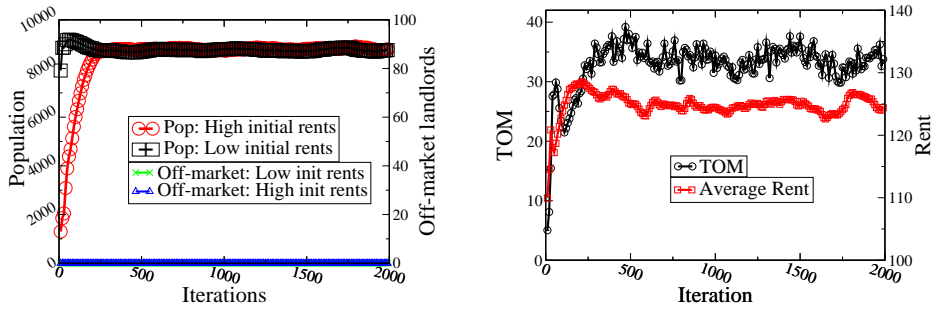


Figure 4: *Left*: The steady state population and number of landlords off-the-market. The ‘Pop : high initial rents’ curve is from an initialization following the procedure in Section 3.3.2 with initial rents distributed between 180 and 200. The ‘Pop : low initial rents’ curve corresponds to a standard initialization as described in Section 3.3.2. *Right*: The average TOM of residences accepted over the last 15 iterations and their average rent for a standard initialization.

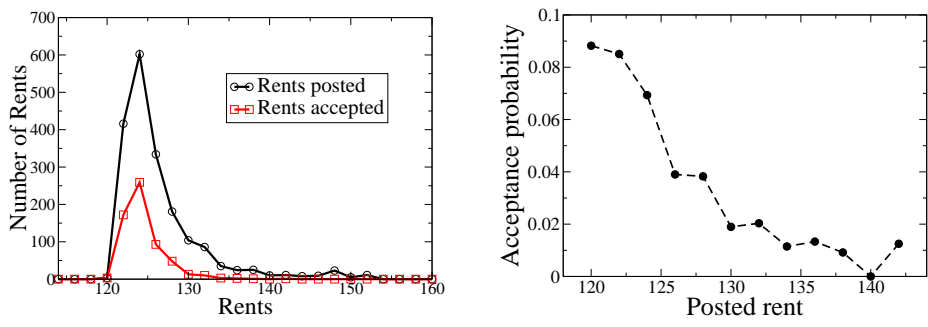


Figure 5: *Left*: Rents posted and accepted in last 15 iterations at the steady state, after 2000 iterations. *Right*: The probability of renting each iteration as a function of posted rent. There is some ‘noise’ at the higher rents due to the small number of rentals.

The maximum offered rent by landlords is lower than the maximum reservation rent; it is below 150 in Figure 5-*Left*. Landlords find that for higher rents it takes longer to find a tenant (because those tenants with low incomes can no longer afford it, and wealthier tenants prefer cheaper accommodation) and so offer relatively low rents. The lower bound of offered rent in our results is greater than the lowest of the tenants' housing budgets: although landlords might get profit with any rent strictly above 100, the minimum offered rent in our simulation is above 110 and the lowest income tenants are homeless. This is in part due to high search costs  $C_L$  (equal to 100) compared to the expected benefit of having a residence on the market with a low posted rent. The expected duration of residence is long compared to search times and hence search costs. For the lowest rents, the gains from minor reductions in search times are less than the loss from lower rents over the entire residence duration.

Note that at constant population, rent changes are predominately transfers in surplus between tenants and landlords. The major factors in changing the total welfare are changes in population or the withdrawal of landlords from the market.

## 4.2 Tenants' Information Level

The percentage of offers seen by each tenant  $S_T$  is varied between 5 and 100%. The results show that the population is not greatly affected above a low threshold by alterations in the percentage of offers seen by tenants (Figure 6-*Left*). The effects at low levels of information can be seen in Figures 6 & 7-*Left*. The percentage of offers seen by tenants ceases to alter the steady state configuration above a threshold value which can be seen to be approximately 0.5% or 5 observations from Figure 7-*Right*. It appears that a relatively low level of information gives an accurate impression of the market state to tenants. This is, in part at least, due to the range of the real distribution of offers being narrow. Moreover the fact that searchers renew their information every iteration excludes any persistence of erroneous perceptions.

Search times of the majority of tenants, with the default level of information  $S_T = 5\%$ , are of the order of 3 or 4 iterations, as can be seen in Figure 7-*Right*. When tenants are very badly informed, they are likely to choose a reservation utility equal to the best offer seen, which lengthens the TOM. This is because they expect the additional waiting costs to be very low in comparison to the expected gain in terms of future rents. We see in comparing Figures 6 & 7-*Left* with Figure 7-*Right* that once the expected search times of tenants cease to follow the increase in the number of offers seen, the effect of increasing tenants' information is negligible.

Note finally that increasing tenants' information from very low levels improves their welfare as they are more likely to refuse higher rents.

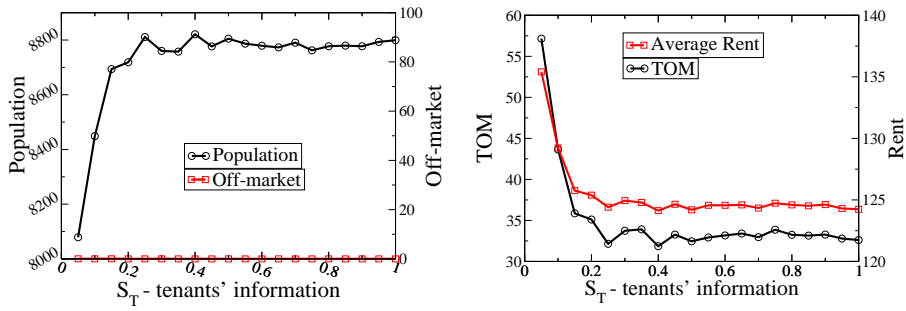


Figure 6: *Left*: The variations in population and the number of landlords off-the-market as a function of the percentage of offers seen by tenants. *Right*: The average rent and the average TOM.

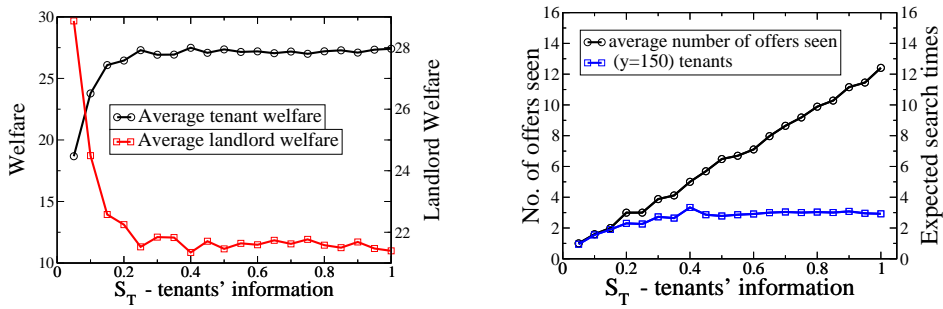


Figure 7: *Left*: The average welfares of tenant and landlord agents are shown as a function of the percentage of offers seen by tenants. *Right*: The number of residences seen by tenant agents with respect to the percentage of the distribution that they see, and the expected search times of ‘middle income’ tenants.

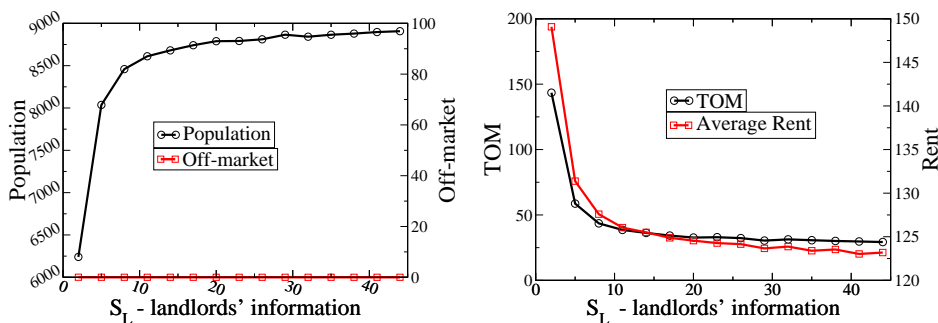


Figure 8: *Left*: The variations in population and the number of landlords off-the-market as a function of landlords' information. *Right*: The average rent and the average time-on-the-market (TOM).

### 4.3 Landlords' Information Levels

Landlords must choose their posted rent. This decision is based on their maintenance costs but also on their information on the state of the market. Information is a critical variable in search markets and is costly to obtain. This is why we now examine the effect of the amount of information available to landlords on the market outcome. This is done by varying the percentage of times-on-the-market of recent rentals and of vacant residences seen by landlords  $S_L$ .

#### 4.3.1 Homogeneous Landlords

Increasing landlords' information decreases rents, Figure 8-*Right*. Landlords' welfare falls, Figure 9-*Left*, and the population increases, as shown in Figure 8-*Left*. Figure 9-*Right* shows that the variance in posted and accepted rents decreases as landlords see larger (and hence more similar) information samples. These results highlight the crucial role of landlords' information.

In order to decide their asking rent, landlords need accurate two dimensional information, that is rents offered and their associated times-on-the-market. Landlords' information on TOM for different rents is based on a finite sample accumulated over  $F$  iterations. The TOM of many residences in each rent interval are required for accurate estimates of the rent/TOM relationship using the smoothing procedure (an exponential fit). Indeed for these reasons, their information is not perfect even with  $S_L = 100\%$ .<sup>6</sup> Furthermore, in a dynamic market this information may be outdated.

The over-estimations of the optimal rent of less informed landlords, shown in Figure 10, result from their underestimation of TOM. Ill-informed landlords

<sup>6</sup>Indeed increasing landlord's memory  $F$  has an effect similar to that of increasing  $S_L$  at steady-state, but  $F$  plays an important role in dynamic adjustment that is unrelated to  $S_L$ . The parameter *size* also has a role similar to that of  $S_L$  as the level of information available to agents depends directly on the size of the city, see Section A.

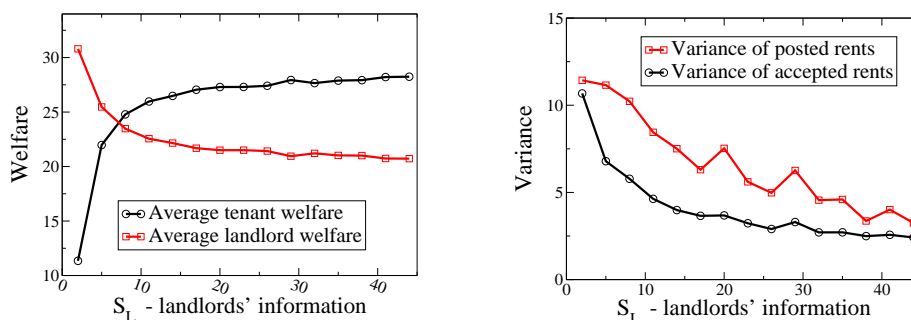


Figure 9: *Left*: The average welfares of tenant and landlord agents are shown for variations in the level of landlord’s information. *Right*: The average variance of the distributions of posted and accepted rents over 1000 iterations, after convergence to a steady state.

are less likely to see the long waiting times (TOM) for very high rents which are rarely accepted. This leads to higher asking rents. As the landlords are homogeneous, and make the same errors on average, this pushes the market rents upwards. Every high posted rent, if refused by tenants, increases their expected search times as tenants’ search is undirected. This necessarily affects searchers’ optimal reservation utilities, pushing the market towards higher rents. In contrast, increasing landlords’ information makes them sharper competitors, leading to reduced rents.

### 4.3.2 Heterogeneous Landlords

In order to further test the effect of landlords’ information on the steady-state of the market we perform simulations with landlords who are heterogeneous in information. There are two types of landlord, those with the default level of information  $S_L = 20$  and those with  $S_L = 5$ , values that were chosen because Figure 9 shows that the steady state changes significantly between these two values when they are shared by all landlords.

Figure 11-*Right* shows the increases in average rents and times-on-the-market with the proportion of ill-informed landlords. This is because, as described in Section 4.3.1, errors made by ill-informed landlords tend to lead to higher asking rents. This changes the distribution seen by tenants who have no option but to lower their reservation utilities. As a consequence, well-informed landlords react to the reduced TOM by increasing their offers. Figure 11-*Left* shows that consequently the population falls as more landlords are ill-informed. Overall the welfare reduces because higher rents reduce the population, Figure 12-*Right*.

In Figure 12-*Left* we see that, following the rent increase, the welfare of both types of landlords increases as the proportion of ill-informed landlords rises. However, the better informed always have higher welfares. This results from their more accurate appreciation of the state of the market, see Figure

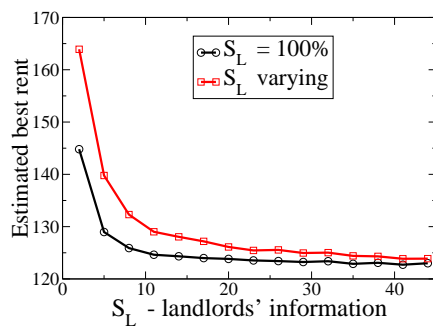


Figure 10: The average estimated best rent, over 1000 iterations after convergence to a steady-state, in simulations in which  $S_L$  for all agents has the value on the x-axis. The average best rent for an agent searching on the same market but seeing 100% of available information is also shown.

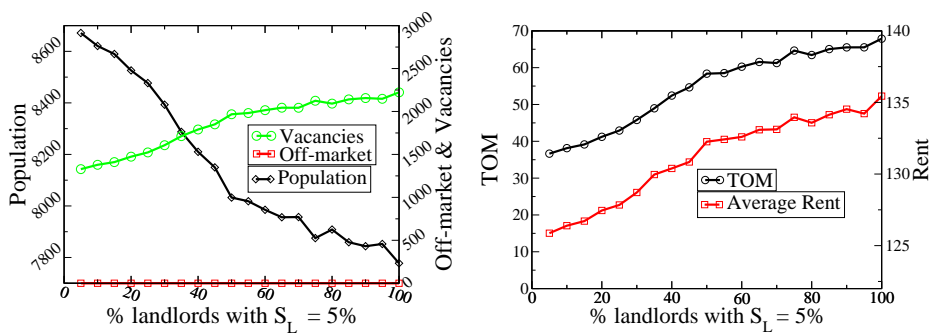


Figure 11: *Left*: The variations in population and the number of landlords off-the-market as a function of the percentage of landlords who see 5% of the available information while all other landlords see 20%. *Right*: The corresponding average rent and the average time-on-the-market (TOM).

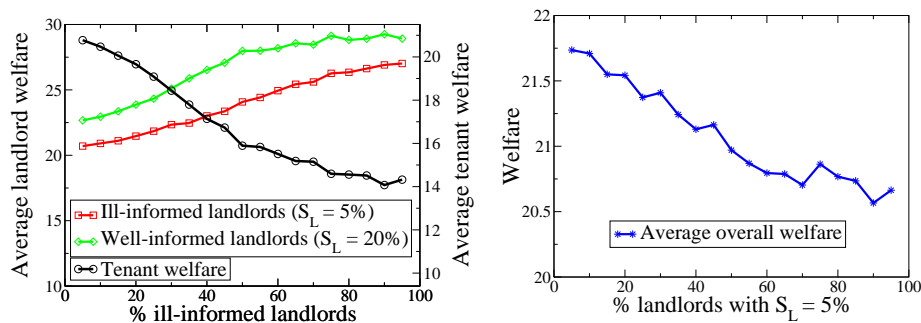


Figure 12: *Left*: The average welfares of tenants and both types of landlord as a function of the percentage of landlords who see 5% of the available information while all other landlords see 20%. *Right*: The corresponding average total welfare.

12-*Left*. In summary, there are positive externalities (or, more precisely, market effects) of ill-informed on well-informed landlords, the former moving the market rent upwards.

## 4.4 Dynamically varying the discount rate

### 4.4.1 Discount rate

The discount rate incorporates the value of time, represented by the real interest rate.<sup>7</sup> The discount rate was varied from less than 1% per annum to over 17% per annum. Increasing the discount rate means an increase in the impatience of all agents. That is, at constant rents and TOM, for both categories of agent the value of a match increases with respect to the value of continuing to search. More specifically, changing the discount rate alters all four terms in the right-hand sides of Equations 3 & 6.

There ensues two contradictory effects: Landlords have a tendency to post lower rents, while tenants are willing to accept higher rents, conditionally on their income. It is not obvious which of these effects should dominate. In general, one may anticipate that the effects of changes in the discount rate depend on the relative influence of tenants and landlords in the market. As landlords post prices which cannot be negotiated, while tenants decide whether or not to accept the offer received, we can expect landlords' decisions to lead the market.

Figures 13 show that for the default values of the other parameters, the average rent is lower with a higher discount rate. This shows that changes in landlords' behaviour, due to a change in discount rate, have a greater impact on market outcomes than the corresponding changes in tenants' behavior. In-

<sup>7</sup>Note that for our agents only the current discount rate plays a role in their decision. See Liu and Mei (1994) for a discussion of risk and time-varying expected discount rates.

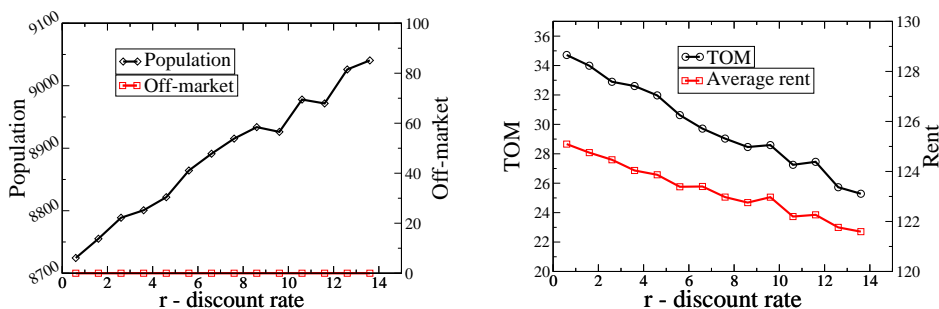


Figure 13: *Left*: The variations in population and the number of landlords off the market. *Right*: The average rent and the average time-on-the-market for residences rented over the last 15 iterations. Both graphs for a variation in the annual discount rate of both agent types.

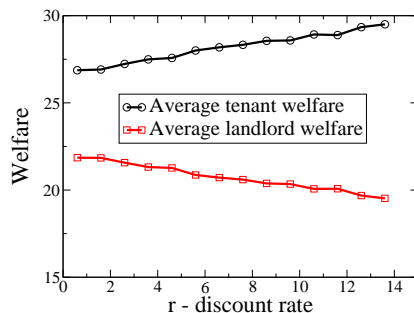


Figure 14: The average welfares of tenant and landlord agents are shown for variations in the annual discount rate.

creases in the discount rate also lead to a reduction in TOM and an increase in population. Therefore, the average welfare of tenants is improved and that of landlords dis-improved with increasing discount rates, as can be seen in Figure 14.<sup>8</sup>

#### 4.4.2 Discount rate shock

The role of information in the context of a dynamic evolution of real estate markets is an important subject that has already been analyzed empirically by Fisher et al. (2003), Clayton et al. (2008). In order to examine this question we introduce exogenous shocks to the discount rate. Two aspects of information play an important role in the decisions of landlords: Firstly the proportion of

<sup>8</sup>Simulations with high landlord market power ( $\sigma = 2\%$ ,  $S_L = 5\%$  and  $S_T = 0.5\%$ ), show that tenants welfare can dis-improve with a rising discount rate but that landlords are always worse off as the discount rate increases.

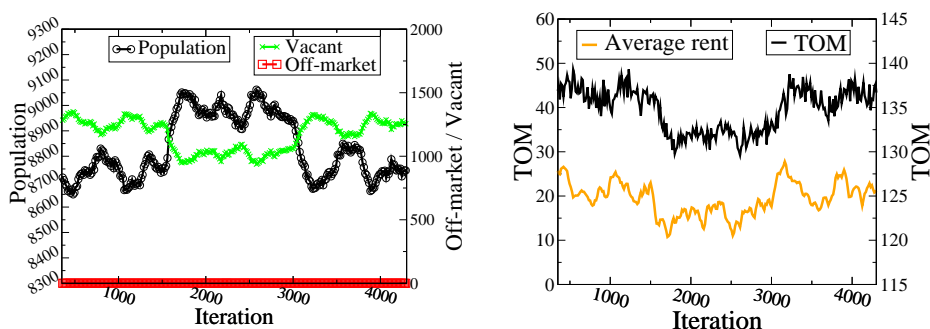


Figure 15: *Left*: The variations in population, vacancies and the number of landlords off the market, with the varying discount rate  $r$  shown *Right*. *Right*: The exogenous variation of the discount rate and the corresponding average TOM.

available information seen and secondly the length of their memory. At the steady state, these two parameters have an equivalent role: both increase the quantity (and therefore quality) of information. However, in an evolving market, the length of memory becomes a two-edged sword. It increases the quantity of information but much of this information may be out-of-date.

The discount rate was varied from 2% to 10% at 1500 iterations and reduced again to 2% at 3000 iterations. The adjustments in the rent and the TOM due to the changes in the discount rate can be seen in Figure 15-*Right*. As expected from the comparative statics shown in the previous subsection, both the average rent and TOM reduce after the increase in the discount rate. This causes an increase in population due to the larger number of tenants who can afford housing (see Figure 15-*Left*). Opposing adjustments occur when the discount rate comes back to its previous value. This gives us the opportunity of exploring the dynamics of the market in situations of both rising prices and falling prices.

All landlords who review their rent after the increase at 1500 iterations immediately account for the change in the discount rate and therefore post lower rents. Their beliefs on the state of the market evolve more slowly due to their memory of past transactions. Therefore, as tenants' reactions to the new situation are not taken into account immediately, accepted rents reduce abruptly, see Figure 16-*Left*.

However, the average TOM of agreed rents reduces considerably more slowly. Tenants change immediately their reservation utility in reaction to the flow of new low rents. Therefore the average individual acceptance probability reduces due to newly increased value of waiting for these particularly low rents. This hinders the decrease in TOM that would otherwise result from the greater number of tenant agents who can afford housing. Once the rent distribution stabilizes, that is the newly posted rents cease to be cheaper than those on the market,

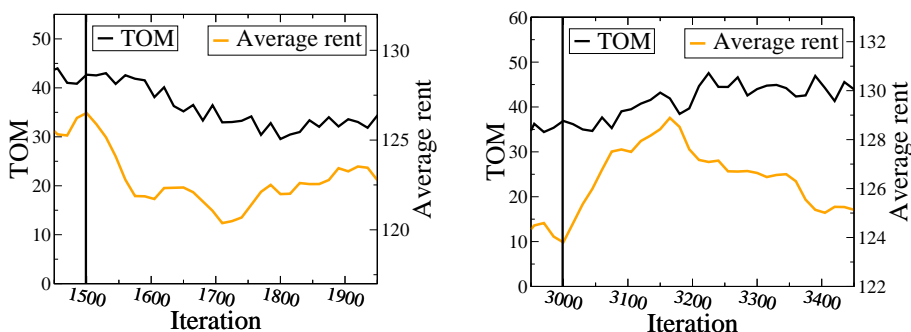


Figure 16: *Left*: The variations in TOM and average rents, around the transition of the discount rate from  $r = 2\%$  to  $r = 10\%$  at 1000 iterations. *Right*: The variations in TOM and average rents, around the transition of the discount rate from  $r = 10\%$  to  $r = 2\%$  at 2000 iterations.

average individual acceptance probabilities increase. We observe in Figure 16-*Left* that just before the average TOM reaches its new steady-state value the rent is at its lowest level. Coupled with the greater number of tenant agents who can now afford housing, this causes the volume and population to rise until the new steady-state is reached. Figure 17-*Left* shows that the population rises by approximately 250 in 200 iterations, equivalent to about  $2\frac{1}{2}$  years. As the number of departures is a constant fraction of the population, at the steady-state the volume of transactions is directly related to the population. While the population is rising the volume of transactions is greater than at a steady-state with the same population. Once the rents have ceased to reduce the volume of transactions increases for a short period, around 1570 iterations, as seen by the sharp rise in the population in Figure Figure 17-*Left*. In fact the volume of transactions increases by over 15% temporarily before lowering to its steady state value that, like the new population, is approximately 3% above its previous steady-state value. The higher volume of transactions in conjunction with a smaller number of vacancies at the new steady-state keep TOM low.<sup>9</sup> Changes in the ratio of transaction volumes to vacancies are an essential element that differentiate ‘hot’ and ‘cold’ markets.

After the reduction in the discount rate at 3000 iterations opposite adjustments are seen: an increase in average rent, TOM and the vacancy rate with a decrease in population. A decrease in volume follows from the falling population seen in Figure 17-*Right*. The rent increases immediately as landlords are instantly informed of the reduction in the discount rate, see Figure 16-*Right*. What’s new here is first that the population falls immediately with the increase

<sup>9</sup>The average TOM for landlords is proportional to the number of vacancies divided by the volume of transactions in an iteration. Here, the change in TOM is primarily due to the change in the number of vacancies, which changes by around 20% rather than to the 3% change in volume.

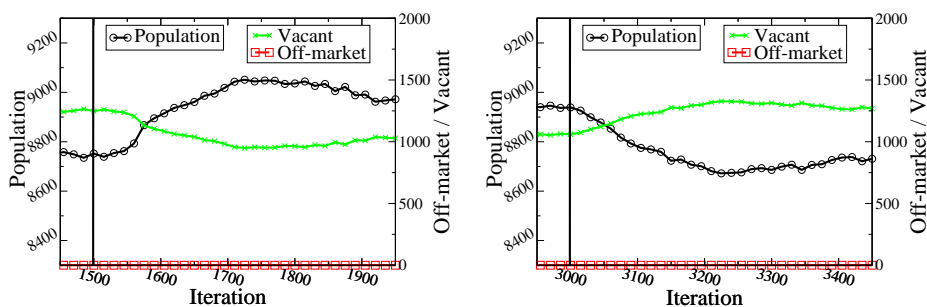


Figure 17: *Left*: The variations in population, vacancies and the number of landlords off the market, around the transition of the discount rate from  $r = 2\%$  to  $r = 10\%$  at 1000 iterations. *Right*: The variations in population, vacancies and the number of landlords off the market, around the transition of the discount rate from  $r = 10\%$  to  $r = 2\%$  at 2000 iterations.

in rent as poorer tenants have a hard income constraint, see Figure 17-*Right*.

Secondly, there is a marked overshoot in rents, see Figure 16-*Right*. This can be attributed to the fact that the eventual negative effects of asking excessive rents take time to be understood by landlords. This is due to both the low frequency of acceptance of high rents, which means that they are often unobserved by individual landlords, and secondarily the relatively long time required for these durations to happen.

## 5 Discussion of results

We know that a perfectly competitive market should have rents offered at landlords' maintenance costs (Bertrand price competition): in a situation where every tenant would be able to choose the best offer among several, any landlord making an offer below others would very quickly attract a tenant. Rents would thus be pushed down to landlords' maintenance costs i.e. at 100. What drives the market away from this configuration is primarily the frictions due to the search process. Due to search costs, the matching of a tenant and a landlord produces a benefit to both of them. Because tenants can visit only one residence per time unit and accept or refuse it without recall, landlords have the power to extract a part of this benefit, which explains rents above landlords' maintenance costs.

On the opposite, we know from existing theoretical labor-market models that in a model with frictions and homogeneous workers, the equilibrium would have a single wage, equal to the workers reservation wage. In this situation, firms are able to extract the whole surplus from the match and as a result, no searcher participates in the market, which is known as the Diamond paradox (Diamond, 1971). However, if workers differ in their reservation wages, due to heterogeneous outside options for instance, a distribution of wages emerges

(Albrecht and Axell, 1984, Eckstein and Wolpin, 1990). This also ties in with the consumer search literature, where price dispersion has been shown to result from sellers playing mixed strategies against potential buyers who have different reservation prices, see McMillan and Rothschild (1994). Following an analogous mechanism, in our housing-market model landlords facing tenants with heterogeneous reservation rents react by setting different offers.<sup>10</sup>

In contrast to those theoretical models, differences in reservation rents in our model are not solely the result of heterogeneities in the value of the outside option for searchers. They also come from the existence of idiosyncratic preferences and from the heterogeneity in the information received by different agents: tenants seeing different samples from the distribution of offers decide different reservation rents.

Moreover, the distribution of offered rents differs from the uniform distribution of reservation rents: although high income agents can accept any rent sufficiently below their reservation rent to cover the associated search costs, we observe that the maximum rent offered by landlords is lower than the maximum reservation rent. Landlords find that for higher rents it takes longer to find a tenant (because those tenants with low incomes can no longer afford it, and wealthier tenants prefer cheaper accommodation which they know to exist from their information on offered rents) and so offer relatively low rents compared to richer tenants housing budgets. Existing theoretical models can give us clues to better understand the distribution of offered and accepted rents. In a search model with heterogeneous workers, it has been shown that the distribution of offered wages differs from the distribution of reservation wages because unemployed individuals with high outside opportunity only flow to jobs with high wages (Eckstein and Van den Berg, 2007). Similarly in our model, high income agents can accept any rent that is sufficiently below their reservation rent to cover the associated search costs. In contrast, low budget searchers can only accept low rent offers. Therefore, the acceptance probability of low rent offers is higher, which distorts the distribution of offered rents with respect to the distribution of reservation rents.

Furthermore, Bontemps et al. (1999) demonstrate theoretically that with heterogeneous searching workers and heterogeneous firms, the minimum offered wage is higher than the minimum reservation wage. This parallels the observation in our model that the maximum rent offered by landlords is lower than the maximum reservation rent. Actually, landlords find that for higher rents it takes longer to find a tenant (because those tenants with low incomes can no longer afford it, and wealthier tenants prefer cheaper accommodation) and so offer relatively low rents compared to richer tenants housing budgets.

What is new in this model with respect to analytical models is that agents do not have perfect information regarding their expected benefit from waiting. Moreover, landlords need sufficient information in two dimensions to have an accurate appreciation of the market state. The dramatic difference in the sen-

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<sup>10</sup>In van der Vlist et al. (2002), the heterogeneity is in tenants having different arrival rate of offers when housed and when in temporary accommodation.

sitivity to changes in the two information parameters ( $S_T$  for tenants and  $S_L$  for landlords) is due to the fundamental asymmetry in the market exposed in Sections 3.1 & 3.2. Landlords individually post prices which cannot be negotiated, while tenants decide whether or not to accept the offer received. The idiosyncratic preferences of tenants are also absent from the search models cited in this Section, though they were introduced in housing search models by Arnott (1989). The addition of these preferences adds an important realistic element to the model and their stochastic nature has a stabilizing influence. Finally, the results in section 4.4 shows that this set up allows the analysis of the dynamics of the housing market, of which the understanding is a key question.

## 6 Conclusion

Our dynamic model includes imperfect information and heterogeneous interacting agents. It leads to price dispersion, nonzero search times and vacancies, three essential ingredients of any realistic housing model. The matching probability depends endogenously on the posted price of apartments. It is a general equilibrium model that provides a basis for examining policy questions such as rent control and its welfare and distributional effects, the welfare effects of the taxation of vacant housing or the general equilibrium effect of providing social housing.

In our model landlords set rents which tenant agents accept or refuse. This is a reasonable representation of the rental market. Landlords act upon their partial knowledge of the market in order to maximize their profits. Their knowledge of the market state is in the form of probable times-on-the-market before renting for the full range of possible rents. This allows the calculation of the expected profit and hence rational maximization. The heuristics of real world agents are simulated here by a regression and profit calculation, with a larger number of individual information points than real agents normally know. Greater information for landlords dis-improves their overall utility due to greater competition.

Tenants, with idiosyncratic preferences and heterogeneous in income, are also partially informed of the state of the market and use their information to decide the minimum utility they are willing to accept from a residence. Their search is undirected, that is they have equal probability of visiting any available offer in a given iteration. Greater information for tenants improves their overall welfare. We have examined the comparative static and dynamic effects of a change in the discount rate.

Our main aim has been to construct a model that allows hypotheses on the functioning of the urban rental market to be investigated. We believe that a dynamic model based on straightforward micro-economic behaviors with imperfect information is a good approach. We have found robust and simple agent dynamics (or rules) that reproduce the essential features of the rental housing market and results from analytical search models that have been developed to analyze labor as well as housing markets.

One of the most interesting possible extensions is to alter the number of

units owned by landlords. Heterogeneities in the level of information among landlords could represent the difference between large commercial landowners, who would also have greater private information, and small private owners. For example, large landlords are likely to be better able to absorb vacancies (as discussed by Blanck and Winnock (1953)), and more able to adapt their rental strategies to market conditions.

Making the tenant side of the market open - that is having a constant flow of arrivals of tenant agents - instead of a fixed number of searching tenants would allow the composition of the town to be more endogenous. This would also mean that the vacancy rate would represent market frictions only and not a mixture of market frictions and those tenants who are unable to pay market rates as is currently the case. Transferring our model to one where tenant agents engage in directed search is also a promising extension.

The current set-up allows the investigation of the distributive effects of policy decisions among tenant agents of varying incomes. Rent control is one possible example, as is the level of information among tenants. These two effects have been examined in static simulation models by Bradburd et al. (2005, 2006). It would be interesting to test whether the effects are similar in our more realistic model.

There is great scope to complexify the model for both types of agent. Tenants could be differentiated by their work places, housing preferences, household sizes, transportation modes etc. Landlords could own different numbers of apartments, and apply different rent setting rules.

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## A Sensitivity tests

- The *size* parameter determines the number of both landlords and tenants in the closed town. It plays an important role in model as the quantity of information available to agents is affected by their number. Increases in the *size* parameter, seen in Figure 18-*Left*. therefore have an effect similar to that of increasing the landlords' information. This finite size effect is a reasonable feature of the model.
- The parameter  $\sigma$  determines the level of idiosyncrasy of tenant agents' preferences for housing. Increases in this parameter cause a greater sorting among tenants and the accommodation they prefer, however landlords capitalize on tenants greater aggregate willingness-to-pay by raising rents. The rise in rents, see Figure 18-*Right*, reduces tenant agents' average welfare.
- Tenants' information  $S_T$  has less affect on the steady-state than landlords' information reflecting the relative market power of both category of agent. Increases in  $S_T$  benefit tenants by decreasing rents and hence increasing their welfare, see Figures 6-*Right* and 7. Appendix 4.2 presents the effects of tenants information levels in more detail, it is notable that the positive effect of increasing  $S_T$  saturates at low levels.

- Increases in the discount rate  $r$  increase the impatience of both agent types but as landlords are more influential in the market average rents fall with rising  $r$ , see Section 4.4.1.
- The length of landlords memory  $F$ , which also determines the regularity of rent updates, plays a similar influence on the steady-state as that of the parameter of landlords' information, see Figure 19-*Left* and Section 4.3.1. That is, when landlords have longer memories they are better informed. However, the repartition between memory length and vision of the market is not neutral during dynamic adjustments of the market, see Section 4.4.2.
- When the landlords' maintenance costs  $C_L$  are below the tenants' housing budgets changes to these costs play a secondary role, see Figure 19-*Right*. They can move the market slightly but do not change landlords' participation decisions. Once the maintenance costs rise above poorer tenants agents' housing budgets significant effects are seen. Many landlords withdraw from the market due to the effective drop in demand which lengthens TOM.
- Increasing the expected duration of residence  $X$  decreases the relative weight of search costs for both types of agent. Landlords search times (TOM) are generally longer than those of tenants. They have a greater influence on the market, as their decisions determine the choice set of tenants, and so as  $X$  increases the capture more of the increase in surplus as rents rise, see Figure 20-*Left*. This has the effect of reducing the population as some tenants can no longer afford the market rents. The average TOM also increases.
- The maximum possible increase above the highest rent observed  $I_{max}$  plays a small role as the proportion of maximum increases is low for all but very low values of  $I_{max}$ , see Figure 20-*Right*. Once  $I_{max}$  is above 3% increases in the parameter do not effect the steady-state configuration.

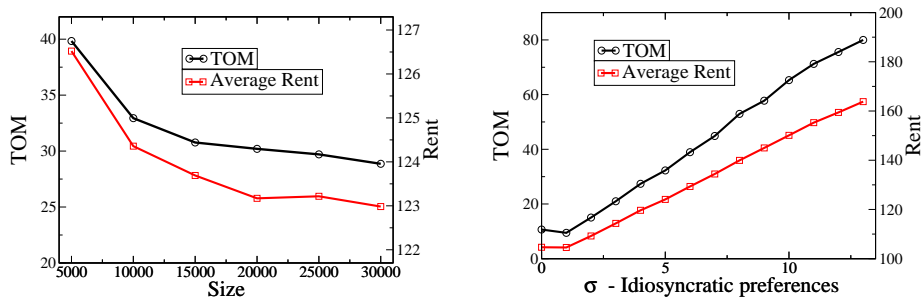


Figure 18: *Left*: The variations in average rent and the average TOM as a function the size of the simulation. *Right*: The variations in average rent and the average TOM as a function tenants' idiosyncratic preferences.

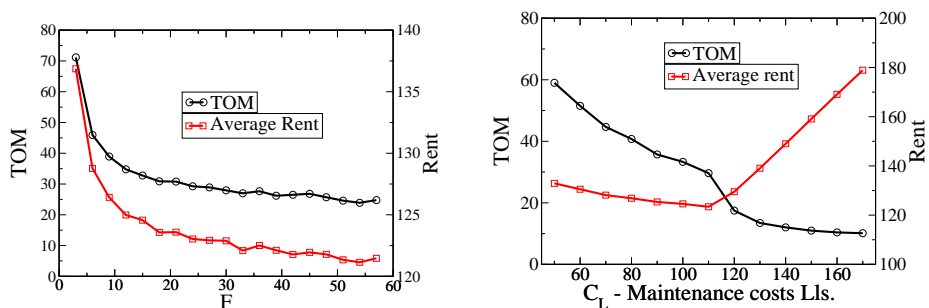


Figure 19: *Left*: The variations in average rent and the average TOM as a function the length of landlords' memory. *Right*: The variations in average rent and the average TOM as a function of landlords' maintenance costs.

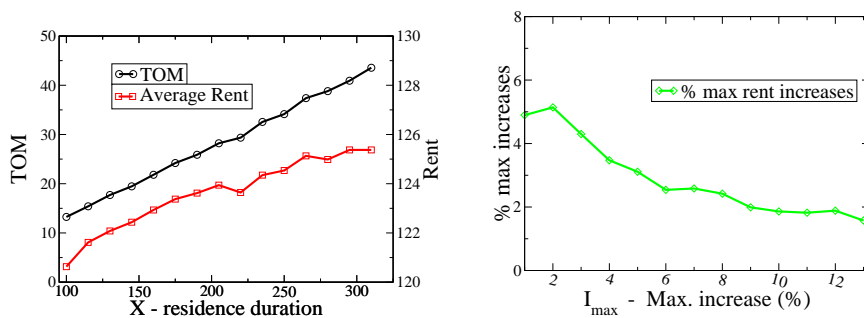


Figure 20: *Left*: The variations in average rent and the average TOM as a function the expected duration of residence. *Right*: The percentage of maximum rent increases averaged over 1000 iterations as a function of the maximum possible rent increase parameter, see Section 3.2.