CAHIER D'ÉTUDES
WORKING PAPER

N° 179

RENTAL HOUSING MARKET AND DIRECTED SEARCH

JULIEN PASCAL

DECEMBER 2023

BANQUE CENTRALE DU LUXEMBOURG
EUROSYSTÈME

Rental Housing Market and Directed Search

Julien Pascal [*]

Abstract

This paper introduces new empirical findings concerning the rental housing market in the Paris metropolitan area. Combining a new dataset gathered from online advertisements for Parisian rentals with a hedonic model that incorporates both apartment features and property-specific photographs, two main stylized facts are established. First, with comparable property features, landlords who ask for lower rent attract a greater number of applicants, consistent with predictions from standard directed search models. Second, many landlords employ a two-stage pricing approach, initially advertising a high rent and then reducing it after a "wait-and-see" period. This previously unreported feature is consistent with the slow Dutch auction mechanism studied in the auction literature and observed in the property sales market.

Keywords: Rental Housing Market; Hedonic Model; Directed Search Models; Landlords' Pricing Strategies; Machine Learning

JEL Classification: R31, R21, C21, D83, C45

[*]December 2023. Julien Pascal: Banque centrale du Luxembourg, Département Économie et Recherche, 2 boulevard Royal, L-2983 Luxembourg (julien.pascal@bcl.lu). This paper is based on the third chapter of my PhD thesis, that was defended in June 2020 at the Institut de Sciences Politiques, Paris (Pascal, 2020). This paper should not be reported as representing the views of BCL or the Eurosystem. The views expressed are those of the author and may not be shared by other research staff or policymakers in the BCL or Eurosystem.

Résumé non technique

Au Luxembourg, environ 28,9 % des ménages étaient locataires en 2021, proche de la moyenne des pays de l'Union européenne (30,1 %). En France, plus de 35 % des ménages étaient locataires et en Allemagne presque 50 %. Malgré l'importance du marché immobilier locatif pour les ménages, les interactions entre propriétaires et locataires sont rarement étudiées, notamment à cause d'un manque de données microéconomiques sur l'activité de recherche des locataires ou sur les stratégies de prix des propriétaires.

Ce papier présente de nouveaux résultats, basés sur des données émanant d'une plateforme internet mettant en relation propriétaires et locataires dans la région parisienne. Cette plateforme permet non seulement d'observer les caractéristiques des biens locatifs mis en ligne, mais aussi le nombre de locataires ayant contacté le gérant d'un certain logement. En utilisant ces données, il est possible d'établir que le processus d'appariement sur le marché locatif est plus directionnel qu'aléatoire.

Ces deux types de processus, qui sont à la base de l'étude économique des marchés frictionnels tels que le marché du travail ou du logement, peuvent différer sur leurs prescriptions en termes de politiques publiques. Il est donc important de choisir le modèle d'appariement qui peut mieux expliquer les données. Le papier présente également une analyse empirique des stratégies de prix pratiquées par certains propriétaires, qui est complémentée par une analyse des théories économiques qui pourraient expliquer ces stratégies.

Non-technical summary

In Luxembourg, approximately 28.9% of households were renters in 2021, close to the average of European Union countries, which stood at 30.1%. Over 35% of households were renters in France, and almost 50% in Germany. Despite the significance of the rental housing market for households, our understanding of the interactions between landlords and tenants is limited, primarily due to a lack of microeconomic data on tenants' search activity or landlords' pricing strategies.

This research paper presents new findings based on data sourced from an online platform that connects landlords and tenants in the Paris region. This platform not only provides the characteristics of rental properties listed online, but also the number of potential tenants who contacted the manager of a particular property. Using this data, the research paper finds that the rental market is better described by a directed matching model than by a random matching model.

These two types of models, which form the foundation of the economic study of frictional markets such as the labor or housing markets, can differ in their policy implications. Therefore, it is essential to select the model that better explains the data. The paper also presents an empirical analysis of the pricing strategies employed by some landlords, complemented by an analysis of economic theories that could explain these strategies.

1 Introduction

Real estate, as the world's predominant investment class, wields profound influence over global economies and societies. The 2008-10 financial crisis starkly highlighted the intricate ties between the housing market and the broader economic landscape. However, the ramifications of housing dynamics extend far beyond financial markets. Housing plays a pivotal role in shaping socio-economic outcomes, labor mobility, political sentiments, and even social dynamics such as marriage. For instance, Ganong and Shoag (2017) linked rising house prices in major US cities to reduced internal migration and increasing economic disparities among states. Similarly, other studies have connected housing market conditions to labor market behaviors (Brown and Matsa, 2019), national productivity (Herkenhoff, Ohanian, and Prescott, 2018), political populism (Adler and Ansell, 2020), and marital choices (Wei, Zhang, and Liu, 2017).

While a significant body of literature examines the processes of buying and selling houses, the rental property market remains relatively understudied. This focus in economic literature may be attributed to two main factors. First, home ownership has consistently been a focal point of political discourse for several decades. Governments in major economies have often aimed to raise home ownership rates. For instance, in the UK, Margaret Thatcher initiated the "right-to-buy" program in the 1980s, allowing residents in social housing to purchase their homes. Fischer and Sard (2017) found that in 2015, the US government allocated over 190 billion USD (exceeding 1% of GDP) to assist Americans in home buying. Similarly, French governments championed home ownership through various initiatives since the 1980s, as documented by Laferrère, Pouliquen, and Rougerie (2017). In Luxembourg, 3.1% of public administration expenditures in 2018 were subsidies and tax benefits related to the residential real estate market, primarily granted to owner-occupiers (Kaempff, 2018). Tax subsidies in favor of housing represented 2.5% of Luxembourg's GDP (Girshina, Koulischer, and von Lilienfeld-Toal, 2022). Second, while transaction data for house sales is readily available in developed economies (usually through legal requirements, such as notary records in France) the rental market suffers from data scarcity. For example, France lacks a comprehensive national dataset on rental agreements.[1] Data on landlords' pricing strategies or tenants' property search methods are even more elusive. This data deficit contrasts sharply with the importance of the rental market. In 2019, approximately 36% of US households chose to rent, while in the Euro area, this percentage was around 30% in 2020. Countries like Germany and Switzerland report even higher figures, with renters making up nearly 50% and 60% of their pop-

[1] The 'Caisse des Allocations Familiales' (CAF), a French governmental agency, collects data from tenant eligible for rent allowance, but does not share it with the public. Another potential source is Clameur, a private agency collecting data on rent to publish rent indices. Again, the underlying data is not available to the public.

ulations, respectively.[2]

This paper seeks to bridge the knowledge gap in the rental housing market by creating a dataset from online advertisements for Parisian rental properties between May and July 2019. A unique aspect of this study is the collection of information from both sides of the rental market by applying web scraping techniques to a popular website. Usually, housing search behavior is not collected. However, this novel dataset not only provides comprehensive details about properties, but also the number of inquiries landlords receive for each listing on the website.

Using this innovative dataset, I present two primary findings. Firstly, I provide evidence suggesting that the rental property market aligns more with a directed search model than a random search one. As anticipated by the standard directed search model, I demonstrate that properties priced lower than expected, based on their observable features, attract a larger pool of potential tenants. Secondly, I identify a novel feature about landlords' pricing strategies. A large proportion of landlords adopt a tactic similar to the slow Dutch auction, as previously explored in the literature (Adams, Kluger, and Wyatt, 1992). Specifically, some landlords initially set a higher asking price than what a hedonic regression model would predict, only to reduce it later. To my knowledge, this empirical observation is a new contribution to the literature. While the phenomenon of sticky downward listing prices has been documented in the real estate sales market, there is limited evidence on pricing strategies in the rental market.

This paper relates to several strands of the literature. Firstly, it adds to the empirical studies on frictional models, particularly those determining whether search is random or directed. The nature of the search — whether directed or random — is crucial because each type has distinct policy implications. Hosios (1990) shows that random search models with ex-post bargaining tend to be inefficient. An efficient decentralized equilibrium is only achieved if a specific condition is met, linking the elasticity of the matching function to the bargaining power of the involved parties. Otherwise, congestion externalities arise, suggesting agents might be searching excessively or insufficiently compared to the optimal level. This inefficiency indicates potential policy interventions to enhance efficiency. In contrast, Moen (1997) demonstrates that directed search models are second-best efficient. In such models, given the existence of frictions in a given market, the decentralized equilibrium mirrors what a central planner would achieve. Prices in directed search models are pre-set and known, and participants focus their search on sub-markets they find appealing. This structure ensures the Hosios condition is inherently satisfied. Consequently, regulation might improve welfare in a random search context but not necessarily in a directed search scenario. For instance in the labor market context, Moen and Rosén (2004) demonstrate

[2] See https://ec.europa.eu/eurostat/cache/digpub/housing/bloc-1a.html

that poaching activities don't skew training decisions in directed search models. However, Acemoglu (1997) found that poaching in random search models leads to less-than-optimal training investments, making training subsidies beneficial for overall welfare.

The extent to which the search process is random or directed has mostly been explored within the labor market context. Faberman and Menzio (2018) use US survey data from the 1980s, illustrating that the US labor market aligns well with a directed search model that takes into account the heterogeneity of workers and firms. Banfi and Villena-Roldan (2019) analyze data from a Chilean online job board spanning 2008 to 2014, concluding that directed search dominates the online labor market they examine. Their findings suggest that even if many job listings omit wage details, workers likely form wage expectations from textual descriptions and job prerequisites. Similarly, Marinescu and Wolthoff (2020) analyze data from an online US job board, revealing patterns consistent with directed search behavior. Specifically, for similar job titles, a wage increase of 10% correlates with a 7.7% surge in applications. Belot, Kircher, and Muller (2022) examine an online job-matching platform in the UK, determining that search patterns align with standard directed search models. They observe that a 1% wage hike leads to roughly a 0.7% rise in potential applicants. Some studies have also explored search behavior within the housing market. Genesove and Han (2012) examine US survey data from 1987 to 2008, finding that the US property market during this timeframe best fits a random search model. Piazzesi, Schneider, and Stroebel (2020) delve into the online housing market, leveraging email alert settings from a prominent home buyers' advertisement platform in the San Francisco Bay Area. These alert settings serve as proxies for search behaviors, suggesting that a random search model with segmented housing markets is a suitable representation of the data. This paper enriches the existing body of work by broadening the analysis to an underexplored frictional market: the rental property sector.

In many ways, studying the rental property market offers certain advantages over analyzing the labor or housing markets. As previously described, many online job offers lack wage information, leading to questions about whether wages are posted or subject to negotiation. For instance, Brenzel, Gartner, and Schnabel (2014) demonstrate that both wage determination processes are present in Germany. In the rental property context, most listings include an advertised rent, and there is compelling evidence suggesting these rents operate on a "take-it-or-leave-it" basis. Baietto-Beysson and Vorms (2012) note that French real estate agents consider rent negotiation "very unlikely" during the signing of the initial tenancy agreement.[3] Supporting this, Chapelle and Eyméoud (2022) show that rents observed from French online listings align almost perfectly

[3] "[Le] candidat à la location est en position de négocier avec le bailleur? Les professionnels estiment que c'est très rare. Cela peut cependant se produire dans les marchés détendus, alors que dans les marchés tendus, où le bailleur est en mesure de choisir son locataire, le loyer pratiqué est presque toujours identique à celui de l'offre." (Baietto-Beysson and Vorms (2012), page 26)

with rent indices derived from official rental lease contracts. This suggests that rent negotiations during the initial tenancy agreement are rare, at least in France. However, in the property market, numerous studies emphasize that sellers might use advertised prices to attract more potential buyers, as highlighted by Han and Strange (2016). Post-advertisement bargaining, including well-known bidding wars among potential buyers, is also prevalent (Han and Strange, 2014). The housing market introduces additional intricacies, such as buyers who are simultaneous sellers, as they are selling an existing property to purchase another (Wheaton, 1990). Therefore, the rental property market presents a more straightforward environment where the debate between random and directed search can yield more definitive insights.

Secondly, this paper relates to the literature that studies dynamic pricing behaviors in durable goods markets, especially the housing market. While in a straightforward directed search model, landlords would advertise a "take-it-or-leave-it" rent without modifying it, the data reveals some market participants following a slow Dutch auction strategy. They initially set a high rent and then reduce it after a wait-and-see period. Adams, Kluger, and Wyatt (1992) are the first to study the slow Dutch auction in the housing market. The authors analyze situations where a seller encounters potential buyers with private, unknown valuations. Sellers can choose between a fixed posted price or a slow Dutch auction, where the initial price decreases over time until a buyer emerges. The authors find that buyers always prefer a fixed posted price. However, when buyers are less patient than sellers, the slow Dutch auction becomes the optimal choice for sellers, as noted by Shneyerov (2014). This aligns with the theory of intertemporal price discrimination (Stokey, 1979), suggesting that a monopolist should use a decreasing price schedule when buyers have varying discount rates. Carare and Rothkopf (2005) further indicate that higher transaction costs for buyers who delay bidding increase the revenues for sellers using a slow Dutch auction. Such transaction costs for buyers revisiting the same item might explain the findings of Lucking-Reiley (1999) that a Dutch auction resulted in 30% higher revenues than a first-price auction in an online collectible card market. Fuchs and Skrzypacz (2010) explore a bargaining scenario where a seller negotiates with a buyer, when other buyers may arrive randomly. In this context, the seller opts for a decreasing pricing function, with strategic delays in price updates. In a market dominated by sellers with only a few buyers, transactions happen rapidly, with buyers capturing most of the surplus. Conversely, in a market saturated with buyers but limited sellers, trades tend to be slower due to strategic delays, allowing sellers to secure most of the surplus. In a related contribution, Salant (1991) examines the optimal pricing behavior of house sellers and the decision to employ a broker in a finite-horizon model. The seller strategically selects a series of progressively lower asking prices. If the property remains unsold after several periods, they enlist a broker, usually raising the asking price to account for the broker's commission. Merlo and Ortalo-Magne

(2004) find that most house sellers indeed opt for decreasing listing prices. Using housing sales data from the UK, they observe that less than 0.4% of sellers increased their listing prices. In addition, price changes are infrequent but significant, with an average 11-week gap leading to a 5.3% price reduction. Merlo, Ortalo-Magné, and Rust (2015) shows that adding the costs of changing the listing price to a finite-horizon model similar to Salant (1991) can replicate this sticky downward trend in listing prices. This paper enriches this extensive literature by highlighting that a similar sticky downward trend in rents is evident in the rental property market.

Thirdly, this paper connects to literature that explores new data sources and formats to address economic questions. In terms of data sources, I collect observations directly from an online platform, creating a dataset with unique attributes. Specifically, I capture the search behavior of potential tenants across approximately 50,000 rental listings using standard web scraping methodologies. While theoretically feasible, obtaining information on tenant search behavior in the traditional "physical" rental market would have been impractically expensive and time-intensive. Recently, there's been a surge in studies employing web-scraped data to explore economic issues, particularly those related to the rental housing market. For instance, Boeing, Wegmann, and Jiao (2023) employ web scraping techniques to collect rental listings from across the United States, revealing significant discrepancies between online asking rents and rent indices derived from conventional survey data, which emphasizes the affordability crisis in the rental housing market. Harten, Kim, and Brazier (2021) use web-scraped data to delve into Shanghai's informal and illegal bed space rental market, where landlords transform individual and commercial units into dormitories. Similarly, Franco and Santos (2021), Garcia-López, Jofre-Monseny, Martínez-Mazza, and Segú (2020), and Koster, Van Ommeren, and Volkhausen (2021) use web-scraped data to assess the influence of short-term rentals on the broader housing markets in Portugal, Spain, and the United States, respectively.

In terms of alternative data formats, I incorporate the aesthetic characteristics of rental properties using listing photos. I employ the convolutional neural network (CNN) from Talebi and Milanfar (2018) designed to emulate human judgments of photo aesthetics. Within a hedonic pricing model, this aesthetic factor proves both positive and statistically significant, even after accounting for numerous other influential factors. Other research exploring the visual attributes of properties and their impact on prices includes Zhang and Dong (2018), who derive a street greenery index in Beijing from Google Street View images, finding that visible street greenery can raise property prices by nearly 10%. Lindenthal (2020) uses outdoor images to show that properties in neighborhoods with architectural cohesion command a price premium. In their hedonic pricing model, Ahlfeldt, Heblich, and Seidel (2023) use the count of geo-tagged photos on social media as a proxy for local amenities. Similar to the present paper, Poursaeed, Matera, and Belongie (2018) apply a CNN to assess the appeal of real estate properties using both interior and exterior images, focusing on the perceived luxury of a property. Their primary goal is predictive accuracy, and they discover that incorporating this luxury index into another neural network enhances price prediction capabilities. Further contributions using new data formats include Shen and Ross (2021), who construct a hedonic model that factors in the "soft" information from real estate listing textual descriptions via natural language processing (NLP) algorithms. This paper adds to the existing body of work by presenting an innovative approach to integrating real estate aesthetics.

The structure of this paper is as follows: Section 2 provides key descriptive statistics on the housing market in France, emphasizing the rental market in the Paris metropolitan area, and details the data collection process. In Section 3, I introduce a hedonic pricing model for the rental housing sector. This model is used to compute deviations from predicted rents, which positively correlate with the number of tenants expressing interest in property visits. Section 4 examines the rent-setting strategies employed by landlords and Section 5 discusses the welfare and efficiency implications of the findings. Concluding remarks are presented in the final section.

2 Overview of the French Rental Housing Market and Data Collection Methodology

This section begins with a detailed examination of the rental housing landscape in France, particularly focusing on the Parisian market. It then outlines the data collection process and presents essential descriptive statistics from the gathered dataset.

2.1 Rental Housing Dynamics in France and the Paris Metropolitan Region

In France, as of 2020, over 35% of individuals were tenants. Of these, 58% resided in the private rental sector, with the remainder in the public rental sector where rents are not determined by market forces (Laferrère, Pouliquen, and Rougerie, 2017). In 2013, private landlords owned 93.5% of accommodations in the private rental sector. There are distinct differences between homeowners and tenants. For example, in France, 80% of homeowners reside in houses, whereas 75% of tenants live in apartments. Furthermore, tenants in the private rental sector tend to be younger (below 30 years old), single, divorced, or single parents.

Focusing on the Paris metropolitan area, as of January 2023, the city of Paris had an estimated population of 2.1 million, while the broader Ile-de-France region housed around 12.4 million people.[4] The rental housing market in this area is notably tight. Since 2007, rents in the city of Paris have risen at a faster rate than in the rest of the Ile-de-France region, as depicted in Figure 1. For instance, between 2007 and 2018, average rents in Paris increased by over 30%, compared to about 25% in the inner surrounding departments and 20% in the outer departments. During this period, wages in the metropolitan area grew by roughly 20%, while the overall price index saw a more modest increase of just under 15%. This suggests that the demand for rental accommodations has been outstripping supply.

Dietrich-Ragon (2013) provides a qualitative perspective, noting that a single apartment listing online can attract between 30 to 50 applicants on the same day for a group visit. Prospective tenants often need to earn three times the monthly rent and provide a comprehensive application file. The tightness of the Parisian rental market, relative to the rest of France, is further highlighted by the time taken to secure a social housing unit. For instance, while regions like Cantal or Creuse have an average wait time of 3 months, in Paris, it is a staggering 39 months. Hence, the Parisian housing rental market can be viewed as sharing similarities with other large cities in which the supply of housing has not kept pace with a surge in demand.

Online platforms have become increasingly significant for rental property search. In 2013, 37% of French tenants sought accommodations through online ads or newspapers, 39% used real estate agencies, and 19% relied on word of mouth (Chapelle and Eyméoud, 2022). Given that French internet use rose from 68.9% in 2010 to 92.3% in 2018, and smartphone use jumped from 39% in 2013 to 75% in 2018, it seems likely that more tenants now use online platforms for their housing search.[5] In the US, Piazzesi, Schneider, and Stroebel (2020) found that over 90% of home buyers use the internet for their search, with 76% considering real estate websites as a crucial information source.

[4] See https://www.insee.fr/fr/statistiques/1893198 and https://www.insee.fr/fr/statistiques/6968304

[5] Survey respondents are individuals aged 12 years and older. Source: https://www.statista.com/statistics/732147/smartphone-penetration-in-france/

Figure 1: Evolution of rents, wages and price index in the Paris metropolitan area: 2007 - 2018

Sources: OLAP and INSEE
Notes: Rent indexes are from OLAP. Other observations are from INSEE. The wage index is based on the annual after-tax income of a full-time worker. The term inner suburbs ("petite couronne") refers to the inner ring of departments surrounding Paris, namely Hauts-de-Seine, Seine-Saint-Denis, and Val-de-Marne. The term outer suburbs ("grande couronne") refers to the outer ring of departments, which are Yvelines, Essonne, Seine-et-Marne, and Val-d'Oise.

2.2 Data collection methodology

This subsection outlines the data collection process and highlights key features of the website from which the data were sourced. Rent data were gathered between May and July 2019 from the platform LouerAgile, yielding approximately 50,000 listings. By October 2020, LouerAgile underwent a rebranding to "Jinka"[6] and transitioned from an online platform to a mobile application. During the data collection period, LouerAgile functioned as an aggregator of online listings from prominent players in the Parisian rental housing market. This included listings from established real estate agencies such as Orpi, Foncia, and Logic-Immo, as well as listings managed directly by private landlords, like PAP or leboncoin.[7] Each listing on the website provided details like rent, number of rooms, bedrooms, surface area, and location.

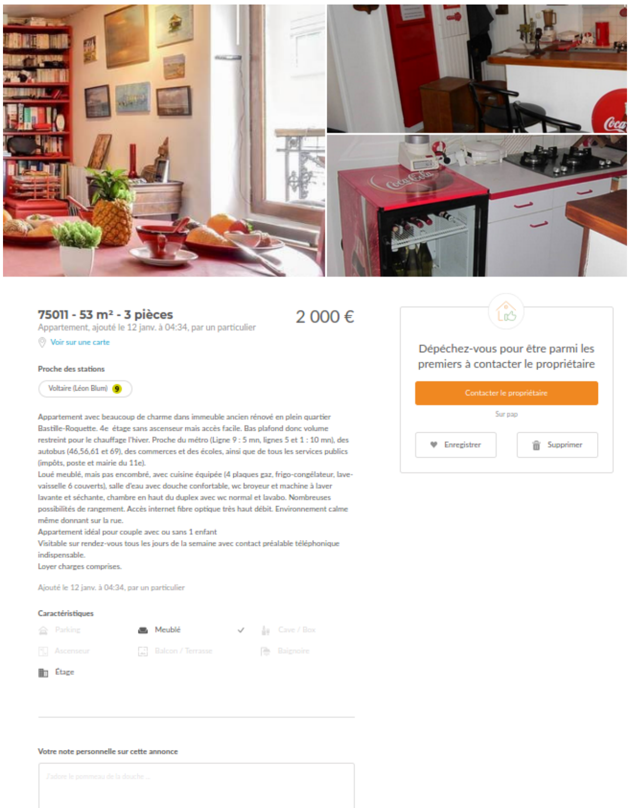
Rental listings were accessible either directly on the website or via email notifications. The platform allowed users to filter listings based on specific criteria. To ensure a broad range of visible listings, I set minimal filters: a maximum rent of 5000 euros per month and a minimum surface area of 8 square meters. The selected locations encompassed Paris, as well as a subset of nearby municipalities, including Asnières-sur-Seine, Boulogne-Billancourt, Créteil, Ivry-sur-Seine, Montreuil, Nanterre, and Saint-Denis. The rental property meeting these criteria would accumulate on a personalized home page, with the latest listings being displayed first. From this personalized

[6]Available at https://www.jinka.fr/
[7]See https://www.orpi.com/, https://fr.foncia.com/, https://www.logic-immo.com/, https://www.pap.fr/ and https://www.leboncoin.fr/

home page, a preview of listings was available. Each listing could be clicked to get a detailed description of the rental property. There was also a text describing the property, written by private landlords or real estate agents. Most listings also featured several photos of the accommodation. For potential tenants wishing to reach landlords, the only method was to click the "contact the owner" button ("contacter le propriétaire"). A representative example of a typical listing can be seen in Figure 2.

The website provided a unique feature enabling researchers to observe interactions between the two sides of the rental market. In fact, LouerAgile displayed the number of times a landlord or real estate agency had been contacted by potential tenants. However, during the data collection period, this count was only made public once it reached a threshold of 10 contacts. If the count was below this threshold, it remained undisclosed and the website would display a message inviting users to be one of the first to contact the owner. For instance, Figure 2 depicts a listing where the landlord received 32 contacts via the platform. Admittedly, the data was inherently asymmetric: while property details are comprehensive, information about tenants is limited, with the only available data being the frequency of their contact with landlords.

Figure 2: Screenshots from the website



(a) Example of a typical listing on the website

(b) Example of a listing where the landlord was contacted 32 times

Sources: Screenshot from LouerAgile.

2.3 Descriptive statistics

This subsection provides key descriptive statistics for the Parisian rental housing market, based on web-scraped data from LouerAgile. Table 1 reports essential descriptive statistics for variables used as explanatory factors in the hedonic model described in the subsequent section. In the sample, accommodations' surfaces range from 8 to 300 square meters, with a median size of 34 square meters. The median number of rooms and bedrooms are 2 and 1, respectively, while the median floor level is 3. The median rent per square meter is 34.5 euros. Table 1 also reveals that 68% of listings are managed by a real estate agency; about 50% of accommodations are furnished rentals; 41% feature elevator access; and fewer than 9% feature a terrace or balcony. Table 2 presents a detailed breakdown of these summary statistics by municipality. This indicates that the sample predominantly consists of accommodations in the city of Paris, accounting for 86% of all listings. Compared to other municipalities, accommodations in Paris tend to be smaller, pricier, more frequently managed by real estate agencies, and are often located on higher floors.

Figure 3 builds upon the information presented in Table 1 and 2 by offering detailed maps of the Paris metropolitan area. The first panel reveals that population is particularly dense in the two-digit arrondissements, namely the 10th to 20th arrondissements, which form the outer ring of Paris.[8] In contrast, the central areas of Paris, represented by the one-digit arrondissements, are less densely populated. Figure 3b highlights that the two-digit arrondissements also have a higher average number of listings. However, the western two-digit arrondissements receive more listings than would be suggested by population alone. Figure 3c confirms the well-documented fact that rent per square meter decreases as one moves further from the city center, as discussed in studies like Brueckner, Thisse, and Zenou (1999) and Marchiori, Pascal, and Pierrard (2023). Figure 3d shows that as one moves away from the city center, accommodations tend to be larger. Figures 3e and 3f indicate that the average number of rooms and bedrooms increase with distance from the city center. Figures 3g and 3h illustrate weaker negative correlations between the distance to the city center and the percentage of accommodations that are furnished or managed by real estate agencies.

Table 1: Dwelling characteristics

Characteristic	Statistic	Value	Characteristic	Statistic	Value
Surface (m^2)	Mean (SD)	40.9 (26.7)	**Elevator**	No	29906 (59.2%)
	Median [Min, Max]	34.0 [8.00, 300]		Yes	20622 (40.8%)
Rent/m^2	Mean (SD)	36.1 (10.1)	**Balcony/terrace**	No	46179 (91.4%)
	Median [Min, Max]	34.5 [5.62, 86.1]		Yes	4349 (8.6%)
Rental agency	No	16179 (32.0%)	**Floor**	Mean (SD)	3.14 (2.20)
	Yes	34349 (68.0%)		Median [Min, Max]	3.00 [0.00, 31.0]
# Rooms	Mean (SD)	1.93 (1.03)		Missing	11694 (23.1%)
	Median [Min, Max]	2.00 [1.00, 7.00]	**# Bedrooms**	Mean (SD)	1.51 (0.725)
Furnished	No	25446 (50.4%)		Median [Min, Max]	1.00 [1.00, 6.00]
	Yes	25082 (49.6%)		Missing	26295 (52.0%)

Source: Author's calculation based on data from LouerAgile
Notes: The sample includes 50,528 observations. The variables "Rental agency", "Furnished", "Elevator", "Balcony/terrace" are categorical variables equal to 1 ("Yes") when the accommodation was managed by a real estate agency; rented furnished; had access to an elevator (for an apartment); had a balcony or a terrace. Categorical variables are equal to 0 ("No") otherwise. Table 1 also reports the proportion of missing values for each variable (when applicable).

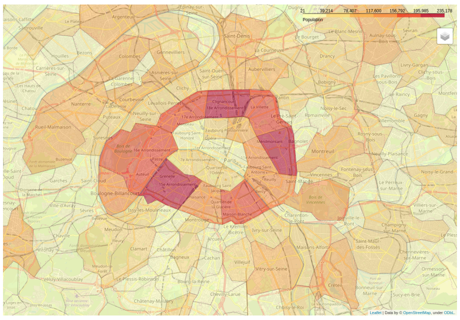
[8] An arrondissements is a subdivision of a large municipality (Paris, Lyon, and Marseille)

Table 2: Dwelling characteristics by municipality

		Asnieres sur Seine (n=1254)	Bobigny (n=172)	Boulogne-Billancourt (n=2094)	Creteil (n=515)	Ivry sur Seine (n=378)	Montreuil (n=831)	Montrouge (n=622)	Nanterre (n=583)	Paris (n=43435)	Saint-Denis (n=644)
Surface (m^2)	Mean (SD)	44.1 (22.9)	44.4 (26.9)	43.2 (24.3)	44.2 (23.9)	36.4 (18.6)	42.9 (23.7)	40.4 (20.0)	50.0 (35.0)	40.5 (27.0)	41.9 (20.1)
	Median [Min, Max]	40.0 [9.00, 160]	40.0 [10.0, 226]	38.0 [8.00, 209]	41.0 [8.00, 220]	33.0 [10.0, 130]	38.0 [9.00, 200]	37.0 [9.00, 145]	44.0 [9.00, 300]	33.0 [8.00, 215]	40.0 [9.00, 100]
Rent/m^2	Mean (SD)	26.1 (7.48)	19.3 (7.84)	31.6 (7.44)	22.8 (9.22)	27.6 (8.68)	25.3 (7.30)	28.1 (6.90)	23.9 (8.43)	37.6 (9.50)	23.3 (8.74)
	Median [Min, Max]	24.3 [7.81, 69.4]	18.9 [7.94, 49.4]	30.4 [8.50, 75.0]	20.9 [5.63, 55.0]	25.8 [9.62, 64.9]	23.8 [8.93, 64.7]	26.8 [10.0, 61.1]	23.0 [5.62, 65.0]	35.7 [18.8, 86.1]	21.4 [6.55, 68.9]
Rental agency	No	416 (33.2%)	130 (75.6%)	603 (28.8%)	287 (55.7%)	234 (61.9%)	329 (39.6%)	198 (31.8%)	346 (59.3%)	13258 (30.5%)	378 (58.7%)
	Yes	838 (66.8%)	42 (24.4%)	1491 (71.2%)	228 (44.3%)	144 (38.1%)	502 (60.4%)	424 (68.2%)	237 (40.7%)	30177 (69.5%)	266 (41.3%)
# Rooms	Mean (SD)	2.09 (1.04)	2.01 (0.991)	2.00 (1.02)	2.10 (1.12)	1.88 (0.809)	2.05 (1.04)	1.99 (0.926)	2.28 (1.27)	1.91 (1.03)	2.12 (0.945)
	Median [Min, Max]	2.00 [1.00, 6.00]	2.00 [1.00, 5.00]	2.00 [1.00, 7.00]	2.00 [1.00, 7.00]	2.00 [1.00, 4.00]	2.00 [1.00, 7.00]	2.00 [1.00, 5.00]	2.00 [1.00, 7.00]	2.00 [1.00, 7.00]	2.00 [1.00, 5.00]
# Bed rooms	Mean (SD)	1.60 (0.773)	1.50 (0.770)	1.54 (0.737)	1.70 (0.737)	1.42 (0.609)	1.59 (0.826)	1.50 (0.640)	1.79 (0.867)	1.49 (0.720)	1.59 (0.707)
	Median [Min, Max]	1.00 [1.00, 6.00]	1.00 [1.00, 4.00]	1.00 [1.00, 5.00]	2.00 [1.00, 4.00]	1.00 [1.00, 3.00]	1.00 [1.00, 5.00]	1.00 [1.00, 4.00]	2.00 [1.00, 5.00]	1.00 [1.00, 6.00]	1.00 [1.00, 4.00]
	Missing	594 (47.4%)	112 (65.1%)	981 (46.8%)	279 (54.2%)	233 (61.6%)	403 (48.5%)	282 (45.3%)	322 (55.2%)	22749 (52.4%)	340 (52.8%)
Furnished	No	881 (70.3%)	83 (48.3%)	1339 (63.9%)	326 (63.3%)	195 (51.6%)	601 (72.3%)	455 (73.2%)	346 (59.3%)	20827 (47.9%)	393 (61.0%)
	Yes	373 (29.7%)	89 (51.7%)	755 (36.1%)	189 (36.7%)	183 (48.4%)	230 (27.7%)	167 (26.8%)	237 (40.7%)	22608 (52.1%)	251 (39.0%)
Elevator	No	799 (63.7%)	142 (82.6%)	1089 (52.0%)	348 (67.6%)	323 (85.4%)	611 (73.5%)	362 (58.2%)	443 (76.0%)	25297 (58.2%)	492 (76.4%)
	Yes	455 (36.3%)	30 (17.4%)	1005 (48.0%)	167 (32.4%)	55 (14.6%)	220 (26.5%)	260 (41.8%)	140 (24.0%)	18138 (41.8%)	152 (23.6%)
Balcony/terrace	No	1073 (85.6%)	149 (86.6%)	1719 (82.1%)	470 (91.3%)	359 (95.0%)	684 (82.3%)	551 (88.6%)	467 (80.1%)	40127 (92.4%)	580 (90.1%)
	Yes	181 (14.4%)	23 (13.4%)	375 (17.9%)	45 (8.7%)	19 (5.0%)	147 (17.7%)	71 (11.4%)	116 (19.9%)	3308 (7.6%)	64 (9.9%)
Floor	Mean (SD)	2.68 (2.10)	1.60 (1.57)	2.91 (2.16)	2.42 (2.14)	2.24 (2.01)	1.98 (1.70)	2.77 (2.17)	1.95 (1.88)	3.21 (2.20)	2.42 (2.15)
	Median [Min, Max]	2.00 [0.00, 20.0]	2.00 [0.00, 6.00]	3.00 [0.00, 11.0]	2.00 [0.00, 11.0]	2.00 [0.00, 11.0]	2.00 [0.00, 10.0]	2.00 [0.00, 10.0]	1.00 [0.00, 10.0]	3.00 [0.00, 31.0]	2.00 [0.00, 11.0]
	Missing	380 (30.3%)	124 (72.1%)	474 (22.6%)	300 (58.3%)	200 (52.9%)	262 (31.5%)	188 (30.2%)	324 (55.6%)	9045 (20.8%)	397 (61.6%)

Source: Author's calculation based on data from LouerAgile
Source: Table 2 displays a breakdown of the statistics available in Table 1 by municipality. The proportion of mission values for each variable is also reported (when applicable).

Figure 3: Listing characteristics at the municipality level



(a) Population (2017)

(b) Number of listings

(c) Median rent per m^2

(d) Median surface (m^2)

(e) Mean number of rooms

(f) Mean number of bedrooms

(g) Percentage of accommodations furnished

(h) Percentage of listings managed by a real estate agency

Sources: INSEE (for Panel 3a) and author's calculations based on data from LouerAgile.
Notes: Panel 3a shows the population per geographical unit (municipality or arrondissement) as of January 2017. Panel 3b shows the number of listings in the sample per geographical unit. Panels 3c, 3d, 3e and 3f present the median rent per square meter, the median surface of the accommodation, the mean number of rooms and the mean number of bedrooms respectively. Panels 3g and 3h display the proportion of properties rented furnished and the proportion of apartments being managed by real estate agencies. Zoomed versions of each Panel are available in section A of the Appendix.

3 Hedonic pricing model and search behavior

This section begins by analyzing the factors associated with differences in rent through a linear regression model. It then demonstrates that dwellings with unusually low rents tend to attract more applicants, consistent with predictions from standard directed search models.

3.1 Hedonic pricing model

This subsection introduces a hedonic pricing model designed to predict rents based on observable property features. The following subsection focuses on the deviation from the predicted rent rather than the rent itself. Since the analysis of search behavior in the next subsection relies on the *residual rent*, the hedonic pricing model attempts to include all pertinent information to ensure accurate rent predictions. In general, a hedonic pricing model, as introduced by seminal works of Griliches (1961) and Rosen (1974), posits that goods are priced by potential buyers based on their different attributes. A typical hedonic regression model follows the equation:

$$\boldsymbol{y} = X\boldsymbol{\beta} + \boldsymbol{u} \tag{1}$$

where $\boldsymbol{y}$ is a vector of observed prices (which may be logged), $\boldsymbol{\beta}$ is a vector of coefficients associated with observable characteristics (to be estimated), and $\boldsymbol{u}$ is a vector of error terms. I follow the literature in adopting a similar regression framework to study rents.

One novelty in this study, compared to existing literature on hedonic models for the real estate market, is the incorporation of information from photos to predict rents. This is implemented in a way that ensures the results remain easily interpretable. To convert photos into a numerical value suitable for regression analysis, I employ a convolutional neural network (CNN) inspired by the work of Talebi and Milanfar (2018). CNNs are specialized neural networks optimized for image processing. In their initial stages, convolutional layers process input images, detecting significant image features ranging from basic patterns like vertical or horizontal edges to more intricate visual motifs.[9] The specific CNN from Talebi and Milanfar (2018) was designed and trained to anticipate the distribution of human opinion scores when assessing the aesthetic quality of images. The training images, sourced from three datasets, were previously rated by humans and encompassed a wide variety of scenarios, including real estate photographs.[10] Post-training, the CNN produces a normalized score between 1 and 10, imitating human perceptions of the image's aesthetic value. For reference, the average aesthetic score in the training sample is 5.5, with a

[9] for a review of CNN, see for instance O'Shea and Nash (2015).

[10] More specifically, the authors used the AVA dataset, which contains about 255,000 images obtained from the online community of amateur photographers. Each photo in the sample was scored by an average of 200 people, in response to photography contests. They also used images from LIVE data, which contains photos captured by mobile phone devices, as well as the TID2013 data set, which contains photos released by the firm Kodak.

standard deviation of 1.4. A score of 10 indicates the maximum aesthetic appeal for an image. This aesthetic score potentially captures the intuitive notion that properties deemed aesthetically preferable should command higher rents, all other factors being equal. Such aesthetic appeal could be influenced by factors reviewed in the introduction of this paper, such as architectural cohesion (Lindenthal, 2020), the property's luxurious appearance (Poursaeed, Matera, and Belongie, 2018), or even its proximity to stunning natural elements (Zhang and Dong, 2018).

To assign each listing an aesthetic score, I employed a two-step approach, especially since online listings often feature several photos. Initially, every individual photo was assigned an aesthetic score using the pre-trained CNN from Talebi and Milanfar (2018).[11] Then, a global aesthetic score was assigned to each listing by calculating the median score of all its photos. Figure 4a indicates that most online listings included at least one photo. The distribution of aesthetic scores is depicted in Figure 4b. Scores usually range between 3 and 6, with the median score hovering around 5. For illustrative purposes, Figures 5 and 6 display selected photos from the top 1% and bottom 1% of the aesthetic score distribution. A cursory examination of these images suggests that the CNN's evaluations are consistent with human judgments.

Table 3 presents the outcomes of regressing advertised rents against a range of observable variables. The first column reveals that the monthly rent (in euros) rises as a concave function of the dwelling surface (in square meters). Dwellings with elevator access and furnished dwellings command higher rents. In the second column, introducing the aesthetic score, as determined by the CNN from photos, we observe that dwellings with higher aesthetic ratings tend to be more expensive. Specifically, a one-standard-deviation increase in the aesthetic score raises the monthly rent by roughly 47.8 euros. For comparison, the second column indicates that elevator access raises the monthly rent by approximately 63 euros. This column provides evidence of the CNN's effectiveness at identifying aesthetic attributes that are valued by potential renters. This aesthetic element remains both positive and statistically significant, even after controlling for more traditional hedonic factors.

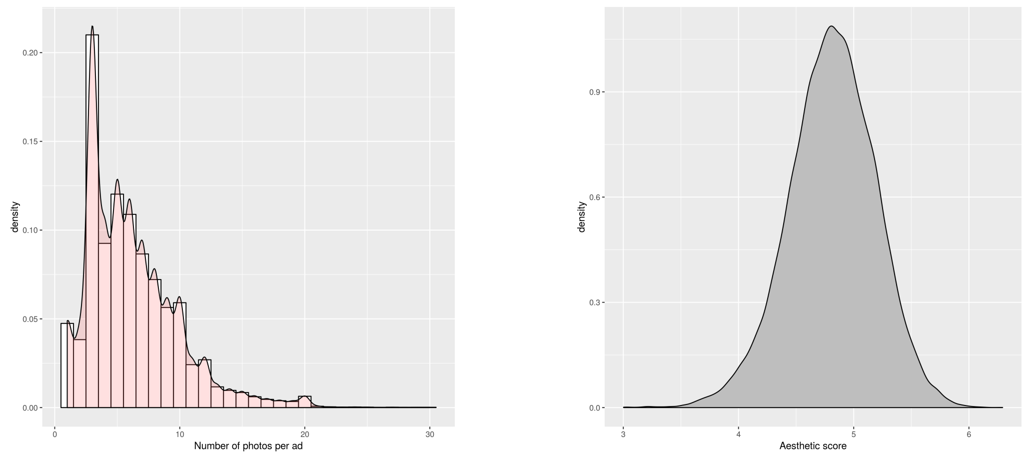
In the third column, when postal code fixed effects are incorporated, the R-squared value rises to 0.89. With these fixed effects in place, properties with a balcony or terrace still command a higher rent. The fourth column introduces a dummy variable for management by real estate agencies. The positive and statistically significant coefficient on this variable suggests that real estate agencies usually set higher rents than private landlords. The fifth column integrates floor fixed effects to account for potential price variations based on floor level. The final column incorporates a vari-

[11] The CNN in Talebi and Milanfar (2018) is designed to reproduce the *distribution* of aesthetic scores that a jury of human could produce when looking at a photo. To summarize the information contained in the distribution, I use the mean aesthetic score.

able for the number of bedrooms, revealing that, when surface area is held constant, apartments with additional rooms or bedrooms command higher rents.

The observation that real estate agencies tend to set higher rents, as evidenced by the positive value on the dummy variable "rental agency", warrants further exploration. One potential explanation lies in the incentives faced by real estate agencies. In France, real estate agencies have several reasons to set higher rents. Firstly, they charge landlords a tenant-finding fee, typically a fixed percentage of the monthly rent. Secondly, they levy monthly management fees on landlords, which are often tied to the rent amount.[12] Until September 2014, real estate agencies had an additional incentive to set higher rents, as they charged tenants a fee for establishing a tenancy agreement, typically a multiple of the monthly rent. However, from September 2014 onwards, tenant-finding fees were capped.[13] On the other hand, real estate agencies might set rents lower to increase the chances of securing tenants. Despite this, the data suggests that real estate agencies usually set higher rents than landlords with similar listings.

Figure 4: Number of photos per listing and distribution of aesthetic scores



(a) Number of photos per listing (b) Distribution of aesthetic scores

Sources: Author's calculations based on data from LouerAgile.
Notes: Figure 4b shows the distribution of aesthetic score attributed to each listing, based on its photos. In a fist step, each photo was assigned an aesthetic score using a CNN based on the work of Talebi and Milanfar (2018). In a second step, each listing was assigned an aesthetic score equal to the median score across its photos. Listings with no photos are not included in Figure 4b.

[12] Source: www.smartloc.fr

[13] Since the ALUR law entered into force on the 15th of September 2014, the costs of establishing a tenancy agreement are defined by law. In a "very tight" zone (Zone très tendue), which includes Paris, costs are equal to 12€ per square meter. In a "tight" zone (Zone tendue), which includes Lyon, Bordeaux and Toulouse for instance, costs are equal to 10€ per square meter. In other zones, tenants pay 8 € per square meter. See https://www.ecologie.gouv.fr/loi-lacces-au-logement-et-urbanisme-renove-loi-alur.

Figure 5: Sample of photos from the top 1% in terms of aesthetic score

Source: Photos from LouerAgile.
Notes: Photos were assigned an aesthetic score using a CNN based on the work of Talebi and Milanfar (2018). Figure 5 displays a selected sample from the top 1% in terms of aesthetic score.

Figure 6: Sample of photos from the bottom 1% in terms of aesthetic score

Source: Photos from LouerAgile.
Notes: Photos were assigned an aesthetic score using a CNN based on the work of Talebi and Milanfar (2018). Figure 6 displays a selected sample from the bottom 1% in terms of aesthetic score.

Table 3: Hedonic regression model

	Dependent variable:					
	Monthly rent (in euros)					
	(1)	(2)	(3)	(4)	(5)	(6)
Surface (m^2)	28.502***	28.061***	27.852***	27.783***	28.307***	28.385***
	(0.211)	(0.226)	(0.189)	(0.190)	(0.215)	(0.355)
Surface^2	−0.010***	−0.009***	−0.017***	−0.017***	−0.017***	−0.019***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Nb rooms	−3.767	2.803	26.291***	26.506***	24.966***	29.639***
	(3.144)	(3.343)	(2.791)	(2.792)	(3.133)	(6.749)
Elevator	68.365***	62.916***	32.140***	31.320***	34.020***	32.803***
	(3.110)	(3.315)	(2.798)	(2.808)	(3.243)	(5.163)
Furnished	210.312***	190.459***	147.181***	149.517***	161.718***	217.045***
	(2.961)	(3.207)	(2.692)	(2.779)	(3.080)	(4.880)
Balcony/terrace	−37.152***	−36.047***	25.838***	24.975***	15.967***	28.651***
	(5.275)	(5.512)	(4.617)	(4.624)	(5.053)	(7.206)
Aesthetic score		126.693***	105.884***	106.228***	110.645***	141.676***
		(4.163)	(3.466)	(3.467)	(3.920)	(6.364)
Rental agency				10.179***	5.021	16.532**
				(3.017)	(3.520)	(7.454)
Nb bedrooms						20.916***
						(7.175)
Constant	85.299***	−503.223***	−119.910***	−128.505***	−175.648***	−354.851***
	(4.845)	(19.952)	(20.104)	(20.263)	(23.024)	(38.700)
Postal code FE	No	No	Yes	Yes	Yes	Yes
Floor FE	No	No	No	No	Yes	Yes
Observations	50,528	42,307	42,307	42,307	33,180	17,439
R^2	0.831	0.840	0.890	0.890	0.899	0.882
Adjusted R^2	0.831	0.840	0.890	0.890	0.899	0.881
Note:						*p<0.1; **p<0.05; ***p<0.01

Source: Author's calculation based on data from LouerAgile

3.2 Residual rent and search behavior

This subsection analyzes the relationship between residual rent and tenants' search behavior. The residual rent, defined as the predicted rent minus the observed advertised rent, appears to correlate with the intensity of tenants' searches. In line with predictions from standard directed search models, properties offered below their predicted value attract more interest from potential renters.

To provide a visual perspective, Figure 7 juxtaposes the residual rent for each listing with the number of contacts that listing received via the platform. As previously explained, listings with fewer than 10 contacts are not shown. Consistent with standard directed search models, Figure

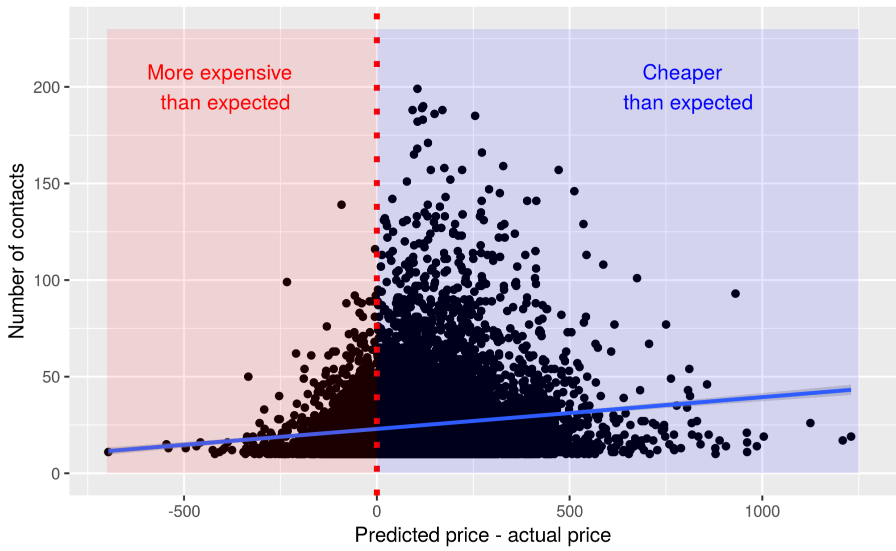
7 indicates a positive correlation: listings that are offered at a more affordable rent than expected (positive residual rent) tend to receive more contacts.

To rigorously determine the relationship between the residual rent and the number of contacts, while accounting for the 10-contacts threshold, I estimate a truncated regression.[14] The model I estimate is as follows:

$$Y_i = \begin{cases} X_i\boldsymbol{\beta} + \varepsilon_i < L, & \text{excluded} \\ X_i\boldsymbol{\beta} + \varepsilon_i \geq L, & \text{included} \end{cases} \tag{2}$$

where Y_i is the log of the number of contacts received through the website and the truncation parameter L is equal to 10. I also maintain the assumption that conditional on X_i, Y_i is normally distributed with mean $X_i\boldsymbol{\beta}$ and variance σ^2. Given the log-linear nature of the model, Table 4 suggests that if a landlord decreases the advertised rent by 10 euros, the number of contacts through the platform should increase by approximately 1.8%.

Figure 7: Deviation from predicted rent and number of contacts



Sources: Author's calculations based on data from LouerAgile.
Notes: The x-axis represents the residual rent deviation, calculated as the difference between the rent predicted by observable features (based on the hedonic model from Table 3) and the observed rent. The y-axis denotes the total number of contacts landlords received via the LouerAgile website. Observations with less than 10 contacts are not observed. The blue line illustrates the predicted line from a naive OLS regression, which does not account for the truncation of the y variable.

[14]It is well known that using OLS in this context results in a truncation bias (Hausman and Wise, 1977). In practice, I use truncreg package in R (Croissant and Zeileis, 2016).

Table 4: Truncated regression

	Dependent variable:
	log number of contacts
Constant	1.56601***
	(0.09016)
Predicted - actual rent	0.001770***
	(0.00014)
σ	1.095269***
	(0.027501)
Log-Likelihood	-6369.5 on 3 Df
Note:	*p<0.1; **p<0.05; ***p<0.01

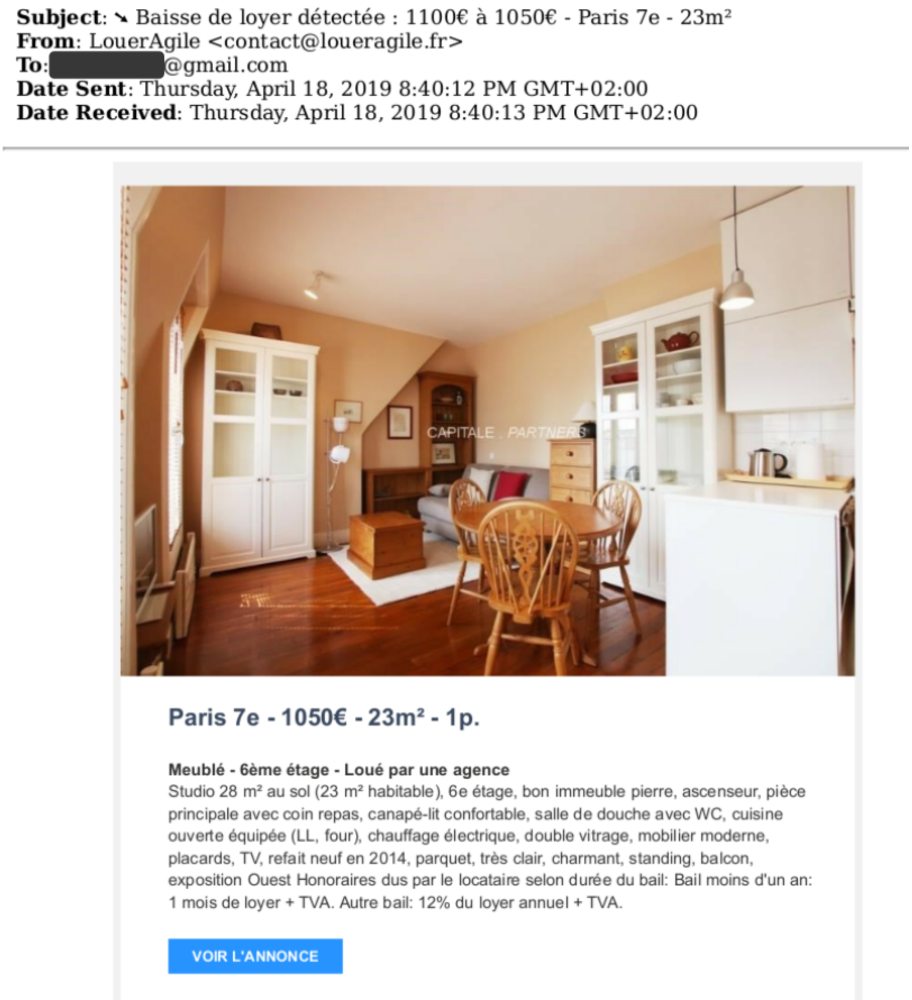
Sources: Author's calculations based on data from LouerAgile.
Notes: This table presents the results of a truncated regression analysis that accounts for the fact that the platform only displayed contact counts of 10 or more.

4 Rent setting dynamics

This section offers new insights on landlords' pricing strategy. Many start by advertising a high rent before lowering towards the one predicted by the estimated hedonic model.

A unique feature of the LouerAgile website facilitated the observation of landlord behavior. The platform sends email notifications to users when the advertised rent for a property is reduced. These emails not only provide details about the initial and updated rents but also include a URL link that directs users to the complete property description, as illustrated in Figure 2. Crucially, this comprehensive description specifies the date when the listing was first uploaded, making it possible to calculate the duration between the initial and updated prices.

Figure 8: Example of an email indicating a rent decline



Source: Screenshot of an email send by LouerAgile during the web scraping period.
Notes: The screenshot displays an email from LouerAgile alerting users about a rent reduction for a specific listing. The email's subject line highlights both the original and the revised rents.

Several key observations can be made regarding the adjustment of advertised rent. First, about 4.9% of the listings in the sample saw a decline in the advertised rent. Second, the median percentage decline in the advertised rent is roughly −6.25% (as shown in Figure 9a). Third, the median duration before an advertised rent reduction is 23 days (as depicted in Figure 9b).

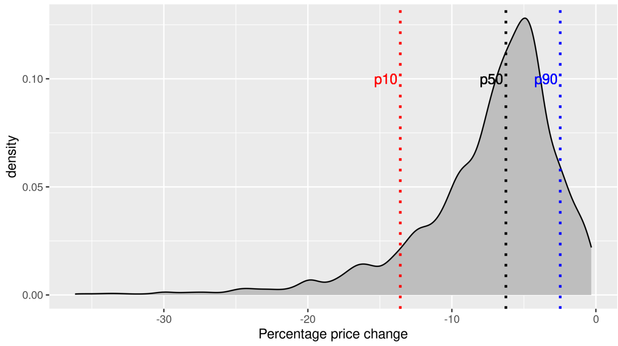
How do these figures compare with prior research? Merlo and Ortalo-Magne (2004) note that 23% of real estate properties for sale experienced a downward price adjustment over a span of 35 months. This implies a 0.65% probability of adjustment every month. In contrast, my findings indicate a 1.26% probability of adjustment every month, suggesting that repricing might occur more frequently in the rental market than in the home buying market. In addition, Merlo and

Ortalo-Magne (2004) state that the average waiting period before a repricing is 11 weeks, with an average price reduction of 5.3%. In comparison, my research shows an average waiting time of only 4 weeks (29.6 days) and an average rent decline of 7.44%. A study by Knight (2002), focusing on the US real estate market between January 1997 and December 1998, offers similar insights. Knight reports an average waiting period of 14 weeks before repricing and an average price reduction of 7.4%. Overall, my findings align with previous research on the real estate market.

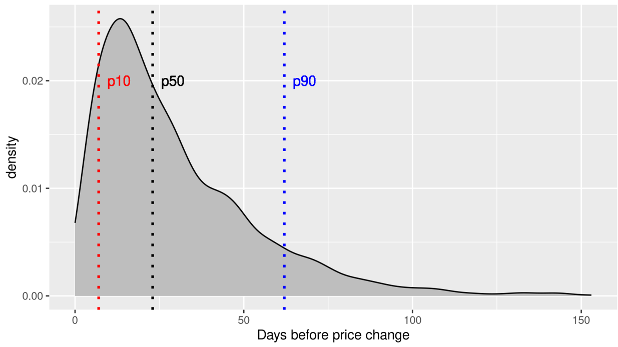
I now examine the differences between listings whose rent has been adjusted and those with no rent adjustment, using three Welch's t-tests. These tests evaluate the null hypothesis that two populations have equal means, when the variances for both groups are unknown and might be unequal. Reading from left to right, Table 5 reveals that listings that adjusted their rent: (i) initially asked for rents that were higher than comparable listings that did not adjust their rent (their deviation from the predicted rent was significantly more positive than that of the control group); (ii) received fewer contacts than listings that did not adjust their rents; and (iii) were more often managed by a real estate agency rather than by landlords. The first two points align well with the findings from the previous section. As demonstrated earlier, listings asking for unusually higher rent tend to attract fewer potential tenants.

The third point, emphasizing that listings managed by real estate agencies are more prone to adjusting rents, can be given different interpretations. Two narratives emerge: one centered on learning and the other on profit maximization. It is plausible that both landlords and real estate agencies initially lack precise knowledge of their property's valuation. Therefore, they might adopt a slow Dutch auction strategy, starting by asking for a high rent and adjusting it based on the observed interest from potential tenants. Given that real estate agencies are professionals, they might be more inclined to reduce the rent if there are few contacts from potential tenants. However, it is somewhat perplexing that real estate agencies might not have a clear grasp of the "fair price" from the outset. Compared to landlords, agencies undoubtedly have a more informed perspective, given their management of multiple properties and access to extensive proprietary data. A different narrative could be that real estate agencies, driven by incentives to set higher rents as discussed in section 3.1, might be more inclined to adopt a strategy that maximizes profit. I delve deeper into this notion in the subsequent section, referencing some theoretical insights from existing literature.

Figure 9: Percentage changes in advertised rent and number of days before rent adjustment



(a) Distribution of percentage changes in advertised rent



(b) Distribution of days leading up to the rent adjustment

Sources: INSEE and author's calculations based on data from LouerAgile.
Notes: Panel 9a illustrates the distribution of percentage changes in advertised rent. Panel 9b shows the distribution of days between rent adjustments. The vertical lines in red, black, and blue denote the 10th, 50th, and 90th percentiles, respectively.

Table 5: Comparison of adjusted and non-adjusted listings using Welch's t-test

	predicted price - actual price	number of contacts per listing	real estate agency
t-statistic	23.286	4.828	-19.305
DF	2,592.344	2,723.005	2,801.946
p-value	$< 2.2e-16$	$1.45e-06$	$< 2.2e-16$
Group with no rent adjustment	2.006	5.086	0.672
Group rent adjustment	-147.637	3.867	0.827

Source: Author's calculation based on data from LouerAgile.
Notes: This table presents the outcomes of three Welch's t-tests to evaluate the hypothesis that two populations have equal means, when the variances might be unequal. Tests compare the mean of listings that adjusted their rent with the mean of all other listings. The first column compares the mean deviation from predicted rents (determined using a hedonic regression model); the second column compares the mean number of contacts each listing received; and the final column compares the proportion of listings advertised by real estate agencies. DF refers to the degrees of freedom, approximated using the Welch-Satterthwaite approximation.

5 Discussion: efficiency and welfare considerations

This section revisits the two primary empirical findings presented in this paper, considering them in the context of prominent results from the theoretical literature, some of which were previewed in the introduction.

Firstly, this paper emphasizes that the search process in the rental market aligns more closely with a directed search model than a random search model. This is evident as tenants are more likely to contact landlords who offer an unusually low rent, a standard prediction of directed search models. A standard result from the search literature states that in markets with frictions, if (i) sellers post their prices in advance with commitment, and (ii) buyers can observe these prices and choose where to search, then the resulting decentralized search equilibrium is constrained efficient. This observation was first made by Moen (1997). The combination of points (i) and (ii) leading to a constrained efficient outcome can be generalized across various settings. For instance, Acemoglu and Shimer (1999) establish that this efficiency result holds even if buyers only observe a subset of posted prices. Menzio and Shi (2011) argue that the efficiency result holds even in a directed search model with aggregate uncertainty on productivity. Schaal (2017) studies a directed search model encompassing both idiosyncratic and aggregate uncertainty, to find that the market outcome retains its constrained efficiency property. Thus, the search literature suggests that the combination of price posting by sellers and directed search by buyers typically results in an efficient equilibrium, even in markets with inherent frictions. Given these theoretical insights, the tendency of tenants to contact more landlords who set unusually lower rents indicates market efficiency. In other words, it is a sign that tenants can effectively use the information presented in online listings and internalize the trade-offs between finding a dwelling rapidly and minimizing the rental cost.

Secondly, I have found evidence that some listings are adjusted according to a slow Dutch auction strategy. This strategy is more frequently used by real estate agencies than landlords, suggesting a higher degree of sophistication. These findings emphasize the complexity of the rental market, which goes beyond the scope of a standard static directed search model. The rent-setting strategy can be interpreted in several ways. According to the literature on finite-horizon dynamic programming models, as featured in Salant (1991) and Merlo, Ortalo-Magné, and Rust (2015), choosing a strategy of downward adjustment to prices is the profit-maximizing strategy for sellers. Therefore, it is logical that real estate agencies, representing the most informed sector of the rental market, use this strategy more often. However, to obtain tractable models, Salant (1991) and

Merlo, Ortalo-Magné, and Rust (2015) assume that buyers are unsophisticated *bidding automata*.

The literature, when viewed from a game theory perspective, offers different insights into the slow Dutch auction. In these studies, interactions between buyers and sellers are fully modeled, but take place within infinite-horizon models. According to Shneyerov (2014), when buyers are less patient than sellers, or as Carare and Rothkopf (2005) suggest, when the cost of revisiting the same property is high, the slow Dutch auction becomes the optimal choice for sellers. In these settings, the seller can intertemporally price discriminate buyers (Stokey, 1979). In addition, Fuchs and Skrzypacz (2010) explain the seller's preference for a slow Dutch auction, especially when facing a random influx of new buyers. In such scenarios, sellers prefer a decreasing pricing function with infrequent updates. In a market dominated by sellers with few buyers, transactions are swift, allowing buyers to capture most of the surplus. In contrast, in a buyer-saturated market with fewer sellers, trades are slower due to strategic delays, which benefits sellers by letting them secure a larger share of the surplus. This behavior, where sellers opt for a series of downward prices, indicates a seller's market with a higher number of buyers than sellers. This interpretation is consistent with the descriptive evidence provided in section 2.3, which emphasizes the "tightness" of the rental market in the city of Paris during the period analyzed.

6 Conclusion

This paper presents new empirical insights into the dynamics of the rental housing market. Drawing from a unique dataset, web-scraped from online listings in the Paris metropolitan area in 2019, I establish two main empirical observations. The dataset, rich with details on property characteristics and tenant search intensity, is crucial for these findings.

First, the rental property market aligns more with a directed search model than a random search model. Properties priced lower than what their observable features suggest tend to attract more attention from potential tenants. This behavior aligns with predictions from standard directed search models. While this may seem intuitive, this result carries significant theoretical and practical ramifications, especially when considering the divergent policy implications of random versus directed search models. To support this finding, I employ a hedonic model for rent, incorporating standard features known to correlate with rental levels and introducing additional aesthetic features derived from property photos using deep learning techniques. Second, I observe that approximately 5% of landlords employ a slow Dutch auction strategy for rent-setting. This approach mirrors behaviors seen in other durable goods markets, like the home buying sector, as noted by Merlo and Ortalo-Magne (2004) and is also a topic of interest in theoretical studies.

In summary, while a standard static directed search model provides a qualitative insight into buyer-seller interactions in the rental property market, more sophisticated frameworks might offer a clearer picture. Future research could delve deeper into models such as those proposed by Salant (1991) and Merlo, Ortalo-Magné, and Rust (2015), to estimate a dynamic programming model that mirrors observed empirical patterns. There is also potential in further theoretical exploration, particularly in endogenizing buyer behavior within these models. Fuchs and Skrzypacz (2010) hint at the possibility that rent adjustment might reflect market imbalances between buyers and sellers. Therefore, another promising research direction could involve using price changes to deduce market structure at a finer geographical scale. Future research avenues might also include conducting analogous studies in various countries, such as large advanced economies like the United States or small open economies like Luxembourg. However, it may be challenging to collect data on the number of applicants for a rental property. Certain websites do offer alternative measures, for example, the frequency with which a listing is saved. These could serve as proxy variables to measure search intensity.

References

ACEMOGLU, D. (1997): "Training and innovation in an imperfect labour market," *The Review of Economic Studies*, 64(3), 445–464.

ACEMOGLU, D., AND R. SHIMER (1999): "Holdups and efficiency with search frictions," *International Economic Review*, 40(4), 827–849.

ADAMS, P. D., B. D. KLUGER, AND S. B. WYATT (1992): "Integrating auction and search markets: the slow Dutch auction," *The Journal of Real Estate Finance and Economics*, 5, 239–253.

ADLER, D., AND B. ANSELL (2020): "Housing and populism," *West European Politics*, 43(2), 344–365.

AHLFELDT, G. M., S. HEBLICH, AND T. SEIDEL (2023): "Micro-geographic property price and rent indices," *Regional Science and Urban Economics*, 98, 103836.

BAIETTO-BEYSSON, S., AND B. VORMS (2012): "Les observatoires des loyers," *Paris: La Documentation française, Agence nationale pour l'information sur le logement, Observatoire des loyers de l'agglomération parisienne, rapport pour le ministère de l'Égalité des territoires et du logement*.

BANFI, S., AND B. VILLENA-ROLDAN (2019): "Do high-wage jobs attract more applicants? Directed search evidence from the online labor market," *Journal of Labor Economics*, 37(3), 715–746.

BELOT, M., P. KIRCHER, AND P. MULLER (2022): "How wage announcements affect job search—a field experiment," *American Economic Journal: Macroeconomics*, 14(4), 1–67.

BOEING, G., J. WEGMANN, AND J. JIAO (2023): "Rental housing spot markets: How online information exchanges can supplement transacted-rents data," *Journal of Planning Education and Research*, 43(3), 525–537.

BRENZEL, H., H. GARTNER, AND C. SCHNABEL (2014): "Wage bargaining or wage posting? Evidence from the employers' side," *Labour Economics*, 29, 41–48.

BROWN, J., AND D. A. MATSA (2019): "Locked in by leverage: Job search during the housing crisis," *Journal of Financial Economics*.

BRUECKNER, J. K., J.-F. THISSE, AND Y. ZENOU (1999): "Why is central Paris rich and downtown Detroit poor?: An amenity-based theory," *European economic review*, 43(1), 91–107.

CARARE, O., AND M. ROTHKOPF (2005): "Slow dutch auctions," *Management Science*, 51(3), 365–373.

CHAPELLE, G., AND J. B. EYMÉOUD (2022): "Can big data increase our knowledge of local rental markets? A dataset on the rental sector in France," *PloS one*, 17(1), e0260405.

CROISSANT, Y., AND A. ZEILEIS (2016): "truncreg: Truncated Gaussian regression models," *R package version 0.2-4, URL https://CRAN. R-project. org/package= truncreg*.

DIETRICH-RAGON, P. (2013): "Qui rêve du logement social?," *Sociologie*, 4(1), 19–42.

FABERMAN, R. J., AND G. MENZIO (2018): "Evidence on the relationship between recruiting and the starting wage," *Labour Economics*, 50, 67–79.

FISCHER, W., AND B. SARD (2017): "Chart book: Federal housing spending is poorly matched to need," *Washington, DC: Center on Budget and Policy Priorities. March*, 8.

FRANCO, S. F., AND C. D. SANTOS (2021): "The impact of Airbnb on residential property values and rents: Evidence from Portugal," *Regional Science and Urban Economics*, 88, 103667.

FUCHS, W., AND A. SKRZYPACZ (2010): "Bargaining with arrival of new traders," *American Economic Review*, 100(3), 802–836.

GANONG, P., AND D. SHOAG (2017): "Why has regional income convergence in the US declined?," *Journal of Urban Economics*, 102, 76–90.

GARCIA-LÓPEZ, M.-À., J. JOFRE-MONSENY, R. MARTÍNEZ-MAZZA, AND M. SEGÚ (2020): "Do short-term rental platforms affect housing markets? Evidence from Airbnb in Barcelona," *Journal of Urban Economics*, 119, 103278.

GENESOVE, D., AND L. HAN (2012): "Search and matching in the housing market," *Journal of Urban Economics*, 72(1), 31–45.

GIRSHINA, A., F. KOULISCHER, AND U. VON LILIENFELD-TOAL (2022): "Tax Subsidies and Housing Affordability," *Swedish House of Finance Research Paper*, (21-08).

GRILICHES, Z. (1961): "Hedonic price indexes for automobiles: An econometric of quality change," in *The price statistics of the federal goverment*, pp. 173–196. NBER.

HAN, L., AND W. C. STRANGE (2014): "Bidding wars for houses," *Real Estate Economics*, 42(1), 1–32.

——— (2016): "What is the role of the asking price for a house?," *Journal of Urban Economics*, 93, 115–130.

HARTEN, J. G., A. M. KIM, AND J. C. BRAZIER (2021): "Real and fake data in Shanghai's informal rental housing market: Groundtruthing data scraped from the internet," *Urban Studies*, 58(9), 1831–1845.

HAUSMAN, J. A., AND D. A. WISE (1977): "Social experimentation, truncated distributions, and efficient estimation," *Econometrica: Journal of the Econometric Society*, pp. 919–938.

HERKENHOFF, K. F., L. E. OHANIAN, AND E. C. PRESCOTT (2018): "Tarnishing the golden and empire states: Land-use restrictions and the US economic slowdown," *Journal of Monetary Economics*, 93, 89–109.

HOSIOS, A. J. (1990): "On the efficiency of matching and related models of search and unemployment," *The Review of Economic Studies*, 57(2), 279–298.

KAEMPFF, B. (2018): "Bulletin BCL 2018-1: Les interventions de l'Etat sur le marché immobilier au Luxembourg," *Online, accessed November 27, 2023* https://www.bcl.lu/fr/publications/bulletins_bcl/Bulletin-BCL-2018_1/Bulletin-BCL-2018_1.pdf.

KNIGHT, J. R. (2002): "Listing price, time on market, and ultimate selling price: Causes and effects of listing price changes," *Real estate economics*, 30(2), 213–237.

KOSTER, H. R., J. VAN OMMEREN, AND N. VOLKHAUSEN (2021): "Short-term rentals and the housing market: Quasi-experimental evidence from Airbnb in Los Angeles," *Journal of Urban Economics*, 124, 103356.

LAFERRÈRE, A., E. POULIQUEN, AND C. ROUGERIE (2017): "Les conditions de logement en France. Edition 2017. Vue d'ensemble. Le logement en France depuis trente ans," .

LINDENTHAL, T. (2020): "Beauty in the eye of the home-owner: Aesthetic zoning and residential property values," *Real Estate Economics*, 48(2), 530–555.

LUCKING-REILEY, D. (1999): "Using field experiments to test equivalence between auction formats: Magic on the Internet," *American Economic Review*, 89(5), 1063–1080.

MARCHIORI, L., J. PASCAL, AND O. PIERRARD (2023): "(In) efficient commuting and migration choices: Theory and policy in an urban search model," *Regional Science and Urban Economics*, 102, 103936.

MARINESCU, I., AND R. WOLTHOFF (2020): "Opening the black box of the matching function: The power of words," *Journal of Labor Economics*, 38(2), 535–568.

MENZIO, G., AND S. SHI (2011): "Efficient search on the job and the business cycle," *Journal of Political Economy*, 119(3), 468–510.

MERLO, A., AND F. ORTALO-MAGNE (2004): "Bargaining over residential real estate: evidence from England," *Journal of urban economics*, 56(2), 192–216.

MERLO, A., F. ORTALO-MAGNÉ, AND J. RUST (2015): "The home selling problem: Theory and evidence," *International Economic Review*, 56(2), 457–484.

MOEN, E. R. (1997): "Competitive search equilibrium," *Journal of political Economy*, 105(2), 385–411.

MOEN, E. R., AND Å. ROSÉN (2004): "Does poaching distort training?," *The Review of Economic Studies*, 71(4), 1143–1162.

O'SHEA, K., AND R. NASH (2015): "An introduction to convolutional neural networks," *arXiv preprint arXiv:1511.08458*.

PASCAL, J. (2020): "Search, matching and heterogeneity," Ph.D. thesis, Institut d'études politiques de Paris - Sciences Po.

PIAZZESI, M., M. SCHNEIDER, AND J. STROEBEL (2020): "Segmented housing search," *American Economic Review*, 110(3), 720–759.

POURSAEED, O., T. MATERA, AND S. BELONGIE (2018): "Vision-based real estate price estimation," *Machine Vision and Applications*, 29(4), 667–676.

ROSEN, S. (1974): "Hedonic prices and implicit markets: product differentiation in pure competition," *Journal of political economy*, 82(1), 34–55.

SALANT, S. W. (1991): "For sale by owner: When to use a broker and how to price the house," *The Journal of Real Estate Finance and Economics*, 4, 157–173.

SCHAAL, E. (2017): "Uncertainty and unemployment," *Econometrica*, 85(6), 1675–1721.

SHEN, L., AND S. ROSS (2021): "Information value of property description: A machine learning approach," *Journal of Urban Economics*, 121, 103299.

SHNEYEROV, A. (2014): "An optimal slow Dutch auction," *Economic Theory*, 57, 577–602.

STOKEY, N. L. (1979): "Intertemporal price discrimination," *The Quarterly Journal of Economics*, 93(3), 355–371.

TALEBI, H., AND P. MILANFAR (2018): "NIMA: Neural image assessment," *IEEE Transactions on Image Processing*, 27(8), 3998–4011.

WEI, S.-J., X. ZHANG, AND Y. LIU (2017): "Home ownership as status competition: Some theory and evidence," *Journal of Development Economics*, 127, 169–186.

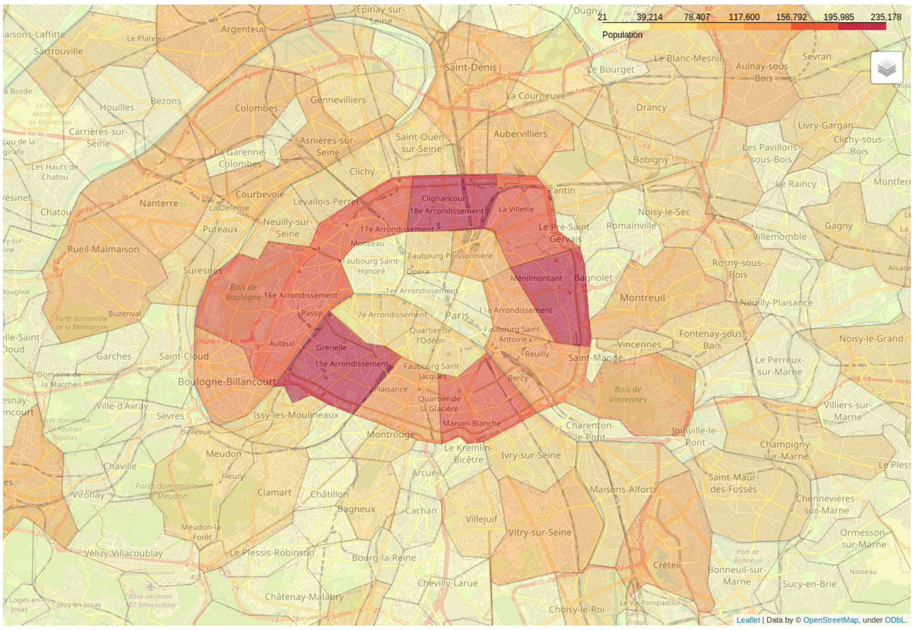
WHEATON, W. C. (1990): "Vacancy, search, and prices in a housing market matching model," *Journal of political Economy*, 98(6), 1270–1292.

ZHANG, Y., AND R. DONG (2018): "Impacts of street-visible greenery on housing prices: Evidence from a hedonic price model and a massive street view image dataset in Beijing," *ISPRS International Journal of Geo-Information*, 7(3), 104.

Appendix

A Maps

Figure 10: Population in the Paris metropolitan area in 2017



Source: INSEE.

Figure 11: Number of listings

Source: Author's calculations based on data from LouerAgile.

Figure 12: Median rent per m^2

Source: Author's calculations based on data from LouerAgile.

Figure 13: Median surface of advertised accommodation (m^2)

Source: Author's calculations based on data from LouerAgile.

Figure 14: Mean number of rooms

Source: Author's calculations based on data from LouerAgile.

Figure 15: Mean number of bedrooms

Source: Author's calculations based on data from LouerAgile.

Figure 16: Percentage of accommodations rented furnished

Source: Author's calculations based on data from LouerAgile.

Figure 17: Percentage of listings managed by a real estate agency

Source: Author's calculations based on data from LouerAgile.

BANQUE CENTRALE DU LUXEMBOURG

EUROSYSTÈME

2, boulevard Royal
L-2983 Luxembourg

Tél.: +352 4774-1
Fax: +352 4774 4910

www.bcl.lu • info@bcl.lu