Housing and discrimination in economics : an empirical approach using Big Data and natural experiments

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Housing and Discrimination in Economics: an Empirical Approach using Big Data and Natural Experiments

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Contents

Abstract

This dissertation is composed of three papers. Two of them aim at better understanding the French housing market while the last one focuses on gender discrimination in politics.

The first chapter documents one of the key parameter to understand the housing market: the supply elasticity of French urban areas. It starts by defining two different concepts related with the supply elasticity. The first one is the intensive margin supply elasticity and designates the reaction of developers following a short run increase in housing prices. It describes how many housing units will be produced if the demand for housing rise. The second one describes an agglomeration cost. In urban economics, cities are the result of agglomeration forces: positive production externalities drive households and firms to concentrate on the same place. However, cities' development is curbed by agglomeration costs as congestion or an increase in land prices. Indeed, the larger the city, the higher the housing prices and the commuting costs. As a consequence, a second key parameter when looking at the housing market is the extensive margin supply elasticity. It describes the magnitude of real estate prices appreciation when the city is growing. Thanks to an important amount of new data collected and an original estimation strategy, this first chapter estimates and decomposes both parameters. It shows that France is characterized by a very low extensive margin when compared with similar studies on the United States. The gap between both countries appears to be related with the high degree of regulation on the French residential land market.

The second chapter focuses on the possibilities offered by Big Data to study the French rental market. Based on the observation that the rental market is poorly documented despite its economic importance, we provide a method to fill this information gap by using rental websites. We present a database built on adds posted on the two main French real estate websites between December 2015 and June 2017. We start by explaining how an algorithm can be used to extract features of online rental posts and structure them in a regular dataset. We discuss the presence of methodological biases and compare our data with the one of the French Housing Survey. Despite the fact that online prices represent posted rents and not signed ones, the two distributions of prices are really close. We attribute this absence of difference by the relative transparency of online platforms which tends to force landlords to reveal the market price and the small bargaining power of renters. We provide estimates of the level of rent of

a representative good in the main French urban areas. Finally, we illustrate one possible use for our database by estimating the distribution of the implicit subsidy related with the access to a social housing unit.

The third chapter focuses on gender discrimination in politics. It exploits a natural experiment in the 2015 French départementales elections during which, for the first time in the history of French elections, candidates had to run by gender-balanced pairs. This arguably confused some voters, who were used to vote for a single candidate and a substitute, and who might have assumed that the first listed candidate was the main one. Using the fact that the order of appearance of the candidates on a ballot is determined by alphabetical order and showing that this rule does not seem to have been used strategically by parties, we argue that the position of female candidates on the ballot is as good-as random. Exploiting this feature, we show that right-wing ballots where the female candidate is listed first receive on average 1.5 percentage points lower shares of vote (a difference of about 4% to 5%), and are 4 percentage points less likely to go to the second round or win the election (a difference of about 5% to 6%). We then use the fact that candidates can report additional information about themselves on the ballot to test for the presence of statistical discrimination. Using a sample of about 12% of the ballots, we show that about 35% of pairs of candidates reported information about themselves on the ballot, and that the gender-discrimination we identified is likely to be statistical: indeed, the effect is driven by ballots on which candidates reported no information at all. We finally show that this discrimination increased the vote shares of political opponents and is correlated with unexplained wage gaps on the labor market.

Chapter 1

Introduction

Three papers composed this PhD dissertation. Two of them are related to urban economics while the last one aims at identifying gender discrimination in politics. In this introduction, we explain the reasoning behind the three papers as well as their links. We start by describing the crucial role played by the housing market in modern urban economics. We show that little is known about French local housing markets and the determinants of their elasticities. Then, we focus on a specific section of the housing market: the rental sector. We argue that the rental component of the housing market is virtually unknown in France despite its fundamental role in the economic process. We show how Big Data methods and particularly web scraping can be used to create new database to describe it. Then, taking a broader approach, we show how Big Data is changing urban economics research by introducing new forms of data and statistical methods. Finally, we explain why Big Data offers new opportunities to better understand discriminatory behaviours.

1.1 Understanding the housing market

1.1.1 The forces of urbanization

According to Fujita and Thisse (2013), urban economics aims at understanding the interactions between space and economic agents. Over the last centuries, one question has been at the heart of the debate in this field: the forces of urbanisation. In 1921, the French geographer Vidal de la Blache wrote in his *Principes de géographie humaine* that all societies, rudimentary or developed, face the same dilemma: "*Individuals must get together to benefit from the advantages of the division of labor, but various difficulties restrict the gathering of many individuals*". Since his work, we know what is behind the urbanisation process. The observed spatial equilibrium is the result of a balance between centripetal agglomeration forces and dispersion centrifugal forces.

Several theories have been put forward to explain centripetal forces. In particular, the father of modern economics, Marshall (1920) explains how external increasing returns explain the location choice of firms: "*When an industry has thus chosen a location for itself, it is likely to stay there long; so great are the advantages which people following the same skilled trade get from near neighbourhood to one another. [...] If one man starts a new idea, it is taken up by others and combined with suggestions of their own; and thus it becomes the source of further new ideas*". Marshall's ideas have been completed and formalised throughout the XX century. Nowadays, the determinants of urban agglomeration economies are better known and we gather them as group of externalities (see Duranton and Puga (2004)). People who live in large cities have a higher probability to find a job which corresponds to their qualification (matching externalities). They can absorb higher fixed costs as they have access to larger markets (sharing externalities), and they are more productive because they have an easier access to knowledge (learning externalities). Nevertheless, urban economics doesn't know much about the "dark side" of urbanisation. Living in a denser area means benefiting from urban agglomeration economies but it also means living in expensive places, facing important commuting costs and breathing polluted air. To understand these urban costs, economic theory tells us that it is necessary to study the housing market.

1.1.2 The role of the housing market

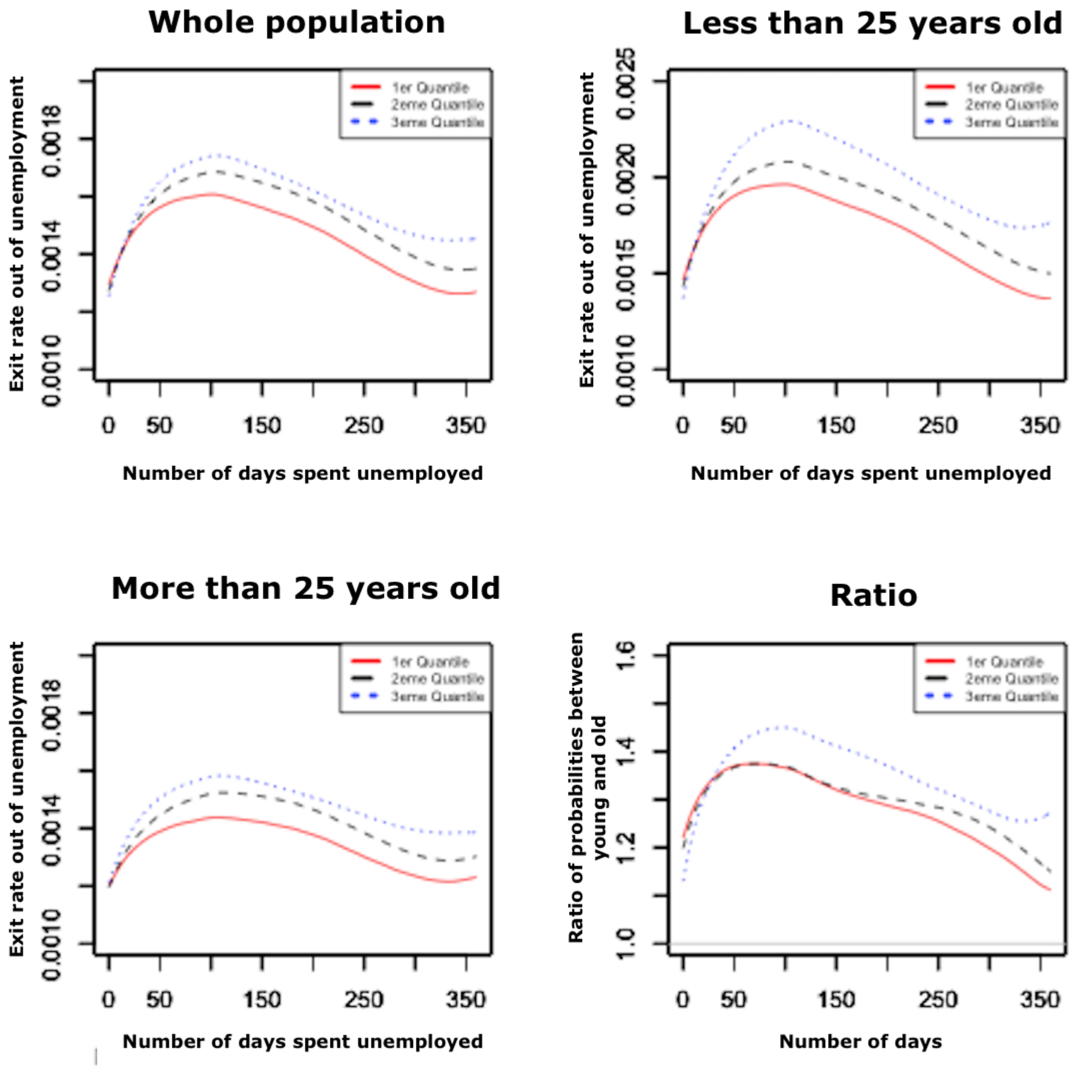
In most urban models, the spatial equilibrium is reached through the housing market. This is the case for instance, in the classical monocentric framework of Alonso (1964), Mills (1972), and Muth (1969). When people decide to live somewhere, they face a trade-off between leaving in the center and paying expensive housing prices or leaving in the suburbs but commuting everyday to go to work in the center. In most urban models, the housing price is such that the general commuting cost offsets the cost of housing: the utility is the same in every part of the city and the spatial equilibrium is reached. Therefore, housing prices reflect the trade-off between being in the dense part of the city, enjoying the benefits of urban density or leaving away and facing important commuting costs. This makes the housing market one of the cornerstones of urban theory.

When a city gets bigger, the first negative sizeable impact of the increase in density is the boost of housing costs. Following this idea, Duranton and al. (2017) provide an elasticity of urban cost with respect to city population. They show that a 10% increase in population in a small city leads to a 0.4% increase in expenditure for its residents to remain equally well off. The effect is driven by the housing market which reacts and changes the indirect utility of economic agents. Nevertheless, the magnitude of the change in housing costs depends on other factors: housing prices might be more reactive in highly regulated areas where new constructions are forbidden (Fischel (2001)) or in areas close to the sea or cliffs where construction costs to change the geographical landscape rapidly become prohibitive (Rose (1989), Saiz (2010)). My first chapter follows this idea. More precisely, it studies the determinants of housing supply elasticities or, putting differently, the determinants of urban costs at a local level. It shows that French local housing markets are heterogeneous and it also highlights the importance of geography and regulation to understand housing elasticities both in the short and the long run.

1.1.3 Housing market and the spatial mismatch

The housing market ability to absorb economic shocks is important to understand urban concentration. But it also has several implications in other markets. For instance, a dynamic city with a high housing supply elasticity might see its housing prices skyrocket after a positive economic shock: this can prevent people from finding a house or moving in dynamic cities during booms. The links between employment and the structure of cities are at the heart of the spatial mismatch literature (see Gobillon, Selod, and Zenou (2007) for a review). Jobs are generally located at the center of cities while cheap houses are found in the suburbs. This spatial disconnection between labour supply and demand creates deprived zones where finding a job is arduous. For instance, Gobillon, Magnac, and Selod (2011) show that in the Parisian area, 70% of disparities in the observed determinants of unemployment survival rates relate to local factors. My master's thesis (Eyméoud and Wasmer (2016)), which is not included in my PhD, followed this idea of spatial mismatch but focused on young people that are particularly impacted. It studied the determinants of unemployment duration with respect to the age and location. More precisely, on a sample of 1 602 626 episodes of unemployment in France between 2002 and 2011, I estimated proportional hazard and Kaplan-Meier models to study the differential exit rates between young and old people in cities with different housing market tightness. In Figure 1.1, I present the exit rate of unemployment estimated with a Kaplan-Meier model.

The hazard functions of people living in dynamic cities are systematically higher. This means that people who leave in a city with a tight housing market leave unemployment faster than those who are located in cities with a slack housing market. I showed that if this is true for old and young people, a young person has an additional gain to move from a non-dynamic city to a dynamic one than an old person who would do the same thing. This highlights that the spatial mismatch problem is particularly salient for young people. The housing market prevents them from joining dynamic cities and it has an important social cost.



Exit rate of unemployment. The top left figure considers the entire population and provides the evolution of the chances of getting out of unemployment for cities where rents are the cheapest (continuous red line), cities where rents are normal (discontinuous black line) and cities where rents are the most expensive (dotted blue line). The top right figure focuses on people under 25, the bottom left figure looks at people over 25 years old. Finally, the bottom right figure displays the ratio of probabilities of getting out of unemployment for young people out of unemployment compared to the rest of the population in the different subsamples of cities.
Source: Eyméoud and Wasmer (2016)

Figure 1.1: Unemployment duration by age and local housing market tightness

1.1.4 The rental market blank

Behind the results, a methodological challenge of my master's thesis was to find a good way characterise the housing market tightness. A noteworthy point was that I had to rely only on raw rental data at the city level provided by CLAMEUR[1] an association of real estate agencies. Indeed, if transactions prices are usually systematically recorded by the fiscal administration or the solicitors, access to rental data to researchers remains limited, in particular at the local level. Yet, this set of data is important for several reasons. First, in 2013 the rental market represents 38% of the housing market. Not having data to study it means forgetting a fundamental part of the housing story. Second, the rental sector is the part of the housing market which welcomes new inhabitants and allows mobility between cities: the heart of the spatial mismatch problem relies on it. Third, it gathers a lot of public policies which are potentially inefficient (see Grislain-Letrémy, Trevien, et al. (2014) or Fack (2006) for the housing allowances case).

All these reasons led my co-author Guillaume Chapelle and I to find new data to study the rental market. My second chapter shows how Big Data can be used to describe local markets. Since December 2015, we have used web scraping methods to periodically collect, clean and analyse housing posts coming from the two largest French rental websites. To get the data from the two websites, we used Python, a programming language which, among lots of things, allows to create programs that mimic web browser requests. First, we found the Uniform Resource Locator (URL) of each post which concerns the rental market in France. Second, we extracted the Hypertext Markup Language (HTML) of each page from the server. Third, we cleaned it and structured it so as to get a structured format for each post. We repeated the process of scraping every month for each website from December 2015 until June 2017 and ended up with a database of 2 millions posts in the rental sector.

1.2 New data in economics: a broader approach

1.2.1 Big data and urban economics

This possibility of exploiting web data to study the housing market highlights a more global phenomenon: cities continuously generate data. Digital applications such as Uber, Deliveroo or Yelp are used by an increasing part of the population and tell us a lot about people habits. Economists have started to use them to study various topics related to urban issues. Among

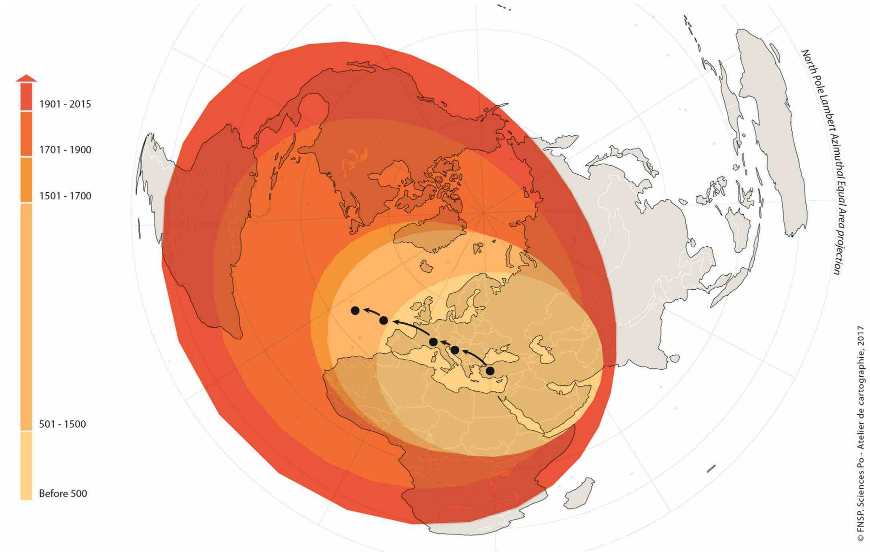
1. CLAMEUR, acronym to know rents and analyze markets on urban and rural areas, is an association governed by the law of 1 July 1901. The CLAMEUR association consists of 5 founding members: PLURIENCE, FONCIA, SNPI, UNIS, UNPI , 28 associate members and associated users (the list of these members is available on the website www.clameur.fr).

others, Davis et al. (2017) use Yelp data to study consumption segregation in New-York, Anderson and Magruder (2012) examine Yelp's effects on restaurant outcomes, Laouénan and Rathelot (2017) study discrimination on Airbnb. The quality of these papers relies on the level of granularity of their observations, which was possible thanks to the scraping of raw user data.

This granularity is important because it sheds light on unstudied part of the cities but also because it helps to better identify economic shock. The Moving Toward Opportunity (MTO) program provides a good illustration of this. In this randomised control experiment launched in the US in the 1990's, selected households received vouchers which enabled them to move from poor areas to rich ones. The official report (Sanbonmatsu et al. (2011)) hardly found any significant economic impact of the program. However, Chetty, Hendren, and Katz (2016) reestimate the effect of the program using geolocalised data which allows to follow households years after the end of the program. They find that people who were less than 13 years old when they moved largely benefited from the program earning 30% more than they counterpart. Hence, the granularity of the data as well as the possibility to track the households changed the final evaluation of the policy. Finally, the benefits of granularity becomes even more salient when considering evaluation of place based policies. By construction, they create lots of sharp spatial breaks that mechanically create control and treatment groups. To have an accurate view of the economic effects at stake and control a maximum number of variables, economists need to work at the smaller available scale.

Moreover, Big Data is not only providing better data, it is changing the scope of questions urban economists can tackle. Consider for instance the appearance of cities. While economists have long been studied amenities and markets (see Bartik and Smith (1987), few studies investigate the importance of the *perception* of cities. This is of particular importance since citizens rank safeness as one of their top priorities regarding housing location. In a recent study, Glaeser et al. (2016) use Google street images to measure the income of New-York areas. Transforming the pictures to "streetscores" and putting them in a support vector regression, the authors build a model which predicts well the local income.

Finally, Big Data provides a tool to shed a new light on old economic questions. In this regard, one of my papers (Laouénan et al. (2018)), which is not included in my PhD, is following a new strand of the economic literature which has recently emerged aiming at studying the impact of local people on past economic events. For instance Serafinelli and Tabellini (2017) who use Freebase.com, a large database owned by Google to emphasize the role of notable individuals on creativity and prosperity, or Schich et al. (2014) who develop a network-based approach to provide a macroscopic perspective of cultural history.



Barycenter of individuals in the database by time period and their dispersion. 5 large historical periods are used (<500 A.D.; 501-1500 A.D.; 1501-1700 A.D.; 1701- 1900 A.D.; 1901-2015 A.D.). The figure shows the barycenter of individuals in the database by time period and their dispersion, from individuals born before 500 A.D. (yellow ellipses) to the most recent period (darker ellipses). Ellipses are constructed from the standard deviations of longitude and latitude.
Source: Laouénan et al. (2018)

Figure 1.3: Barycenter of the database at different periods of time

In our project, we scraped Wikipedia to extract 3.171.703 biographies in 7 different languages[2] and created the largest known database of notable people. Combining the data, we highlighted several historical patterns. For instance, Figure 1.3 above highlights the east-to-the west movement of the barycentre of the database defined by the place of birth and death of well-known people. It follows the world economy theory of Braudel (1985) for whom several world-economies - defined as a geographic area which exercises dominance or influence over peripheries - have followed one another, representing stages of globalization: the sixteenth-century Mediterranean, seventeenth-century Hispanic globalisation, the nineteenth-century British world economy, and the twentieth-century United States-dominated economy. This highlights that contemporary Big Data allows to size differently a problem that was difficult to be addressed quantitatively because of the lack of data.

1.2.2 Unveiling shameful behaviours with Big Data

From a broader perspective, another subfield of economics is likely to be changed by Big Data: the economics of discrimination.

Discrimination has always been a hard phenomenon to study. Since the seminal work of Phillips and Clancy, we know that measuring discrimination is complex because people pre-

2. English and six other major European languages: German, French, Italian, Portuguese, Spanish, Swedish.

fer not to declare embarrassing behaviours in surveys. This is call the social desirability bias (Phillips and Clancy (1972)) which was first shown in a 1950 paper where pollsters went to Denver to ask every citizen if they voted for the presidential election, registered to vote, have a library card or gave to charity during the year. Comparing the differences between the officials data they could access and the answers they collected, they found that a substantial share of citizens preferred to lie and declared socially preferred answers. Several studies have documented this bias (Fisher (1993), Nederhof (1985)) and its persistence even when survey are anonymised.

To overcome the declarative problem, economists have developed several strategies (Bertrand and Duflo (2017)). They all rely on indirect questioning and provide measure of discrimination either at the aggregate level (correspondence test) or individual level (implicit association test). The correspondence methodology consists of creating fictitious individuals that differ only on one characteristic that leads to discrimination (i.e. gender, ethnicity, age). Then, applying for a job, a housing unit or any relevant economic activity where selection takes place and comparing the difference of treatment between the two fictitious individuals, one gets a measure of discrimination in the population of recruiters. This is the main method used by economists to study discrimination. However, it has an important drawback: it only provides an average measure of discrimination. Individuals characteristics of recruiters cannot be used to understand the drivers of discrimination. To go further and get individual measure of discrimination, Greenwald, McGhee and Schwartz developed the Implicit Association Test (IAT (see Greenwald, McGhee, and Schwartz (1998)). It is based on associations between concepts. When competing IAT, a subject is asked to classify, as rapidly as possible, concepts or objects into one of four categories with only two responses (left or right). The logic of the IAT is that it will be easier to perform the task when objects that should get the same answer (left or right) somehow "go together". If IATs has been of great use to better understand the roots of discrimination, it has also been subject to a number of critics. In particular, because IATs differs from explicit choice, some people argue that they only represent psychological features that can be of second order when individuals make choices interacting with their social environments.

Hence, to get ideal measures of discrimination economists must find a situation where agents interact with their environments, make their own choices but are not subject to social desirability bias. Because people are alone behind their screen and feel anonymous, Internet is a perfect framework. The last American election is an enlightening example. According to surveys, Americans no longer care about races. In the same time, anti-immigration speeches of Donald Trump lead him to be become the 45th president of the United States. Stephens-Davidowitz (2014) had access to Google searches and created an aggregate index of racism based on the occurrence of racists requests for various geographical scales. He shows that this index is a strong negative predictor of Obama's results in the 2012 elections even after controlling for local characteristics and is strongly correlated to Donald Trump's results. Interestingly, this index draws a new geographical separation in the US: while the South was, for historical reasons, more likely to have negative stereotypes against black people than the North, Google-based index shows than the Eastern part of the country seems more racist than the West.

However, Google is not the only website which can be used to detect patterns of discrimination. For instance, Laouénan and Rathelot (2017) use Airbnb ratings apartments to measure discrimination against ethnic-minority hosts. Comparing apartments with different reviews, they show that if an ethnic price gap exists when there is little reviews, the difference in prices reduces when more information is provided to the customer. Wu (2017) examines gender stereotyping on the anonymous online forum Economics Job Market Rumors. Analysing the content of the conversations, she shows that discussions about women focus more on physical appearance and family, while discussions about men are more on academic or professional aspects. Additionally, she shows that female economists tend to receive more attention than their male counterpart.

My last chapter deals with gender discrimination in politics. The initial idea my co-author Paul Vertier and I had was twofold. First, we wanted to follow the new frame of gender studies and find an online experiment to study discrimination at a large scale. Second, we aimed at using a machine learning approach to study gender discrimination. This is mainly because discrimination is a complex phenomenon, unlikely to be linear with respect to dependent variables and certainly heterogeneous in the population. The new literature on machine learning based econometrics has been developed to address these issues and better assess local heterogeneity (see Athey and Imbens (2017) for a survey). Most of these papers rely on tree-based methods. Their common idea is to find a good way to divide a group of heterogeneous individuals into homogeneous sub-groups using their characteristics also called features. Ironically enough, searching for an online experiment, we ended up founding a natural experiment which relies on administrative data. Moreover, after spending months using a machine learning approach to characterise heterogeneity of treatment, it turned out that standard econometrics models were in fact perfect to characterise the results in our setting, highlighting the complementarity between econometrics and machine learning.

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Chapter 2

Housing Supply Elasticity

This paper is jointly written with Guillaume CHAPELLE

2.1 Introduction

The housing Supply elasticity has long been a parameter of interest for economists as it seems an important constraint for housing policies and might play a role in real estate cycles. DiPasquale (1999) called our attention about the fact that housing supply was much less documented than housing demand. She explained this gap by the difficulty to document the production decisions (in particular conversions) and the lack of data on the production sector. After, the literature review provided by DiPasquale (1999), the number of contributions trying to estimate the housing supply elasticity increased refining the estimation techniques and highlighting the heterogeneity in supply elasticity across different areas.

Macroeconomics and urban economics both tried to measure this quantity. However both literatures remain poorly connected. Indeed, while both stream of contributions try to estimate the supply elasticity, their approach appear to be different. One goal of this paper is to clarify the distinction between the two approaches. For us, macroeconomics estimates two quantities. A very short run elasticity which corresponds to the price adjustment after a demand shock and a medium run elasticity which corresponds to developers reaction. Because housing takes time to built, the very short run is less elastic. In their framework we can say that firms are price takers and adjust their production level (housing starts) such that their marginal cost equates the price. Starts are the consequence of housing price variation. This literature can easily run cross country comparison as in Meen (2002) or in Andrews, Sánchez, and Johansson (2011) and documents a transatlantic gap showing that European Countries are much more price inelastic than the US. One limit of these contributions is the fact that space and urban growth are absent from their framework.

On the other hand, urban economists take space consumption as the starting point of their analysis. For them, urban growth is the result of positive spatial externalities driving firms and households to concentrate. However, cities do not grow infinitely because their expansion is curbed by agglomeration costs. The most notable one is illustrated in the monocentric model (see Combes, Duranton, and Gobillon (2016) or Saiz (2010) for an illustration) which shows that urban growth drives land and thus housing prices up. Urban economists take a long run perspective where prices are the result of urban growth. So far this literature is mostly focused on the US and showed an important heterogeneity of the elasticity across metropolitan statistical areas. Some scarce papers have also been trying to provide additional information on some European cities. For example Hilber and Vermeulen (2016) estimated the income-price elasticity for the UK while Combes, Duranton, and Gobillon (2016) estimated the land price elasticity with respect to city size for France. However these studies use different specifications and variables providing estimates hard to compare with their US counterparts.

In this work we try to bridge these two streams of literature. For us, given the absence of space and urban growth, macroeconomists are interested in the intensive margin of the housing supply which is the supply when the city size remains fixed. They are looking at the elasticity related to the developers marginal production costs and are interested in housing starts. As a consequence, they should use short run demand shocks in order to estimate the short run supply equation using new housing prices in order to recover the intensive margin supply elasticity.

On the other hand, considering that urban growth is a decennial phenomenon, we think that urban economists are interested in the extensive margin of the housing supply which is the supply when the city size is changing. Since housing prices are the consequence of the city growth, they should estimate the inverse supply equation using long run shocks as in Combes, Duranton, and Gobillon (2016) and Saiz (2010). As they are interested by an agglomeration costs faced by households and firms, it is easily understandable that one should pay attention to rents, or the price of existing unit in order the estimate the extensive supply elasticity.

Collecting an important amount of data on new and existing housing price, housing starts, geographical and regulatory constraint for the main French urban areas, we are able to measure and decompose the two elasticities: the construction elasticity linked to the intensive part of the supply and the agglomeration elasticity related to the extensive supply. To deal with the simultaneity bias, we use the standard Bartik shocks, climate amenities and an instrument derived from macroeconomics (see Monnet and Wolf (2016)): the number of births 20 years before. We also develop a new identification strategy to disentangle the impact of regulation using national rules to instrument a local regulation index. We show that different price series (old vs new) yield different elasticities having different drivers. The construction elasticity based on new prices is mostly driven by regulation. The agglomeration elasticity based on existing price is determined by the share of land already developed and the level of regulation. As far as France is concerned our results also confirm the transatlantic gap, showing a long run elasticity with respect to existing unit price close to 0.333 (vs 1.5 for the US in Saiz (2010)). Given the low level of geographical constraint, regulation might be an important explanatory factor for this gap as in the UK (see Hilber and Vermeulen (2016)).

In section 2.2, we discuss the definition of the supply elasticity, its implication for housing policies and real estate cycles. Section 2.3 introduces our distinction between the construction and agglomeration elasticities and present our empirical specification and identification strategies developed to measure and decompose both concepts. Section 2.4 presents the new dataset gathered to estimate the different types of supply elasticites in France. Section 2.5 provides estimates of the construction and agglomeration elasticities in the short and long run. Section 2.6 presents their respective drivers. Section 2.7 concludes.

2.2 The supply elasticity: A key ingredient to understand the housing market behaviour

2.2.1 Definition

The price elasticity of housing supply describes the way the housing market reacts to an exogenous demand shock. Formally, we can define the behavior and magnitude of the housing supply elasticity as:

$$\beta^S = \frac{\Delta Q}{\Delta P} \times \frac{P}{Q} \tag{2.1}$$

or when changes are small:

$$\beta^S = \frac{\partial Q}{\partial P} \times \frac{P}{Q} = \frac{\partial ln(Q)}{\partial ln(P)} \tag{2.2}$$

Usually, Q is the number of housing starts and P is the housing Price. This quantity describes by how much percentage points will the housing starts increase when housing prices increase by 1 percentage point. This quantity has long attracted the attention of scholars given that the very particular properties of housing[1] can have several implications on the way the market reacts to change in prices.

It is worth noting that urban economists prefer to estimate to inverse supply elasticity:

$$\frac{1}{\beta^S} = \frac{\Delta P}{\Delta Q} \times \frac{Q}{P} = \frac{\partial ln(P)}{\partial ln(Q)} \tag{2.3}$$

where Q is the housing stock. This quantity will describe by how much percentage point will housing price increase if the city size increases by 1%.

2.2.2 The impact of the supply elasticity

It appears important to measure correctly the supply elasticity in order to understand the potential constraints for public interventions and real estates cycles.

Housing is often considered as a merit good (Whitehead and Scanlon (2007)) driving public authorities to intervene on the housing market through subsidies. However, many studies emphasize that policy makers should take into account the supply elasticity when designing their policies. For example, an important amount of funds have been distributed through subsidies or tax benefit in order to enhance the development of deprived areas [2]. Impact studies

1. Housing is often said to be a durable good, a composite good (Rosen (1974)), a local good, an investment good, a consumption good and a merit good at the same time.

2. The Special Enterprise Zones in the US, the UK LEGII or the Zones Franches Urbaines in France are well

have progressively shown that such ”Place Based Policies” tend to be capitalized in land prices offsetting part of the benefit of the programs (Neumark and Simpson (2015)). The standard explanation for such a phenomena invokes urban economics models where subsidies increase the demand for land resulting in a rise in its price particularly strong in inelastic areas. Such interpretation tends to be supported by the results of Poulhès (2015) in France documenting a dramatic increase in commercial real estates driven by inelastic areas where few land is available for additional developments. Some policies as the Low Income Housing Tax Credit in the US are designed to increase the supply of housing for low income tenants but similar mechanisms seem to decrease the efficiency of such programs (see Chapelle and al. (2016)). Moreover, while housing policies represent a major share of transfers toward low income households in Europe, a growing literature tends to demonstrate that housing benefits increase the rent of low income households (Laferrère and Le Blanc (2004), Gibbons and Manning (2006), Fack (2006) or Grislain-Letrémy, Trevien, et al. (2014)). Such a rise of their rents is thus limiting their capacity to increase their housing consumption. It is worth noting that the inflationary impact of these kinds of benefits appear to be much stronger in inelastic areas (Eriksen and Ross (2015)). An important difference in the supply elasticities between French and US cities, could thus explain why French studies tend to find a larger inflationary impact than equivalent studies for the United States.

In addition, the supply elasticity might also be important to understand real estates cycles. Indeed, several papers document the connection between the degree of supply elasticity and the probability of bubble formation or the volatility of housing price. For example, Glaeser, Gyourko, and Saiz (2008) found that inelastic areas had higher price increase and lower construction level during boom. Nonetheless, the difference between elastic and inelastic areas didn’t show clear patterns during bust periods. Similar conclusions were found in Grimes and Aitken (2010), Ihlanfeldt and Mayock (2014) or Huang and Tang (2012). Davidoff (2013) mitigates the importance of supply elasticity on real estates cycles putting forward that the sand states[3] had an elastic supply but experimented the most important real estate cycles. Nevertheless, some papers developed models where the supply elasticity remains key and that can reproduce the stylized facts observed by Davidoff (2013). For example, Nathanson and Zwick (2012) argues that more elastic areas are more likely to be subject to speculative movements that could provoke important real estate cycles. Gao, Sockin, and Xiong (2015) proposed a model where households use housing prices to learn about the economic strength of their neighborhood. In their framework, different elasticities generate different informational noise likely to explain the difference in the cyclical behavior of real estate markets observed in the US.

documented examples of such policies.

3. California, Florida, Arizona and Nevada.

2.3 The construction and agglomeration elasticities

2.3.1 Definitions

Both macroeconomics and urban economics have been trying to estimate the housing supply elasticity. However, both streams of literature does not seem to measure the same quantity. The spirit of their estimation methods appears different. In this section, we argue that macroeconomists are actually looking at the supply elasticity at the intensive margin where housing starts are the consequence of short run price variations whereas urban economists are looking at the supply elasticity at extensive margin where land and housing prices are the consequence of urban growth.

The macroeconomic literature has long been trying to estimate the supply elasticity. Among the most important contributions, one should emphasize the work of Wheaton (1999) who developed a theoretical framework using DiPasquale and Wheaton (1994) empirical work. In his model, the author starts from the idea that housing is a durable good which depreciated very slowly once developed. He thus emphasized the distinction between the stock (housing units available) and flows (investments as construction, restoration and conversion). The main contribution of such model is the distinction between the very short run and the medium run supply elasticities. Indeed on the very short run, the supply is totally inelastic while it becomes more elastic on the medium run once the construction sector begins to increase its production. Prices move first and are followed by an adaptation of the production. Close to this idea, macroeconomists' estimates showed that the very short run elasticity (materialized by the coefficient of the quasi difference over quarters) was smaller than the long run elasticity (coefficient of the price). From this perspective firms are price takers and adapt their production level (housing starts). As land is absent and there is no urban growth, we consider that they are looking at the intensive margin of the supply, they consider the construction elasticity.

For urban economists, space consumption is at the center of their analysis. In this literature, cities are the result of agglomeration forces driving households and firms to concentrate. However, as illustrated in the monocentric model (see Saiz (2010) or Combes, Duranton, and Gobillon (2016)), the urban development goes along with urban costs as the increase in land and thus housing prices. Housing prices are thus the consequence of urban growth, this is what we call the extensive margin of the supply as the city shape is changing. As far as the housing supply is concerned, this should be considered as a long run parameter since urban growth is a decennial process. It takes time to develop new parcels as zoning changes slowly.

One way to illustrate the difference of philosophy between urban economics and the macroeconomics literatures is to look a the consequences of the durability of housing. While in macroeconomics, the durability generates a very short run supply elasticity lower than its medium run value, in urban economics, its main consequence is to generate an asymmetry in the supply elasticity. For Glaeser and Gyourko (2005), negative demand shocks generate stronger price adjustments than positive ones. When a city is declining, the housing price will collapse durably and strongly: there is a kink in the housing supply. The urban decline is the cause of the drop in housing prices while macroeconomics emphasized that strong price adjustment in case of demand shocks might generate overshoot of the construction at the origins of real estate cycles (see Wheaton (1999)). The main reason for this difference seems to be that urban economics look at the stock whereas macroeconomists are interested in the starts.

In this paper we start from this interpretation of both literatures in order to bridge them at the urban level. To do so we introduce the concepts of construction and agglomeration elasticities. We distinguish both concepts using two criteria: the type of housing price used (old vs new) and the quantity variable (Stock vs Starts) associated with a time horizon (Short run vs Long Run). We illustrate the definition in Table 2.1:

	$ln(Q)$	
	Starts (Short run)	Stock (Long run)
New price index	**Construction elasticity**	Biased Agg. elast.
Existing price index	Biased Const. elast.	**Agglomeration elasticity**

Table 2.1: Definition of the construction and agglomeration supply elasticities

As we can see there are two well defined polar cases (the construction and agglomeration elasticities) and two biased cases. The agglomeration elasticity is connected with the urban economics literature and the recent estimates of Saiz (2010) or Combes, Duranton, and Gobillon (2016). In such a framework, prices are the consequence of city growth and the supply elasticity is associated to an agglomeration cost. It is a long term concept as cities take time to grow. As the stock represents the major share of housing consumption, we use the price of existing units as we are interested in the impact of this agglomeration cost on firms and households expenditures. It is usually estimated thanks to the inverse supply equation using cross section or long differences estimates. The biased agglomeration elasticity is the same concept but measured with an inappropriate price variable. Indeed, to assess the agglomeration elasticity, one should use the price of existing units which reflects the average price in the agglomeration as the stock represent the majority of the units.

The construction elasticity, is connected to the macroeconomics literature. It depends on firms production costs which adapt their supply to maximize their profit when the price is varying. In this framework, starts are the consequence of price variations. And we look at short term adjustment of the production which does not require an extension of the city. It is thus a short term concept estimated using panel estimators. We should focus on the price of new units as we are interested in the production decision (i.e. the price received by the developer). The source of the bias when using the existing price index is discussed in Section 2.B in Appendix.

2.3.2 Estimating the construction elasticity: the intensive margin of the supply

We first follow the macroeconomics or time series literature where authors take an investment perspective: housing starts are a consequence of housing price dynamics. Demand shocks have an impact on prices whose deviations from long run equilibrium generate new investments. They have been trying to estimate the investment equation regressing quantities (housing starts or stock) on price level or price variation. One can estimate the supply equation in panel in order to exploit short run variation. The estimated equation is thus:

$$ln(Construction_{k,t}) = \beta^{S}_{int} ln(Price_{k,t}) + \beta^{dev} ln(developed_{k,t}) + \beta X_{k,t} + \lambda_t + \lambda_k + \varepsilon_{k,t} \tag{2.4}$$

Where $\ln(Construction_{k,t})$ is the log number of housing starts, $\ln(Price_{k,t})$ is the log of new housing price (resp. existing units price) when estimating the construction elasticity (resp. the biased construction elasticity) and $X_{k,t}$ are time varying controls[4]. λ_t and λ_k are respectively time and urban area fixed effects. As we are catching the producer's reaction function **keeping the city size constant**, we control for the city size thanks to $ln(developed_{k,t})$ which is the amount of land developed linearly interpolated. Hilber and Vermeulen (2016) use a similar specification to investigate the short run elasticity between income and price. It is worth noting that this estimates of the construction elasticity controlling for population (i.e city size) is very close to the spirit of the stock-flow model developed in DiPasquale and Wheaton (1994) or Caldera and Johansson (2013).

The best way to estimate this equation would be to simultaneously estimate the supply and demand equation as in Brülhart et al. (2017). However, we don't identify short run exogenous supply shocks to instrument the demand. Urban economists tend to estimate the inverse supply elasticity[5]. Nevertheless, estimating the supply equation and the price elasticity appears

4. We mostly have income available.
5. The estimated equation is then:

$$\ln(Price_{k,t}) = \frac{1}{\beta^{S}_{int}} \ln(Construction_{k,t}) + \beta X_{k,t} + \lambda_t + \lambda_k + \varepsilon_{k,t} \tag{2.5}$$

To us, equation 2.5 is closer to the idea of the costs of agglomeration and is more suited to estimate the long run elasticity: prices are the consequence of city growth as in the monocentric model. Both strategies yield the exact same estimates when taking the simultaneity bias into account. However, the first stage is stronger when prices are instrumented which suggests that shocks affect first price and the production sector follows price movements: we can consider this as adjustment at the intensive part of the housing supply.

closer to the spirit of the construction elasticity (IMSE).

The main challenge when estimating equation 2.4 is to be able to deal with simultaneity bias. Indeed, supply and demand might vary simultaneously and such a regression will just describe the succession of possible equilibria. The macroeconomics literature developed 3 main ways to deal with this bias:

The first one relies on the properties of time series: potential investors first observe price movements and then make investment decision. They used investment as dependent variable and lagged value of prices sometimes instrumented in order to deal with the simultaneity bias. For example, Follain (1979) regresses quarterly US housing prices on quarterly housing starts to estimate the supply equation with an error correction models combined with instrumental strategies. He corrects for autocorrelation and the simultaneity bias including lags and using the population as instrumental variable for prices. Poterba (1984) estimates the supply equation regressing the quarterly price of housing on the quarterly value of residential investment on expected price one period ahead instrumented with current price. Topel and Rosen (1988) regress quarterly housing prices on investment in a AR(2) error correction model. Prices are instrumented using weather shocks. One can also quote Mayer and Somerville (2000) who use current and lagged values of changes in non-construction employment, real energy prices, mortgage rates, and the number of married couples as price shifters. Vermeulen and Rouwendal (2007) instrument prices with households' average income suggesting that its impact on new starts will exclusively happen through prices.

As emphasized in Wheaton, Chervachidze, and Nechayev (2014), these early papers based on error correction models (ECM) face some difficulty to deal with the simultaneity problem. As a consequence, these approaches were progressively replaced by vector error correction models (VECM) which are considered to be able to take into account simultaneity and endogeneity bias estimating jointly the supply and the demand equation. For example Caldera and Johansson (2013) adapt a stock flow model to a VECM framework in order to estimate the supply and demand equation for a large sample of OECD countries. At the city level, Wheaton, Chervachidze, and Nechayev (2014) also used this approach in order to estimate the long run supply elasticity for 60 MSAs in the US.

Finally, some papers follow an alternate framework developed in DiPasquale and Wheaton (1994) and argue that the simultaneity bias is not an issue or is likely to be of limited size. For example, Ihlanfeldt and Mayock (2014) regress the number of housing starts on the price controlling for the stock in the previous period. They argue that since price is clearing the housing market (old + new homes), investment and prices are not obviously simultaneously determined and thus no instrumental strategy is required since investment is a small fraction of the stock.

As far as we are concerned, provided that we don't have enough yearly data point per urban areas, we cannot adapt the two first methods based on time series analysis. In addition, the third approach relies on the strong assumption that new and existing units are on the same market with one unique price. As discussed in Section 2.B in the appendix, we don't agree with such an approach since if both types of units are not perfect substitutes we can observe a strong bias in the estimates. In our panel framework illustrated in equation 2.4, we have to instrument $\ln(Price_{k,t})$ with exogenous demand shocks. We use yearly labor market shocks with a Bartik instrument describing how the employment in the city would have evolved if following national trends from its composition in 1990 (see Section 2.F.4 for more details). This is very close to Hilber and Vermeulen (2016) who directly regress a Bartik instrument on housing price as a robustness check. However, the use of Bartik instrument combined with fixed effects appears harder to interpret. Indeed, the initial share is absorbed by the city fixed effect. We thus propose a relatively new instrument to the urban economics literature found by Monnet and Wolf (2016): the short run demographic shocks and more particularly the number of births twenty years before. It can be used to instrument for current prices because it is usually acknowledged that young households aged between 25 and 40 years old tend to be the main responsible for the demand of new housing units. This instrument is relatively strong when migration flows remains limited which appears to be the case in our sample for the 56 most important urban areas. To us, the exclusion restriction appears convincing since, it states that past births should be correlated with current construction in another way than through their impact on the demand for new housing unit translated into higher prices. However, one might also fear that as young people build their own homes and demographic shocks would thus generate a supply shock. The use of two very different instruments allows, however, to discard this concern. Indeed the nice feature arising from both instruments is that they exploit very different sources of exogeneity allowing us to perform meaningful endogeneity tests.

2.3.3 Estimating the agglomeration elasticity: the extensive margin of the supply

The second parameter of interest is the long run elasticity. In the urban literature, house price dynamics are perceived as a consequence of city growth: housing price appreciation is a consequence of an exogenous growth of the city. Scholars estimate the inverse supply elasticity estimating the supply equation (i.e. regressing prices on quantity). For the sake of comparability, we propose to follow Saiz (2010) in order to estimate the impact of long run shocks on house price variations using long differences.

$$\Delta ln(Price)_{1999-2012,j} = \frac{1}{\beta^S_{ext}} \Delta ln(Units)_{99-12,j} + \varepsilon_j \quad (2.6)$$

The inverse supply equation can be interpreted as adjustments on the extensive margin of the city. However, one can also estimate the supply equation[6]. The results remain qualitatively unchanged but the first stage is weaker: this is because on the long run prices are the consequence of the growth of the city. This is why we talk about elasticity at the extensive margin of the housing supply.

In order to identify demand shocks, we follow Saiz (2010) and Combes, Duranton, and Gobillon (2016) using temperature in January, the number of hotel rooms and a Bartik variable as instrument. We can use the Bartik instrument in the short run and in the long run because this instrument does not capture the same things with the different time spans. In the short run, it captures small conjectural shocks more likely to affect prices for example through households' income while on the long run it captures long run trends in the national economy implying a redistribution of the population within the territory. In equation 6, $\Delta ln(Price_{1999-2012,j})$ is the existing house price variation (resp. new house price variation) between 1999 and 2013 when estimating the extensive margin (resp. the biased extensive margin) and $\Delta ln(Units)_{99-12,j}$ is the variation of the number of housing units. It is worth noting that we use the variation of housing units contrary to Saiz (2010) who uses the population. We will perform alternate robustness checks using population to insure comparability between both studies. We are aware that constructions costs are not accounted for. We regrettably weren't able to access to the PRLN dataset or to the local wages in the construction so far. However, to our understanding, this is a limited problem given that most of construction costs comes from labor (Duranton, Henderson, and Strange (2015)) paid at a national minimum wage. Adding regional dummies to account for difference in the regional labor costs does not change our results.

2.3.4 Interpretation of the coefficients

It should be clear that β^s_{ext} and β^s_{int} are not directly comparable as both the price and the quantity variables are different. If the number of housing starts ($Construction_{k,99-12}$) and the housing stock variation ($\Delta Units_{99-12,j}$) are concepts relatively substitutable (construction being the gross housing stock variation while the housing stock variation accounts for destructions and conversions, $\Delta ln(Units)_{99-12,j}$ measures the urban growth and would be comparable with $\frac{Construction_{k,99-12}}{Units_{k,99}}$ but not with $ln(Construction_{k,99-12})$. On the one hand,

6.

$$\Delta ln(Units)_{1999-2012,j} = \beta^S_{ext} \Delta ln(Price)_{99-12,j} + \varepsilon_j \quad (2.7)$$

the intensive margin measures the relationship between the number of starts and prices, β^s_{int} is the percentage change of housing starts when housing prices are growing by 1%. On the other hand, the extensive margin measures the relationship between urban growth and the housing price growth, $\frac{1}{\beta^s_{ext}}$ is the percentage change of housing prices when the city is growing by 1%.

In order to compare the magnitude of the elasticity between short run and long run, one can estimate a short run agglomeration elasticity using a panel framework as defined in Table 2.D.3 in Appendix :

$$\ln(Price_{k,t}) = \frac{1}{\beta^S_{ext}} \ln(Units_{k,t}) + \beta X_{k,t} + \lambda_t + \lambda_k + \varepsilon_{k,t} \tag{2.8}$$

We use this as a complementary robustness check as yearly data on new units are not available leading us to use linear interpolations to reconstruct yearly series. As the evolution of the housing stock follows the same logic as the starts we use the same instruments as when estimating the extensive margin.

2.3.5 Decomposing the Price elasticity

Since a house is immobile, transactions on the housing market are the result of arbitrages for location within a city (see Muth (1969)) and between cities (see Rosen (1979) and Roback (1982)). As a consequence, an important and increasing part of the value of housing capital is linked with its location and is thus capitalized into land price (see Davis and Heathcote (2007) or Bonnet et al. (2016) for a complete review). The importance of the land component arises from the fact that land scarcity for geographical or regulatory reasons can reduce price elasticity (Saiz (2010)) making it dependent on local conditions (city size, geography or levels of regulation). Urban economics and the macroeconomics literatures have been trying to understand what are the main drivers of the supply elasticity.

In time series analysis, (Green, Malpezzi, and Mayo (2005) emphasized the importance of regulation while Andrews (2010) also suggests that competition in the construction sector might be important. In urban economics, Saiz (2010) emphasized the role physical constraints and regulation. Finally, the share of land already developed (Hilber and Vermeulen (2016)), the city size interpreted as the bindness of the geographical constraint (Saiz (2010)) were described as important drivers of the elasticity. The relative importance of each factor remains unclear, while Saiz (2010) interprets his results as the fact that geography remains the main driver of price elasticity in the US, Hilber and Vermeulen (2016) emphasizes the importance of regulation and city size and shows that the relative importance of each factor might change between Local Authorities in the UK.

To wrap up, the estimates of the supply elasticity vary across countries and metropolitan statistical areas. Four main parameters are likely to influence its size, namely geography (Saiz (2010)), city size (Hilber and Vermeulen (2016)), regulation (Green, Malpezzi, and Mayo (2005)) and competition in the construction sector (Andrews (2010)). So far, we didn't find any study trying to connect the supply elasticity at the city level and the macroeconomic estimates. As a consequence we don't know if the observed transatlantic gap between the US and Europe highlighted by macroeconomic papers (Caldera and Johansson (2013) is due to a composition effect (there are more elastic areas in the US or people live in more elastic place) or to the way the construction sector is working.

The construction elasticity

We can try to investigate the determinants of the housing supply elasticity. To do so, we reestimate the equation introducing interaction terms with our measures of regulation and geographical constraint :

$$\begin{aligned}\ln(Construction_{k,t}) = \beta^S \ln(Price_{k,t}) + \beta^R Regulation_k \times \ln(Price_{k,t}) \\ +\beta^{LAND} \times (1 - Available_k) \times \ln(Price_{k,t}) \\ +\beta^{dev} \times \%Developed_k \times \ln(Price_{k,t}) \\ +\beta^{dev} ln(Developed_{k,t}) + \beta X_{k,t} + \lambda_t + \lambda_k + \varepsilon_{k,t}\end{aligned} \tag{2.9}$$

Where $Available_K$ is the share of land available for developments (with a slope below 15$\%$ and not under water) around the city's barycenter as computed in Saiz (2010). We also control for the share of land developed $\%Developed_k$ which is potentially endogenous. We then use the population of the city in 1911 to control for this potential bias. Finally we also assess the impact of several regulations with $Regulation_k$. When trying to identify the impact of regulation on the supply elasticity, one has to deal with a potentially important endogeneity bias. Areas with higher price are likely to be subject to a stricter degree of regulation. Indeed, since housing is an investment good, Fischel (2001) argues that homeowners will preserve the value of their property exerting pressure on local administrations. This intuition is supported by several additional contributions as Hilber and Robert-Nicoud (2013), Solé-Ollé and Viladecans-Marsal (2013), Ferreira, Gyourko, et al. (2009), and Ortalo-Magné and Prat (2014). Saiz (2010) instruments regulation using the characteristics of homeowners[7] and share in protective inspection in local public expenditures. Hilber and Vermeulen (2016) exploit a national

7. The nontraditional Christian share in 1970.

change in the regulatory framework impacting differently local authorities' refusal rate.

Our identification strategies to disentangle the impact of regulation relies on the idea that the national rules decided following very general conditions are independent on local unobserved determinants of housing prices:

The first national rule is the law of February the 5th 1943 on historical building which states that in a perimeter of 500m around a registered or classified building, any modification of a surrounding building should get an additional advice from the Association of French Architects. This should turn the housing supply more rigid because new projects should fulfill particular characteristics and should fulfill some conditions. Figure 2.F.5 illustrates this type of constraint for a French Department. Such a zoning, is likely to be exogenous since the buildings used were classified a long time before our period of study (we focus on these classified before 1960). We compute the share of each area covered by this rule. Another nationwide law, the SRU act studied in Bono and Trannoy (2012) and Gobillon and Vignolles (2016), increased dramatically the intervention of Local Authorities on the housing market. This act increased the bindness of the zoning driving the refusal rate up. Indeed, the SRU Act voted in 2000 forces mayors to increase the number of social housing unit, which consumes more land per unit of land. The private sector will thus tend to extend more rapidly on the extensive margins driving up the number of refusals at the urban area level. We can thus instrument the level of regulation using the share of the urban area concerned by the SRU act on the long run or directly use it as a measure of regulation on the short run.

The agglomeration elasticity

In order to investigate whether the decomposition differs between the extensive and intensive margin of the housing supply, we also decompose the long run inverse supply elasticity. We first use the following specification close to our short run approach[8]:

8. For the sake of comparability, we also follow Saiz (2010) and estimate:

$$\begin{aligned} \Delta ln(P_{1999-2012,k}) = \\ \frac{1}{\beta^{Land}} \times ln(pop)_{1990,k} \times (1 - Available_k) \times \Delta ln(Units)_{99-12,k} \\ + \frac{1}{\beta^{reg}} \times Regulation_k \times \Delta ln(Units)_{99-12,k} + \varepsilon_k \end{aligned} \tag{2.10}$$

We control for non linearity in the effect of land constraint when the city size increases and for regulation. Here $ln(pop)_{1990,k}$ is the log of the city size in 1990 and $Regulation_k$ is instrumented and measured as discussed in the previous section.

$$
\begin{aligned}
\Delta ln(P_{1999-2012,k}) = \frac{1}{\beta^S} \times \Delta ln(Units)_{99-12,k} \\
\frac{1}{\beta^{Land}} \times (1 - Available_k) \times \Delta ln(Units)_{99-12,k} \\
+\frac{1}{\beta^{Reg}} \times Regulation_k \times \Delta ln(Units)_{99-12,k} \\
+\frac{1}{\beta^{Dev}} \times \%Developed_k \times \Delta ln(Units)_{99-12,k} + \varepsilon_k
\end{aligned}
\tag{2.11}
$$

where $Regulation_k$ are different measures of regulation, when taking the refusals of building permits. It is instrumented thanks to the national rules as the law for historical monuments and the SRU act. $\%Developed_k$ is the share of land developed in 1990. It is instrumented thanks to the population of the urban area in 1911.

2.4 Data

2.4.1 Units of observation

The question of the unit of observation is important in urban economics. Here we want to capture the relevant housing market. We follow Saiz (2010) and Combes, Duranton, and Gobillon (2016) and choose the metropolitan statistical areas. However, some other papers as Hilber and Vermeulen (2016) take administrative areas as the UK local Authorities. We will thus perform some robustness checks reproducing our analysis at the department level (larger administrative areas).

We perform our estimates on two different subsamples. Indeed, the computation of the yearly new price index requires to observe enough new transactions each year. This is only possible for the major urban areas. We thus restrict our sample to the the 56 biggest French urban areas when measuring the intensive margin supply based on our panel estimator. As the extensive margin only requires to have enough data points at the beginning and the end of the period, we can extend our samples to the 87 biggest urban areas, however, for the sake of comparability we reproduce our estimates in appendix on the same sample as the one used for the intensive margin.

2.4.2 Measuring Housing Prices

The measurement of housing price dynamics raises two important questions. The first one is the consequence of the heterogeneity of housing unit raising the importance of quality and the distinction between the price of new units and the stock. The second one is connected with the fact that housing is an investment good whose cost can be measured thanks to several concepts: the price, the rent and the user cost.

The importance of quality

In his seminal contribution, Rosen (1974) pointed that housing could be perceived as a composite good. This property has several implications when it comes to measuring changes in price across time. Indeed if the features play an important role to determine the housing prices it might be important to control for changes in housing quality across time for example using repeated sales or hedonic price indexes.

Land price, existing price or new constructions ?

Most studies generally use repeated or hedonic price index based on the transaction on the second hand market. Combes, Duranton, and Gobillon (2016) proposed to deal with the problem of quality using prices on the land market for new housing units controlling for the location within the urban area. Monnet and Wolf (2016) also criticize the use of second hand market transaction emphasizing the fact that new investments (in particular constructions) are more likely to be governed by the price of new units which sometimes diverge from standard price index as pointed in Balcone and Lafferrère (2015).

When studying housing investment dynamics, one can easily think, as argued in Monnet and Wolf (2016), that the main parameter of interest is the elasticity with respect to new unit prices as the housing supply elasticity with respect to the price of existing unit might be affected by the fact that both types of units might not be perfect substitutes as discussed in Section 2.B. In this study we use two complementary series on existing and new prices described in Section 2.F.3.

Price, rent or user cost ?

Since housing is an investment good, it can be bought by a household for its own use or by an investor in order to be rented. One can thus distinguish the transaction price and the rental price. While most of the studies observe the market dynamics through the lens of transaction prices, it remains unclear whether one should look at transaction price or rental price. If on the long run financial theory suggests both should be equivalent, several studies highlighted important divergences between both measures through time resulting in fluctuations in the user cost (Himmelberg, Mayer, and Sinai (2005)) or across space (see Halket, Nesheim, and Oswald (2015)). However, since user costs rely on expectation these measures often rely on strong assumptions.

In this paper, as in most studies with the exception of Brülhart et al. (2017) we only look at housing prices so far[9]. We justify this choice by the fact that producers in France are much more likely to observe selling prices rather than rents as most of them sell directly their products to homeowners or households willing to invest in the rental sector. Besides social housing where rents are controlled, there are few institutions involved on the rental market and most of the constructors are mostly focused on the production of new units.

2.4.3 Measuring Quantities

In the literature, there are many ways to measure the quantity. In urban economics many papers use the population and mostly care about the city size (Saiz (2010), Combes, Duranton, and Gobillon (2016)). However, the number of new units built measured through building permits or the variation of the stock is also measured. The advantage of the stock variation is to account for conversion of existing units and destruction. Related to this latter measure, Brülhart et al. (2017) use the total floor surface dedicated to housing. Such a measure does not account for the division of existing unit but pins down precisely the volume of space dedicated to housing. Papers in macroeconomics often look at housing starts or growth capital formation in the housing sector.

In this paper, we measure quantity thanks to the concept of housing unit. We use the national census of 1990 and 1999 and the continuous census data published from 2002. This gives us the net stock variation which is the most important in the long run. In addition we also use the construction data from sit@del2 database provided by the CGEDD: this gives us the gross variation which is more interesting when looking at production decisions. In order to identify demand shocks and to deal with the simultaneity bias, we have to instrument construction thanks to Bartik type instruments as described in Section 2.F.4. We also instrument demand shocks thanks to the climatic features of the area at the barycenter as reported in Section 2.F.1.

2.4.4 The determinants of supply elasticity

As we already emphasized, the literature has highlighted four main factors likely to influence the degree of elasticity: competition in the construction sector (Caldera and Johansson (2013)), regulation (Green, Malpezzi, and Mayo (2005)), the geographical constraint and its bindness (Saiz (2010), Hilber and Vermeulen (2016)). The literature usually considers the construction sector as competitive (Duranton, Henderson, and Strange (2015)): we can think that

9. However we are currently trying to build a rental price index for several urban areas using the CNAF dataset on housing allowances and rental website, cf. Chapter 3.

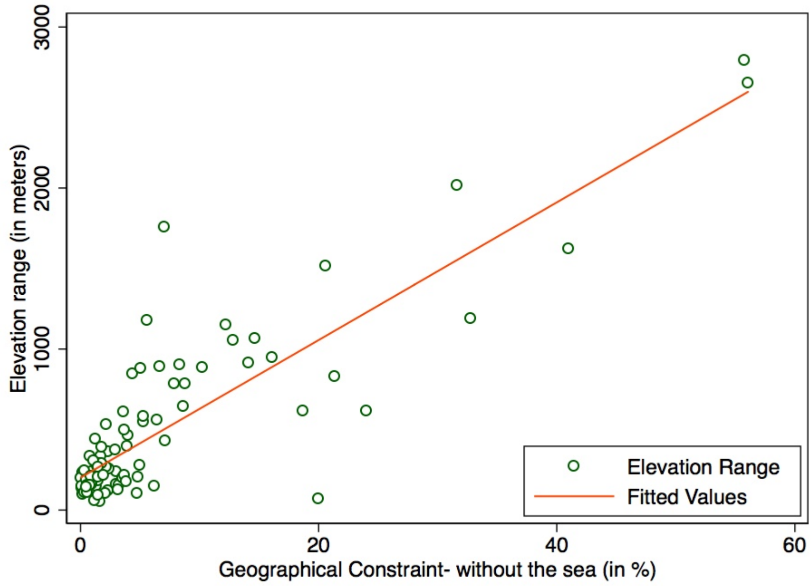
this parameter wouldn't strongly vary across France. We thus turn to the geographical and regulatory constraints and will present how to measure them. While the geographical constraint is considered as exogenous, the regulatory constraint and the share of developed land are considered as endogenous to housing prices. We will thus discuss how to measure and identify exogenous variation in the regulatory constraint.

How to measure the geographical constraint?

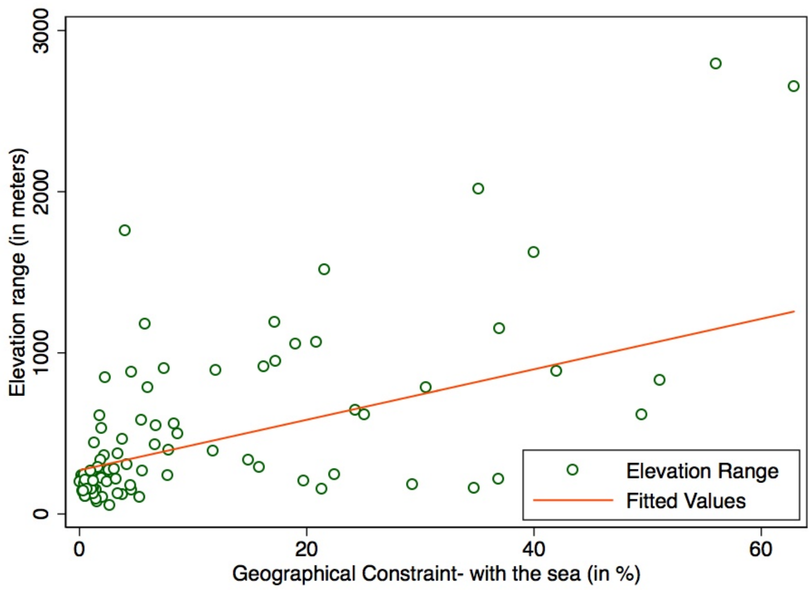
We follow Saiz (2010) to compute the geographical constraint as exposed in Appendix . However, Hilber and Vermeulen (2016) proposed an alternate measure for this which is the difference between the highest and the lowest altitude on the territory. We are able to recover this measure and compare it with land availability. It is worth noting that they are highly correlated (85%), the main difference being that Hilber and Vermeulen (2016) do not take into account the role of oceans for coastal areas (in Saiz (2010) coastal cities are considered as highly constrained). We illustrate this difference in Figure 2.1. If one can think that not controlling for such areas might lead to overestimate the role of regulation our main conclusions remain unchanged using Saiz (2010) or Hilber and Vermeulen (2016) measures.

The main geographical features of our sample of interest are reported in Table 2.F.1. One first striking fact arises when comparing their characteristics with Saiz (2010): French urban areas appear to be poorly constrained. When accounting for internal water and mountainous areas, the average constraint for all urban areas is around 8.6%[10]. This figure rises around 16.6%[11] when accounting for the ocean within a 50km radius. These figures are much smaller than their US counterpart, Saiz (2010) reports an average of 26% for the North American urban areas.

10. 6% for the first 100 UA.
11. 16% for the first 100 UA.



(a) Area lost when the ocean is not accounted



(b) Area lost when the ocean is accounted

Figure 2.1: Correlation between elevation range and the geographical constraint

Developed land

The literature suggests that denser areas are usually more inelastic. We can recover this idea with the bindness of the geographical constraint[12] measured with the level of population at the beginning of the period (Saiz (2010)) or with the share of developed land (Hilber and Vermeulen (2016)). We use the Corine Land Cover database provided by the Copernic Project at the European Level. After removing the areas unavailable because of the geographical constraint, we compute the share of developed land among the remaining land.

The extension of the city is likely to be endogenous with respect to prices, one possibility is to instrument it thanks to past density as in Hilber and Vermeulen (2016): to this end we use the historical data on population kindly provided by the Cassini Project[13].

How to measure the regulatory constraint ?

Regulation appears to play an important role on the housing supply elasticity (Hilber and Vermeulen (2016)). However, it is worth noting that each country has its particular sets of rules that may differ quite importantly in its spirit and which should be accounted for when measuring it. So far two important papers propose different approaches to catch the regulatory pressure.

On the one hand, in the US, Gyourko, Saiz, and Summers (2008) developed the Wharton Land Use Regulation Index (WLURI), a composite index able to reflect the limits on new developments (local political pressures, delays, refusals, limits of rezoning, use of minimum lot size etc...). From a questionnaire addressed to local authorities, the authors are able to measure the strength of the regulatory environment. This index has been widely used in the literature investigating the impact of the regulatory environment. For example, Saiz (2010) averages these indexes at the municipal level to compute an index at the urban area Level. On the other hand, Hilber and Vermeulen (2016) use as a proxy for the regulatory constraint the refusal rate of major projects and use change in national rules as exogenous shocks and identify the causal impact of regulation.

France doesn't have any index comparable to the WLURI. However, the rich amount of data available allows us to construct a set of indices designed to proxy the stringency of different types of regulations. Indeed, while Saiz (2010) uses a multidimensional index, Hilber and Vermeulen (2016) only focus on refusal rates and are silent about zoning or other regulatory constraints as minimum lot size or maximum floor area ratio. We thus propose to provide

12. Saiz (2010) shows that the elasticity depends negatively from the level of the population (ie the bindness of the geographical constraint).

13. http://cassini.ehess.fr/

different measures of regulations able to account for the specificity of the French regulatory environment. Our contribution on this aspect is twofold, we provide original sets of measures of the French regulatory environment and we exploit an original identification strategy using exogenous national rules in order to identify the causal impact of regulation. In this section we provide a brief description of the French regulatory framework introducing our variables and identification strategy.

First of all, France is characterized by an important set of local regulation. The core element of the French urban planning system is zoning[14]. As in many countries the most common system of zoning used is the euclidean system of zoning where different districts are assigned to specific activities (natural space, industrial use, commercial use, residential use, mixed use). One strong specificity of France compared with the US is the fact that local zoning does not represent a constraint for municipalities but rather an opportunity to modify strict national regulation. Indeed, if a French municipalitiy does not have adopted a zoning decree, the resulting regulatory environment ends up stricter than with the existence of zoning since the National Planning Framework (NPF)[15] with its rule of limited ability[16] to construct apply. We collected data describing the ex-post maximum floor area ratio and the municipality under the NPF. However, all these rules of urbanism such as the minimum lot size or the maximum floor area ratio are hard to compare between urban areas and municipalities and are very likely to be endogenous. We thus turn to the common outcome of these rules: the refusals. In a spirit close to Hilber and Vermeulen (2016), we had access to an extraction of the sit@del dataset which is an exhaustive database on building permits containing yearly number of refusals. However, we didn't know the reasons for these refusals. We complete this variable with additional information on the number of permit cancellations resulting from an administrative decision (either from a judge, from the representant of the French state or from the mayor). We are able to distinguish whether the cancellations concerned collective buildings or single units. So far, we focus on the impact of refusals and cancellations that we instrument thanks to national rules, we also investigate the impact of national rules separately. Aggregating these information at the urban area level can mitigate the declaration bias at the municipality level: indeed, if one can think that small municipalities tend to inform the database less precisely, getting data at such an aggregate level might mitigate this problem.

As refusals are very likely to be endogenous, we collected data on the constraints resulting from National Laws that are less likely to be influenced by national politics. First we use the law on historical monuments already described. To create our measurement of the degree of the law, we scraped the exhaustive list of the historical monuments with their characteristics

14. PLU, POS or carte communale (municipality map)
15. Réglement National d'Urbanisme (RNU)
16. With this rule, almost no new development can be made outside the core area of the city.

and date of classification on the Ministry of Culture website and then their geographical location using their Wikipedia page. We then built circles of 500 meters around these monuments to compute the share of the urban area under this restriction as illustrated in Figure 2.F.5 in appendix. We also collected the zoning of the European Environment protection areas (Natura 2000) and computed the share of developable land concerned by this zoning. We also collected the exhaustive database on public forests[17], and computed the share of developable land classified as such of each urban area. Finally, we got access to the exhaustive lists of municipalities under the SRU act from which we compute the surface of the urban unit at the center of each urban area concerned by this act. As illustrated in Table 2.2, the main exogenous drivers of our endogenous measure of regulation - the refusals - appears to be the share of territory concerned by the historical monuments rule and the share of the urban unit concerned by the SRU act. We thus use both measures as instruments or as direct measures in our empirical analysis. We can note that as in Hilber and Robert-Nicoud (2013), the share of developed land appears to be important.

	(1) Refusals	(2) Refusals
% Undevelopable	-0.309	-0.563
	(0.844)	(0.872)
% Developed	2.005	2.759*
	(1.351)	(1.640)
% SRU	1.351***	1.582***
	(0.348)	(0.476)
% Share Hist. Mon.	7.075***	7.754**
	(2.681)	(3.153)
% Natura 2000	1.662	-0.125
	(2.323)	(2.678)
% Public Forests	-0.660	-0.668
	(1.283)	(1.733)
R2	0.304	0.303
Obs	87	56

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.2: Drivers of regulation

17. http://carmen.carmencarto.fr

2.5 Estimates of the agglomeration and construction elasticities

In the following section, we answer two empirical questions. First, we estimate the four elasticities described in Section 2.3 and test whether they are different. Second, we compare the supply elasticity of France with previous studies on the US using similar data and specifications in order to identify the existence of the transatlantic gap suggested in the literature.

2.5.1 The construction elasticity

We first turn to the short run supply elasticity which should allow us to estimate the intensive margin supply elasticity using the new price index and test whether it diverges from the biased intensive supply elasticity estimated using existing unit prices. We restrict our analysis to 56 urban areas for which we have enough observations each year in order to compute the yearly new price index and have a balanced panel.

Table 2.3 presents our baseline estimate of the construction elasticity (IMSE). Given the reduced sample size, we estimate this equation thanks to the LIML. As we can see, the simultaneity bias generates a strong difference between the 2sls and the OLS estimates as we compare columns (1) with columns (2-4). The instrument used in column (2) is the Bartik type instrument usually used in the literature and is strong with a F-stat which is above the adjusted Stock Yogo critical values of 5%. The first stages are reported in Table 2.C.2. The second instrument used in column (3) is the number of young people born between 30 and 20 years before the year under scrutiny. This instrument is even stronger[18] and is more specific to each urban area which removes the concern about the collinearity with the time fixed effects. When jointly testing both instruments as in column (4), we cannot reject their joint exogeneity as indicated by the p-value. This is particularly interesting as both instruments exploit very different sources of variation. The main conclusion of this table is that the construction elasticity for housing is around 0.9. This means that when existing new housing prices increase by 1% the supply of housing units increase by 0.8%. As we already discussed, such a result is not directly comparable with the previous studies in urban economics which tend to estimate the agglomeration elasticity or with macroeconomic estimates which use existing unit price index. We then compare this result with the supply elasticity with respect to second hand transaction prices that we defined as the biased construction elasticity (BIMSE).

18. The F-stat is above the adjusted Stock Yogo critical values of 5%.

	(1) $ln(Construction)$	(2) $ln(Construction)$	(3) $ln(Construction)$	(4) $ln(Construction)$
$ln(Price_{new})$	0.264***	0.826**	0.874***	0.857***
	(0.0890)	(0.330)	(0.288)	(0.264)
$ln(Developed)$	Y	Y	Y	Y
Year & UA FE	Y	Y	Y	Y
R2	0.285	.	.	.
Obs	1006	1006	1006	1006
N. of UA	56	56	56	56
Bartik	N	Y	N	Y
Births T-20	N	N	Y	Y
F-stat		76.27	104.0	62.68
p-value				0.879

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standards error are clustered at the urban area level.$ln(price_{new})$ is the price of new units which is instrumented with Bartik instruments (growth of employment predicted from the national sectorial trends) and the number of births twenty years before (Births T-20). F-stat indicates the strength of the first stage which can be find in Table 2.C.2, they pass the standards threshold of Stock Yogo test. The p-value indicates that the instruments pass the standard exogeneity test.

Table 2.3: Short run estimates of the construction elasticity

Table 2.4 investigates whether the BIMSE computed using the existing unit price index is significantly different from the IMSE estimated in Table 2.3. We can remark that the estimation of the BIMSE using existing unit suggests a much less elastic supply. The Chi-2 test for the equality of both coefficient has a value of 98.45, we can thus reject the equality. Similar conclusion is reached when estimating the inverse supply elasticity in Table 21 in Section 2.C.3. It is worth noting that the first stage shows coefficient much higher for the existing unit price: exogenous shocks have a stronger impact on the price of existing units. The coefficients in the second hand price transaction are always significantly higher. We consider that such result suggests that new housing units and existing units are not perfect substitutes as discussed in Section 2.B. The BIMSE has a value of 0.444. Given the data and the specification used, it is more directly comparable with the macroeconomic estimates found in Caldera and Johansson (2013) and similar in terms of order of magnitude. We should note, that as we argue, this quantity is not comparable with the urban economics literature. It describes by how much developers will increase their supply of housing units in one period, when their an exogenous increase in housing prices. In order to get estimates comparable with the urban economics literature describing how housing prices are changing when the city is growing we need to turn to long run inverse supply elasticities using long differences (i.e. the extensive margin).

	(1) $ln(Construction)$	(2) $ln(Construction)$	(3) $ln(Construction)$	(4) $ln(Construction)$
$ln(Price_{new})$	0.189*		0.885**	
	(0.101)		(0.354)	
$ln(Price_{old})$		0.538***		0.444**
		(0.109)		(0.180)
$ln(Developed)$	Y	Y	Y	Y
Year & UA FE	Y	Y	Y	Y
R2	0.274	0.292	.	.
Obs	839	839	839	839
N. of UA	56	56	56	56
Bartik	N	N	Y	Y
BirthsT-20	N	N	Y	Y
F-stat			36.18	223.1
p-value			0.960	0.397

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standards error are clustered at the urban area level. $ln(price_{new})$ and $ln(price_{old})$ are the prices of new and existing units which are instrumented with Bartik instruments (growth of employment predicted from the national sectorial trends) and the number of births twenty years before (Births T-20). F-stat indicates the strength of the first stage which can be found in Tables 2.C.4 and 2.C.6, they pass the standards threshold at 5%. The p-value indicates both instruments pass the exogeneity test. A chi-2 test was run to compare the two elasticities of column (3) and (4) and yields a value of 98.45 rejecting the equality of both coefficients.

Table 2.4: Short run estimates of the construction elasticity with the two indexes (1998-2013)

2.5.2 The agglomeration elasticity

We now reproduce Saiz's (2010) baseline estimates using a long difference over 12 years. The number of units in our baseline specification is higher because we are less demanding on housing price as we only need to have enough observations for 1999 and 2012. This allows us to increase our sample size.

We turn to the agglomeration elasticity in Table 2.5. The simultaneity bias appears to be relatively strong as illustrated by the difference between column (1) and (2-4). Our instruments appear to be strong and pass the standard Stock Yogo critical value of 5%. The first stage is reported in Table 2.D.2 in Appendix. We can't reject the exogeneity of the instrument when used together. The order of magnitude is relatively close to the BIMSE as illustrated by the estimates in Section 2.5.1 where we restrict our estimates to the same sample of cities. This might suggest that existing unit prices capitalize short run shocks. However, as already mentioned, both coefficients are not directly comparable. One can interpret this coefficient as follows: a one percent increase in the city size increases the housing prices by 3%. This finding is close to the estimates of Combes, Duranton, and Gobillon (2016), who find an elasticity of 2% in Table 7 with a specification close to ours. The difference is mainly explained by the fact that they use the variation in population instead of the number of housing units. Using the population yields estimates close to theirs. It is worth noting that they also use a larger sample and look at the housing price at the city center while we use a stratified housing price index closer to the idea of a representative unit in the urban area.

	(1) $\Delta\ ln(Price_{old})$	(2) $\Delta\ ln(Price_{old})$	(3) $\Delta\ ln(Price_{old})$	(4) $\Delta\ ln(Price_{old})$
$\Delta\ ln(Units)$	0.962***	2.778***	3.461***	3.064***
	(0.283)	(0.710)	(0.975)	(0.675)
R2	0.120	.	.	.
Obs	87	87	87	87
Bartik	N	N	Y	Y
Temperature	N	Y	N	Y
F-stat		25.43	15.89	16.53
p-value				0.457

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

$\Delta ln(price_{old})$ is the long difference of existing unit prices. $\Delta ln(Units)$ is the long difference of the number of units which is instrumented with the Temperature in January and labor market shocks (Bartik). F-stat indicates the strength of the first stage reported in Table 2.D.2, they pass the standards threshold of the cue with limited information at 5%. The p-value indicates that we can't reject the exogeneity of the instruments.

Table 2.5: Long Difference estimates of the inverse agglomeration supply elasticity with existing prices

Table 2.6 presents our estimate of the biased extensive margin supply elasticity using the new price index. As in the short run, the simultaneity bias appears to be relatively strong as illustrated by the difference between column (1) and (2-4).

	(1) $\Delta\ ln(Price_{new})$	(2) $\Delta\ ln(Price_{new})$	(3) $\Delta\ ln(Price_{new})$	(4) $\Delta\ ln(Price_{new})$
$\Delta\ ln(Units)$	0.636**	1.116*	1.429**	1.230**
	(0.274)	(0.573)	(0.714)	(0.523)
R2	0.0598	.	.	.
Obs	87	87	87	87
Bartik	N	N	Y	Y
Temperature	N	Y	N	Y
F-stat		25.43	15.89	16.53
p-value				0.660

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

$\Delta ln(price_{new})$ is the long difference of new prices. $\Delta ln(Units)$ is the long difference of the number of units which is instrumented with the Temperature in January and labor market shocks (E). F-stat indicates the strength of the first stage reported in Table 2.D.2, they pass the standards threshold of the cue with limited information at 5%. The p-value indicates that we can't reject the joint exogeneity of the instruments.

Table 2.6: Long Difference estimates of the biased inverse agglomeration elasticity

Table 2.7 summarizes the difference between the biased agglomeration elasticity (BEMSE) and the agglomeration elasticity (EMSE). We can observe that they diverge considerably and are significantly different from one another. This tends to confirm our intuition according to which we are looking at two clearly different concepts and that the BEMS is more related with the developer production costs.

Finally, we can compare the agglomeration elasticity (EMSE) with Saiz (2010). In his contribution the inverse supply elasticity estimated for the US metropolitan area is around 0.6 whereas we find an inverse supply elasticity with respect to existing prices around 3 for the existing unit. We can then confidently conclude that these estimates suggest an important difference between Europe and the US in terms of housing price sensitivity with respect to demand shocks as documented in the literature documenting the inflationary impact of housing policies.

	(1) $\Delta\ ln(Price_{old})$	(2) $\Delta\ ln(Price_{new})$	(3) $\Delta\ ln(Price_{old})$	(4) $\Delta\ ln(Price_{new})$
$\Delta\ ln(Units)$	0.962***	0.636**	3.064***	1.230**
	(0.283)	(0.274)	(0.675)	(0.523)
R2	0.120	0.0598	.	.
Obs	87	87	87	87
Bartik	N	N	Y	Y
Temperature	N	N	Y	Y
F-stat			16.53	16.53
p-value			0.457	0.660

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

$\Delta ln(price_{new})$ and $\Delta ln(price_{old})$ are respectively the long difference of new and existing unit prices. $\Delta ln(Units)$ is the long difference of the number of units which is instrumented with the temperature in January and labor market shocks (Bartik). F-stat indicates the strength of the first stage reported in Table 2.D.2, they pass the standards threshold of the cue with limited information at 5%. The p-value indicates that we can't reject the exogeneity of the instruments.

Table 2.7: Long Difference estimates of the inverse agglomeration elasticity with existing and new prices

2.5.3 Comparison of the coefficients

As we already mentioned, it is not possible to compare the extensive supply (agglomeration elasticity) and intensive supply (construction elasticity). Nevertheless, one can compute the short run agglomeration elasticity that is comparable with the long run construction elasticity. To be able to compare our estimates with the findings of the previous literature we report our results using both housing units and population as independent variable. Columns (1) and (2) in Table 2.8 present our estimates of the long run agglomeration elasticity. As already mentioned, these estimates are very close the one of Combes, Duranton, and Gobillon (2016) when using population as independent variable even if our sample is only composed of the most important cities. These estimates are directly comparable with the short run agglomeration elasticity provided in columns (1) and (2) of Table 2.9 and it appears as expected that the short run is more inelastic than the long run. This appears to confirm the prime intuition developed in Combes, Duranton, and Gobillon (2016), that the longer the time horizon, the more elastic the extensive supply elasticity (i.e. the agglomeration cost).

This discussion on time horizon appears important for the economic literature. Indeed, while papers based on monocentric models as Chapelle and Wasmer (2016) investigate the impact of infrastructure on the size of the city on the long run, exogenous population shocks go along with an increase in land price. On the very long run, such an increase in land price might be mild as exposed in Combes, Duranton, and Gobillon (2016) but to us the increase in the city size can be slowed down on the medium run by our medium run extensive margin supply elasticity. As a consequence, understanding the drivers of the the extensive margin can help us to understand the timing at which cities converge to their long run equilibrium after an exogenous shock.

	(1) $\Delta\ ln(Price_{old})$	(2) $\Delta\ ln(Price_{old})$	(3) $\Delta\ ln(Price_{new})$	(4) $\Delta\ ln(Price_{new})$
$\Delta\ ln(Pop)$	2.626***		1.753***	
	(0.599)		(0.443)	
$\Delta\ ln(Units)$		3.834***		2.726***
		(1.075)		(0.853)
R2	.	.	.	.
Obs	56	56	56	56
Bartik	Y	Y	Y	Y
Temperature	Y	Y	Y	Y
F-stat	22.79	7.981	22.79	7.981
p-value	0.630	0.887	0.102	0.0825

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

$\Delta ln(price_{new})$ and $\Delta ln(price_{old})$ are respectively the long difference of new and existing unit prices. $\Delta ln(Units)$ is the long difference of the number of units which is instrumented with the Temperature in January and labor market shocks (Bartik). F-stat indicates the strength of the first stage reported in Table 2.D.2, they pass the standards threshold of the cue with limited information at 5%. The p-value indicates that we can't reject the exogeneity of the instruments.

Table 2.8: The medium/long run extensive margin (same sample as the panel)

	(1) $ln(Price_{old})$	(2) $ln(Price_{old})$	(3) $ln(Price_{new})$	(4) $ln(Price_{new})$
$ln(Pop)$	4.024***		2.079***	
	(0.343)		(0.281)	
$ln(Units)$		9.525***		5.078***
		(1.556)		(0.986)
Year & UA FE	Y	Y	Y	Y
R2	.	.	.	.
Obs	839	839	839	839
N. of UA	56	56	56	56
Bartik	Y	Y	Y	Y
Births T-20	Y	Y	Y	Y
F-stat	90.45	19.23	90.45	19.23
p-value	0.923	0.469	0.00912	0.258

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standards error are clustered at the urban area level. $ln(price_{new})$ and $ln(price_{old})$ are the prices of new and existing units which are instrumented with Bartik instruments (growth of employment predicted from the national sectorial trends) and the number of births twenty years before (Births T-20). F-stat indicates the strength of the first stage which can be found in Tables 2.C.4 and 2.C.6, they pass the standards threshold at 5%. The p-value indicates both instruments pass the exogeneity test. A chi-2 test was run to compare the two elasticities of column (3) and (4) and yields a value of 98.45 rejecting the equality of both coefficients.

Table 2.9: The sort run extensive margin (1998-2013)

2.6 Decomposing the two elasticities

We now try to determine what are the main drivers of the supply elasticity on the extensive and intensive margin. The idea of this section is to decompose the elasticities between the parts due to geography and the part due to regulation. This might help us to understand the difference between the supply elasticity with respect to the two indexes, between the extensive and intensive margins and between the US and France.

2.6.1 The construction elasticity

We first turn to the short run specification, in order to decompose the intensive supply margin for new housing units in Table 2.10. Column (1) introduces our measure for the geographical constraint which appears strongly significant. According to the estimate, an urban area with a constraint of 100% would then have its elasticity divided by 2, going from 1.5 to 0.75. However, it is worth noting that as we already emphasized, French urban area are actually poorly constrained when compared with the similar measure for the US. In column (2), we introduce an indicator for the percentage of the urban unit concerned by the SRU Act. This Act forces mayors to intervene on the housing market in order to increase the share of social housing unit. As already mentioned, we consider this act as exogenous as it comes from a national rule designed according to an arbitrary threshold. All the urban units in our sample are concerned, their degree of concern depends on a legacy of the past: past social housing units built in their area which are mainly a legacy from the 70s. This appears also to decrease significantly the supply elasticity. We add another exogenous measure of regulation in column (3): the share of area concerned by the historical monuments law. This also enters significantly into the regression and a small variation of such a zoning appears to have a major impact. Finally, we include the share of developed land instrumented thanks to the population in the urban area in 1911. This never turns significant contrarily to the findings of Hilber and Vermeulen (2016). In a last specification, we include an endogenous indicator of the degree of regulation: the refusal index computed at the urban area level. When instrumented with the share of historical monuments it appears to play an important and significant role. We don't instrument with the SRU act, as on the short run this instrument is weak and not significant on regulation. We use it on the long run when it becomes binding because of the social housing sector expansion as illustrated in Chapelle (2015). Such rebates could be compensated on the other sales to the private households. To sum up, both regulation and geography appear to be important drivers of the short run supply elasticity but given the features of the French urban areas, regulation is strongly responsible for the relative inelasticity of the French housing supply.

	(1) $ln(Construction)$	(2) $ln(Construction)$	(3) $ln(Construction)$	(4) $ln(Construction)$	(5) $ln(Construction)$
$ln(Price_{new})$	1.486***	2.615***	3.039***	2.752***	7.336
	(0.476)	(0.909)	(1.024)	(1.004)	(4.497)
$ln(Price_{new})$ x % Undevelopable	-0.747*	-1.031**	-1.278**	-1.671**	-2.241
	(0.384)	(0.497)	(0.564)	(0.701)	(1.399)
$ln(Price_{new})$ x % SRU		-0.328**	-0.331*	-0.332**	
		(0.162)	(0.171)	(0.167)	
$ln(Price_{new})$ x % Hist. Mon			-4.171*	-5.995**	
			(2.414)	(3.016)	
$ln(Price_{new})$ x % Developed				2.007	
				(2.051)	
$ln(Price_{new})$ x Refusals					-0.324
					(0.232)
$ln(Developed)$	Y	Y	Y	Y	Y
Year & UA FE	Y	Y	Y	Y	Y
R2	.	.	.	.	.
Obs	1006	1006	1006	1006	1006
N. of UA	56	56	56	56	56
Bartik	Y	Y	Y	Y	Y
Births T-20	Y	Y	Y	Y	Y
Pop 1911	N	N	N	Y	Y
Hist Mon	N	N	N	N	Y
F-stat	16.16	4.762	3.483	2.956	0.860
p-value	0.420	0.851	0.688	0.924	0.173

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standards error are clustered at the urban area level. F-stat indicates the strength of the first stage, which pass the Stock Yogo critical value at 5% in the baseline and is then weaker when increasing the number of interaction terms. The p-value indicates that we can't reject the exogeneity of the instruments in any of the specifications. SRU designed the % of the urban unit covered by the SRU Act, % hist mon designed the % of the urban area concerned by restrictions due to a proximity to an historical monument. % undevelopable is the % of land not developable because under water or with a slope above % percent. % developed designs the share of the urban area already built, it is instrumented with the population in 1911 and is never significant Finally refusal is the average number of refusal in the municipality of the urban area, we instrument this index with the % of area covered by the historical monuments.

Table 2.10: Decomposition of the construction elasticity with new unit price

2.6.2 The biased construction elasticity

We can turn to the decomposition of the elasticity with respect to existing unit price. Geography also seems to play an important role as illustrated in column (1) of Table 2.11. So does the percentage of the urban area covered by the SRU act and the historical monuments regulation. The percentage of land developed still does not seem to play any significant role suggesting that the land constraint is not binding for French urban areas. Finally our refusal index still enters significantly and has a strong and negative impact on the supply elasticity. The coefficient on the regulation index appears to be stronger than when looking for the new price index. Part of the bias could comes from the fact that regulation is capitalized into the land price of existing units which benefit from the positive externalities of regulation. Regulation might then accentuate the low elasticity of substitution between both goods, thus increasing the differences between both types of units.

	(1) $ln(Construction)$	(2) $ln(Construction)$	(3) $ln(Construction)$	(4) $ln(Construction)$	(5) $ln(Construction)$
$ln(Price\_old)$	0.712***	0.952***	1.294***	1.424***	8.583***
	(0.225)	(0.245)	(0.305)	(0.400)	(3.257)
$ln(Price\_old)$ x % Undevelopable	-0.569*	-0.523*	-0.755**	-0.535	-1.926***
	(0.300)	(0.302)	(0.333)	(0.466)	(0.697)
$ln(Price\_old)$ x % SRU		-0.0300**	-0.0282**	-0.0280**	
		(0.0134)	(0.0135)	(0.0135)	
$ln(Price\_old)$ x % Hist. Mon.			-4.790**	-3.633	
			(1.950)	(2.695)	
$ln(Price\_old)$ x % Developed				-1.187	
				(2.030)	
$ln(Price\_old)$ x Refusals					-0.598**
					(0.244)
$ln(Developed)$	Y	Y	Y	Y	Y
Year & UA FE	Y	Y	Y	Y	Y
R2	.	.	.	.	.
Obs	840	840	840	840	840
N. of UA	56	56	56	56	56
Bartik	Y	Y	Y	Y	Y
Births T-20	Y	Y	Y	Y	Y
Pop 1911	N	N	N	Y	N
SRU	N	N	N	N	Y
Hist. Mon	N	N	N	N	Y
F-stat	83.59	57.35	39.23	9.350	2.693
p-value	0.125	0.253	0.363	0.434	0.664

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standards error are clustered at the urban area level. F-stat indicates the strength of the first stage, which pass the Stock Yogo critical value at 5% in the baseline and is then weaker when increasing the number of interaction terms. The p-value indicates that we can't reject the exogeneity of the instruments in any of the specifications. SRU designed the % of the urban unit covered by the SRU Act, % hist mon designed the % of the urban area concerned by restrictions due to a proximity to an historical monument. % undevelopable is the % of land not developable because under water or with a slope above % percent. % developed designates the share of the urban area already built, it is instrumented with the population in 1911 and is never significant Finally refusal is the average number of refusal in the municipality of the urban area, we instrument this index with the % of area covered by the historical monuments and the % covered by the SRU act.

Table 2.11: Decomposition of construction elasticity with existing unit price

2.6.3 The biased agglomeration elasticity

We now turn to the extensive supply margin decomposition. Table 2.12 shows the decomposition of the inverse supply elasticity with respect to new housing prices. As we can see in column (1) the percentage of geographical constraint appears important, however when controlling for the percentage of land already developed (instrumented with the population in 1911) as in column (2) it becomes insignificant. However, when controlling for the level of regulation (we control for endogeneity using the national rules: the percentage of area covered by the SRU act and the historical monuments) as in column (3) it remains significant. When controlling for the geographical constraint, the level of regulation and the percentage of land developed, results are puzzling because the first stage is too weak as illustrated by the F-stat in column (4), we thus run a "horse race" removing the variation of housing units. In such a specification only the share of developable land remains significant. We can interpret such a result as the fact that using new housing prices is still close to an estimate of the production function. On the long run, the main driver of the elasticity might be the technical challenge faced by developers when the city is growing on its extensive margin and has to develop on less productive land parcels with more technical challenges.

	(1) $\Delta\ ln(Price_{new})$	(2) $\Delta\ ln(Price_{new})$	(3) $\Delta\ ln(Price_{new})$	(4) $\Delta\ ln(Price_{new})$	(5) $\Delta\ ln(Price_{new})$
$\Delta\ ln(Units)$	0.389	-0.186	-2.029*	-3.248**	
	(0.475)	(0.549)	(1.052)	(1.378)	
$\Delta\ ln(Units)$ x % Undevelopable	1.556***	-0.255	1.527***	2.517***	1.538**
	(0.535)	(1.183)	(0.533)	(0.831)	(0.661)
$\Delta\ ln(Units)$ x % Developed		12.99*		-6.691*	-1.466
		(7.150)		(4.044)	(3.072)
$\Delta\ ln(Units)$ x Refusals			0.254**	0.389***	0.0592
			(0.113)	(0.149)	(0.0453)
R2	.	.	.	.	.
Obs	87	87	87	87	87
Bartik	Y	Y	Y	Y	Y
Temperature	Y	Y	Y	Y	Y
N Hotels rooms	N	Y	Y	Y	Y
Pop in 1911	N	Y	Y	Y	Y
SRU	N	N	Y	Y	Y
Hist Mon	N	N	Y	Y	Y
F-stat	12.45	1.419	5.159	1.891	3.508
p-value	0.588	0.931	0.708	0.951	0.344

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standards error are robust. F-stat indicates the strength of the first stage, which pass the Stock Yogo critical value at 5% in the baseline and is then weaker when increasing the number of interaction terms. The p-value indicates that we can't reject the exogeneity of the instruments in any of the specifications. % undevelopable is the % of land not developable because under water or with a slope above 15% percent. % developed designates the share of the urban area already built, it is instrumented with the population in 1911 and is never significant Finally refusal is the average number of refusal in the municipality of the urban area, we instrument this index with the % of area covered by the historical monuments and the % covered by the SRU act.

Table 2.12: Decomposition of the inverse supply elasticity with new prices

2.6.4 The extensive margin supply elasticity

Table 2.13 shows the decomposition of the inverse supply elasticity with respect to existing housing prices. As in the previous table in column (1) the percentage geographical constraint appears important, however when controlling for the percentage of land already developed (instrumented with the population in 1911) as in column (2) it becomes insignificant. When only controlling for regulation and the share of undevelopable land, as for the short run, regulation appears more important than when looking at new prices. This is in line with the idea that regulation is distorting the substitutability between new homes and the existing stock. This idea is confirmed by the horse race in column (5) which suggests that the degree of regulation and the share of land developed are much more important than the geographical constraint which turns not significant while it was the only significant variable in the previous table.

	(1) $\Delta\ ln(Price_{old})$	(2) $\Delta\ ln(Price_{old})$	(3) $\Delta\ ln(Price_{old})$	(4) $\Delta\ ln(Price_{old})$	(5) $\Delta\ ln(Price_{old})$
$\Delta\ ln(Units)$	2.410***	1.228	-2.937***	-0.717	
	(0.609)	(0.820)	(1.036)	(1.475)	
$\Delta\ ln(Units)$ x % Undevelopable	1.205*	-2.807	1.247**	-0.263	-0.546
	(0.687)	(1.768)	(0.525)	(0.889)	(0.827)
$\Delta\ ln(Units)$ x % Developed		28.56***		10.17**	11.88***
		(10.69)		(4.327)	(3.844)
$\Delta\ ln(Units)$ x Refusals			0.522***	0.289*	0.219***
			(0.111)	(0.160)	(0.0566)
R2	.	.	.	.	.
Obs	87	87	87	87	87
Bartik	Y	Y	Y	Y	Y
Temperature	Y	Y	Y	Y	Y
N Hotels rooms	Y	Y	Y	Y	Y
Pop in 1911	N	Y	Y	Y	Y
SRU	N	N	Y	Y	Y
Hist Mon	N	N	Y	Y	Y
F-stat	12.45	1.419	5.159	1.891	3.508
p-value	0.392	0.950	0.0585	0.126	0.184

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standards error are robust. F-stat indicates the strength of the first stage, which pass the Stock Yogo critical value at 5% in the baseline and is then weaker when increasing the number of interaction terms. The p-value indicates that we can't reject the exogeneity of the instruments in any of the specifications. % undevelopable is the % of land not developable because under water or with a slope above 15% percent. % developed is the share of the urban area already built, it is instrumented with the population in 1911 and is never significant Finally refusal is the average number of refusal in the municipality of the urban area, we instrument this index with the % of area covered by the historical monuments and the % covered by the SRU act.

Table 2.13: Decomposition of the inverse supply elasticity with existing prices

In a last exercise we reproduce Saiz (2010)'s specification for France as illustrated in Section 2.D.3. If we take the existing price and compare the estimates with Saiz's results, we can disentangle where does the transatlantic gap comes from. As we already stated when analyzing our results on existing housing prices, most of the difference comes from the role of regulation as the geographical constraint is much lower in France. As in Saiz, the chart in Section 2.D.4 shows a positive correlation between the supply elasticity and housing price variation. When comparing the US and France, one might say that if the supply elasticity appears important in both countries to understand price dynamics, regulation appears more important in particular when considering the elasticity with respect to the existing unit price which is closer to the concept of agglomeration cost for us.

2.7 Conclusion

In this paper we identified a gap between the macroeconomics and the urban economics literature when considering the housing supply elasticity. Using the distinction between the extensive supply of housing and intensive supply of housing, we showed that there exists two supply elasticities: the construction and agglomeration elasticities.

The first one is related with the production cost of developers and should be estimated using short run variation with the price for new units. The fact that the same specification using existing unit prices yields different estimates suggests that new and existing units are not perfect substitutes as illustrated in Section 2.B. For France, we found that the supply elasticity is about 0.9 (vs 0.5 when estimated with existing prices) and is strongly influenced by regulation in the short run. Using the new price index in long difference, one can identify also the production function of producers when dealing with the extensive margin. This value is slightly lower than its short run value and seems to be mostly driven by the technical challenges implied by developing land parcels less suited for developments as the geographical constraint appears to be its main significant driver.

The second type of housing supply elasticity is the extensive supply margin elasticity related to urban growth and should be considered as a cost of agglomeration as in Saiz (2010) and estimated using existing unit prices as the existing stock represents most of the households housing expenditures. In France, it is about 0.3 and is mostly driven by the share of land already developed and the degree of regulation while the geographical constraint appears to play a minor role. This cost is much higher than in the US and appears to strongly depend on the time horizon considered, while it appears highly inelastic in the very short run, when estimated in panel, it turns more elastic on the medium run when estimated with long difference over 12 years. One can think that the cross sectional approach of Combes, Duranton, and Gobillon (2016) is the long run agglomeration cost. To us, the drivers of the medium run investigated in our paper provide an indication of the factors slowing the convergence toward the long run equilibrium following an exogenous shock as an improvement in transport infrastructures.

Our results can be summarized in Table 2.14:

		Starts (Short run)	Stock(Long run)
New price index	Name	**Construction elasticity**	Biased Aggl. elast.
	Value	0.9	0.8
	1st Driver	Regulation	Geography
	2nd Driver	Geography	
Existing price index	Name	Biased Const. elast.	**Agglomeration elasticity**
	Value	0.5	0.3
	1st Driver	Regulation	Regulation
	2nd Driver		% of land developed

Table 2.14: Summary of the estimates of the housing supply elasticities for France

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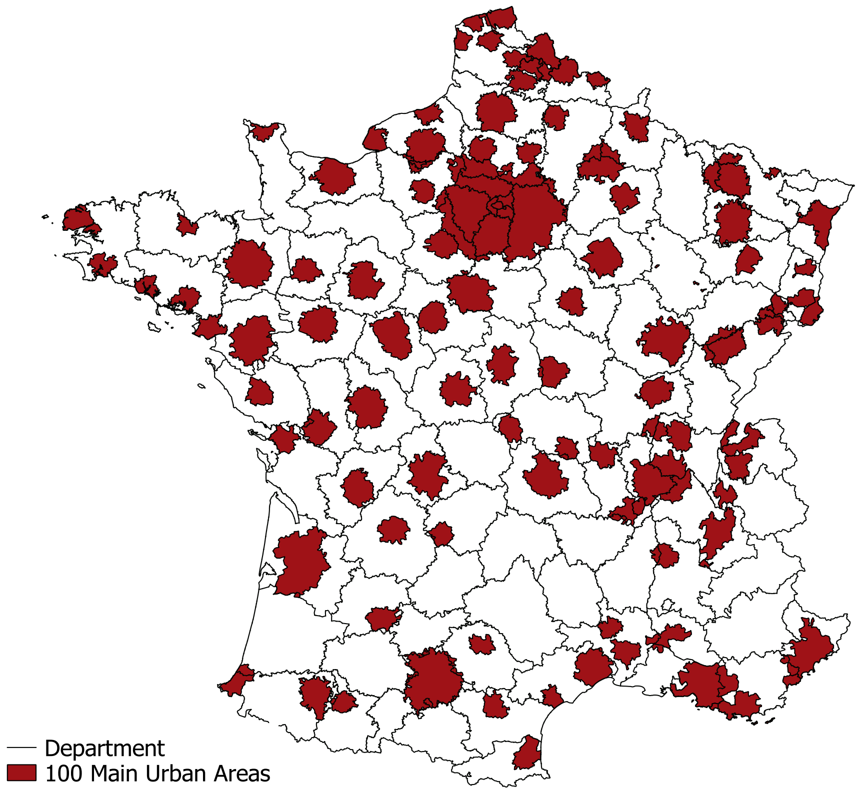
Appendix

2.A Map of French Departments and Urban Areas



Source : IGN Geofla (c)

Figure 2.A.1: French Departments and the main Urban Areas

2.B Theoretical framework for the intensive supply margin

As the extensive margin of housing supply is already well grounded theoretically (see Combes, Duranton, and Gobillon (2016) or Saiz (2010)), we propose to develop a simple framework in order to understand the intensive margin of housing supply. In this model, competitive producers react to an exogenous short run demand shock. As we consider the demand addressed to the producer: one should account that the housing stock is not uniform, there is the existing stock (O) and there are new housing units (N) usually flats or single units in the suburbs more distant from the CBD and the amenities. As a consequence, the representative household does not consider them as perfect substitutes. We then, represent housing consumption with the following CES utility function where s is the elasticity of substitution between old and new housing units:

$$H = (\alpha N^{\frac{s-1}{s}} + (1-\alpha)O^{\frac{s-1}{s}})^{\frac{1}{s-1}} \tag{2.12}$$

The representative household budget constraint is :

$$Income = p_O \times O + p_N \times N \tag{2.13}$$

We consider that the existing stock is fixed:

$$O = \bar{O} \tag{2.14}$$

The demand for new housing unit, that is faced by the production sector is then :

$$N = \frac{Income}{p_N + p_O(\frac{(1-\alpha)p_N}{\alpha p_O})^s} \tag{2.15}$$

The price for existing units should clear the demand of existing unit :

$$\bar{O} = \frac{Income}{p_O + p_N(\frac{\alpha p_O}{(1-\alpha)p_N})^s} \tag{2.16}$$

Here p_N represents the annualized cost of housing paid by the household to the producer whereas p_O represents the annualized cost of housing paid by the household to an absentee landlord. To close the model, we add a competitive production sector for new housing units as in Hilber and Vermeulen (2016). We then just state that the price of new housing units should equate its marginal production cost :

$$p_N = C'(N) \tag{2.17}$$

To illustrate the implications of the imperfect substitutability between new housing unit and the existing stock, we solve numerically and simulate this model. We have three endogenous variables p_O, p_N and N and three equilibrium conditions represented in equation 2.15, 2.16 and 2.17. We set α to 0.5 [19] and choose O such that $p_N = p_O$ before the shock. We take a simple convex production function with increasing marginal cost for C(N) as in Hilber and Vermeulen (2016). The idea of the simulation exercise is to look how the relative price of existing units with respect to new units varies when there is an exogenous income shock. The model allows to account for the fact that the housing stock can only adjust through the extensive margin : the production of new housing unit. Results are displayed in Figure 2.B.1.

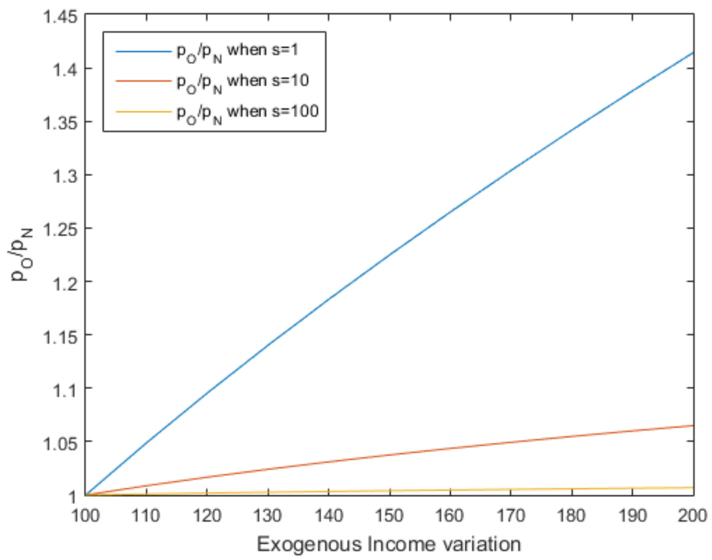


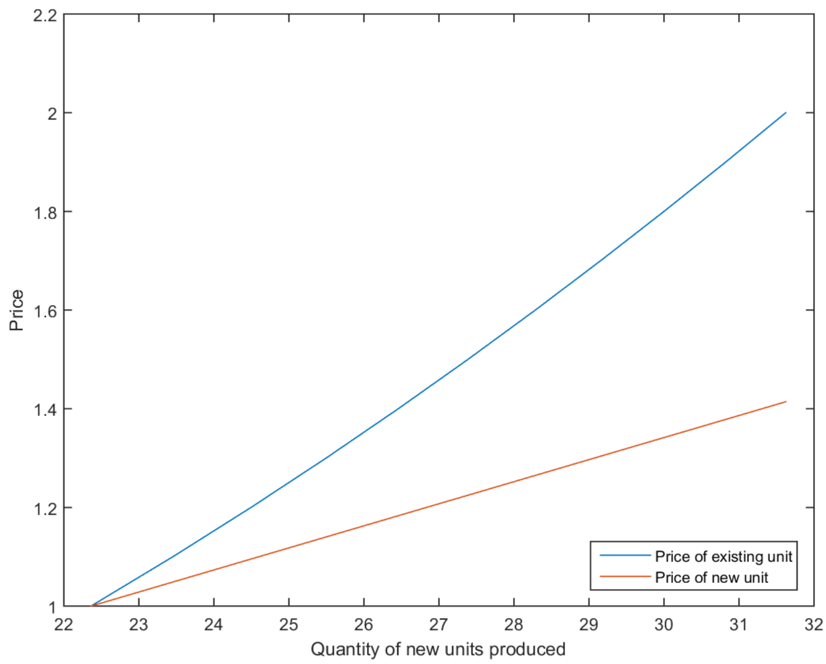
Figure 2.B.1: Impact of an exogenous Income shock on the relative price of existing and new housing units with different elasticities of substitution

The Model is solved numerically with $\alpha = 0.5$, O is determined such that p_N=p_O in an initial step. $Cm = N$. Prices are normalized to one in the first period when income is at its lower level. We depict the evolution of the ratio between the price of existing price with respect to the price of new units when the income of households increases exogenously. The blue line depicts the case where the elasticity of substitution (s) is set to 1 (very inelastic), in the red one s is set to 10 (more substitutable) while the yellow illustrates the case where existing and new units are almost perfectly substitutable (s=100)

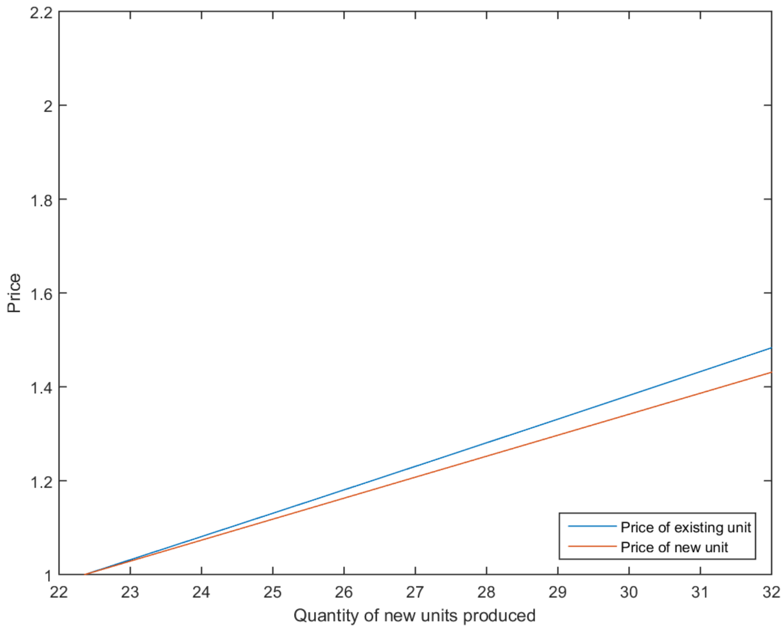
Figure 2.B.2 illustrates our point. In our model, unless existing units and new housing units are perfect substitutes, when representing the relationship between prices and quantities the slope of the relation between old price and the production and new price and the production

19. results are not sensitive to α

is not the same. Using existing units price variation is thus likely to bias the estimate of the housing supply elasticity. The fixity of the existing stock combined with the imperfect substitutability between both types of units could suggest a more inelastic housing supply than its true value which is driven by the production function. The resulting bias between estimates using new price index and old price index can be viewed as the difference between the intensive margin supply elasticity (IMSE) and the biased intensive margin supply elaticity (BIMSE).



(a) Bias in the supply equation when s=1



(b) Bias in the supply equation when s=10

Figure 2.B.2: Displacement along the supply curve resulting from demand shocks and existing unit price variations

The Model is solved numerically with $\alpha = 0.5$, O is determined such that p_N=p_O in an initial step. $Cm = N$. Prices are normalized to one in the first period when income is at its lower level. The blue line shows the supply curve estimated thanks to existing unit price while the red one shows the true relationship between the supply and the demand such that (p_N=Cm). In the top panel the elasticity of substitution (s) is set to 1 (very inelastic) whereas s is set to 10 (more elastic). While the "true" Supply elasticity in which is the relationship between the quantity supplied by the production sector and the price for new units remains the same, the less substitutable both types of unit, the more biased the supply elasticity estimated thanks to existing units prices.

2.C Intensive Margin of Housing Supply : robustness checks and first stage

2.C.1 Descriptive statistics and First Stage of the Baselines Estimates

	Mean	Std.Dev.	Obs	min	max
Population	572961.1	1480139.4	56	83374	11173886
N. of Housing units	266793.3	685360.0	56	36782	5173317
% of Land Unavailable (25km)	15.1	18.2	56	0	63
% of Land Unavailable (50km)	19.4	21.1	56	0	72
% of Land developed	12.6	6.1	56	5	33
ln(Refusal Index)	8.2	0.9	56	7	11
% of the UU covered by SRU	43.7	27.5	56	0	100
% covered by the his. Mon. restr.	4.0	1.6	56	1	8

Table 2.C.1: Descriptive statistics (Short run sample)

	(1) $ln(Price_{new})$	(2) $ln(Price_{new})$	(3) $ln(Price_{new})$
Bartik	2.093***		1.186***
	(0.237)		(0.267)
Births T-20		0.699***	0.528***
		(0.0679)	(0.0775)
$ln(Developed)$	Y	Y	Y
Year & UA FE	Y	Y	Y
R2	0.950	0.952	0.953
Obs	1006	1006	1006
N. of UA	56	56	56

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standards error are clustered at the Urban area level.

Table 2.C.2: First stage of the supply equation (new) (1994-2013)

2.C.2 Robustness Checks using the transaction price index for existing units

	(1)	(2)	(3)	(4)
	$ln(Construction)$	$ln(Construction)$	$ln(Construction)$	$ln(Construction)$
$ln(Price_{old})$	0.528^{***}	0.370^{*}	0.550^{**}	0.444^{**}
	(0.114)	(0.200)	(0.219)	(0.180)
$ln(Developed)$	Y	Y	Y	Y
Year & UA FE	Y	Y	Y	Y
R2	0.292	.	.	.
Obs	839	839	839	839
N. of UA	56	56	56	56
Bartik	N	Y	N	Y
Births T-20	N	N	Y	Y
F-stat		325.9	253.1	223.1
p-value				0.397

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standards error are clustered at the Urban area level. The first stage is the same as the one for new units, it is reported in Table 2.C.6

Table 2.C.3: Short run estimates of the supply elasticity with existing unit price (1998-2013)

	(1)	(2)	(3)
	$ln(Price_{old})$	$ln(Price_{old})$	$ln(Price_{old})$
Bartik	1.849^{***}		0.774^{**}
	(0.316)		(0.355)
Births T-20		0.704^{***}	0.600^{***}
		(0.0849)	(0.0971)
$ln(Developed)$	Y	Y	Y
Year & UA FE	Y	Y	Y
R2	0.941	0.943	0.944
Obs	839	839	839
N. of UA	56	56	56

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standards error are clustered at the Urban area level.

Table 2.C.4: First stage of the supply equation (old)(1998-2013)

	(1) $ln(Construction)$	(2) $ln(Construction)$	(3) $ln(Construction)$	(4) $ln(Construction)$
$ln(Price_{new})$	0.189*	0.763*	0.880**	0.885**
	(0.101)	(0.396)	(0.366)	(0.354)
$ln(Developed)$	Y	Y	Y	Y
Year & UA FE	Y	Y	Y	Y
R2	0.274	.	.	.
Obs	839	839	839	839
N. of UA	56	56	56	56
Bartik	N	Y	N	Y
Births T-20	N	N	Y	Y
F-stat		4.270	67.38	36.18
p-value				0.960

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standards error are clustered at the Urban area level.

Table 2.C.5: Short run estimates of the supply elasticity with price of new units (1998-2013)

	(1) $ln(Price_{new})$	(2) $ln(Price_{new})$	(3) $ln(Price_{new})$
Bartik	1.849***		0.774**
	(0.316)		(0.355)
Births T-20		0.704***	0.600***
		(0.0849)	(0.0971)
$ln(Developed)$	Y	Y	Y
Year & UA FE	Y	Y	Y
R2	0.941	0.943	0.944
Obs	839	839	839
N. of UA	56	56	56

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standards error are clustered at the Urban area level.

Table 2.C.6: First stage of the supply equation (new)(1998-2013)

2.C.3 Robustness checks estimating the short run inverse supply

	(1) $ln(Construction)$	(2) $ln(Price_{old})$	(3) $ln(Construction)$	(4) $ln(Price_{new})$
$ln(Price_{old})$	0.444**			
	(0.180)			
$ln(Construction)$		2.253***		1.130**
		(0.864)		(0.452)
$ln(Price_{new})$			0.885**	
			(0.354)	
$ln(Developed)$	Y	Y	Y	Y
Year & UA FE	Y	Y	Y	Y
R2	.	.	.	.
Obs	839	839	839	839
N. of UA	56	56	56	56
Bartik	Y	Y	Y	Y
BirthsT-20	Y	Y	Y	Y
F-stat	223.1	3.254	36.18	3.254
p-value	0.397	0.397	0.960	0.960

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standards error are clustered at the Urban area level. F-stat indicates the strength of the first stage, they pass the standards threshold of Stock Yogo test at 5% (Births) and 10%(Bartik) . The p-value indicates that we can't reject the exogeneity of the instruments.

Table 2.C.7: Comparison of the inverse elasticity and the elasticity (1998-2013)

	(1) $ln(Price_{old})$	(2) $ln(Construction)$	(3) $ln(Price_{new})$	(4) $ln(Construction)$
Births T-20	0.686***	0.521*	0.600***	0.521*
	(0.0737)	(0.287)	(0.0971)	(0.287)
Bartik	3.282***	0.737	0.774**	0.737
	(0.269)	(1.046)	(0.355)	(1.046)
$ln(Developed)$	Y	Y	Y	Y
Year & UA FE	Y	Y	Y	Y
R2	0.974	0.277	0.944	0.277
Obs	839	839	839	839
N. of UA	56	56	56	56
Bartik	Y	Y	Y	Y
Births T-20	Y	Y	Y	Y

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standards error are clustered at the Urban area level.

Table 2.C.8: First Stage for the Comparison of the inverse elasticity and the elasticity (1998-2013)

2.D Extensive Margin of Housing Supply : First Stages and Robustness Checks

2.D.1 First Stage of the long difference

	Mean	Std.Dev.	Obs	min	max
Population	413860.4	1203747.5	87	79279	11173886
N. of Housing units	191429.3	557708.4	87	33047	5173317
% of Land Unavailable (25km)	12.9	16.6	87	0	63
% of Land Unavailable (50km)	16.6	20.0	87	0	72
% of Land developed	12.1	6.5	87	4	33
ln(Refusal Index)	7.9	0.9	87	6	11
% of the UU covered by SRU	35.4	28.2	87	0	100
% covered by the his. Mon. restr.	4.1	1.7	87	1	11

Table 2.D.1: Descriptive statistics (Long run sample)

	(1) $\Delta\ ln(Units)$	(2) $\Delta\ ln(Units)$	(3) $\Delta\ ln(Units)$
Temperature	0.0126***		0.0101***
	(0.00247)		(0.00259)
Bartik		0.959***	0.598**
		(0.238)	(0.238)
R2	0.230	0.158	0.282
Obs	87	87	87

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.D.2: First Stage for the Long Difference estimates of the inverse supply elasticity

2.D.2 Estimates of the short run extensive supply margin

Time Horizon	Short Run		Long run
ln(Q)	Starts	Stock	Stock
Price Index			
New units	**Intensive margin**	SR Biased Ext. margin	LR Biased Ext. margin
Existing units	Biased Int. margin	**SR Extensive margin**	**LR Extensive margin**

Table 2.D.3: Definition of the intensive and extensive margin supply elasticities

	(1) $\Delta\ ln(Units)$	(2) $\Delta\ ln(Pop)$
Bartik	0.713**	1.226***
	(0.282)	(0.244)
Temperature	0.00640**	0.00710***
	(0.00285)	(0.00245)
R2	0.231	0.462
Obs	56	56

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.D.4: First Stage for the Long Difference estimates of the inverse supply elasticity with population and units (same sample as the panel)

	(1) $ln(Pop)$	(2) $ln(Units)$	(3) $ln(Pop)$	(4) $ln(Units)$
Births T-20	0.173^{***}	0.0917^{***}	0.173^{***}	0.0917^{***}
	(0.0285)	(0.0263)	(0.0285)	(0.0263)
Bartik	0.804^{***}	0.276^{***}	0.804^{***}	0.276^{***}
	(0.104)	(0.0959)	(0.104)	(0.0959)
Year & UA FE	Y	Y	Y	Y
R2	0.704	0.914	0.704	0.914
Obs	839	839	839	839
N. of UA	56	56	56	56

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standards error are clustered at the Urban area level.

Table 2.D.5: First Stage The sort run extensive margin (1998-2013)

2.D.3 Reproducing Saiz's (2010) specification for France

	(1) $\Delta\ ln(Price_{old})$	(2) $\Delta\ ln(Price_{old})$	(3) $\Delta\ ln(Price_{old})$	(4) $\Delta\ ln(Price_{old})$	(5) $\Delta\ ln(Price_{old})$
$\Delta\ ln(Pop)$	2.651***	1.716***	1.669***		
	(0.506)	(0.520)	(0.518)		
$\Delta\ ln(Pop)$ x % Undevelopable		3.421**	-77.70***	-85.27***	-66.25***
		(1.592)	(23.55)	(24.67)	(21.01)
$ln(Pop\_1911)$ x $\Delta\ ln(pop)$ x % Undevelopable			6.461***	7.337***	5.506***
			(1.886)	(1.988)	(1.700)
refusals x $\Delta ln(Pop)$					0.240***
					(0.0713)
R2	.	.	.	.	.
Obs	87	87	87	87	87
Bartik	Y	Y	Y	Y	Y
Temperature	Y	Y	Y	Y	Y
N Hotels rooms	N	N	Y	Y	Y
Pop in 1911	Y	Y	Y	Y	Y
SRU	N	N	N	N	Y
Hist Mon	N	N	N	N	Y
F-stat	27.49	15.54	6.965	7.031	4.576
p-value	0.807	0.980	0.753	0.0289	0.488

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standards error are robust. F-stat indicates the strength of the first stage, which pass the Stock Yogo critical value at 5% in the baseline and is then weaker when increasing the number of interaction terms. The p-value indicates that we can't reject the exogeneity of the instruments in any of the specifications. % undevelopable is the % of land not developable because under water or with a slope above 15% percent. % developed designates the share of the urban area already built, it is instrumented with the population in 1911 and is never significant Finally refusal is the average number of refusal in the municipality of the urban area, we instrument this index with the % of area covered by the historical monuments and the % covered by the SRU act.

Table 2.D.6: Decomposition of the inverse supply elasticity with existing prices (Saiz (2010))

	(1) $\Delta\ ln(Price_{new})$	(2) $\Delta\ ln(Price_{new})$	(3) $\Delta\ ln(Price_{new})$	(4) $\Delta\ ln(Price_new)$	(5) $\Delta\ ln(Price_{new})$
$\Delta\ ln(Pop)$	1.080**	-0.115			
	(0.462)	(0.494)			
$\Delta\ ln(Units)$ x % Undevelopable		4.176***	-37.20	-39.36*	-43.00**
		(1.515)	(23.00)	(21.37)	(20.63)
$ln(Pop)$ x $\Delta\ ln(Pop)$ x % Undevelopable			3.287*	3.444**	3.737**
			(1.834)	(1.723)	(1.663)
$\Delta\ ln(Pop)$ x Refusals					-0.00724
					(0.0706)
R2	.	.	.	.	.
Obs	87	87	87	87	87
Bartik	Y	Y	Y	Y	Y
Temperature	Y	Y	Y	Y	Y
N Hotels rooms	N	N	Y	Y	Y
Pop in 1911	Y	Y	Y	Y	Y
SRU	N	N	N	N	Y
Hist Mon	N	N	N	N	Y
F-stat	27.49	15.54	5.139	7.031	4.449
p-value	0.952	0.903	0.697	0.826	0.668

Standard errors in parentheses

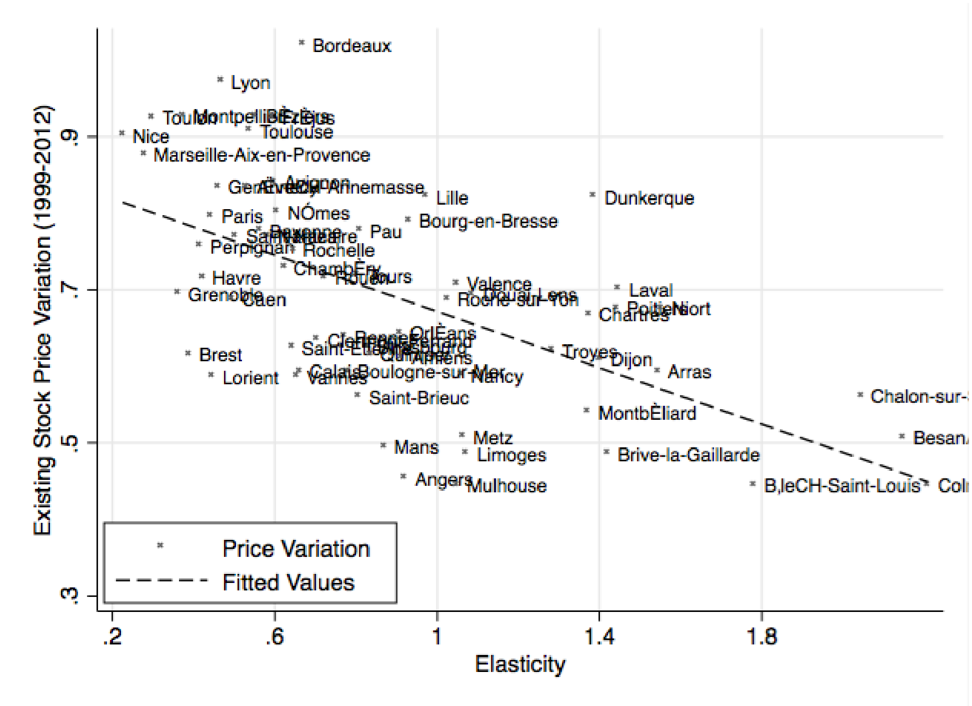
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standards error are robust. F-stat indicates the strength of the first stage, which pass the Stock Yogo critical value at 5% in the baseline and is then weaker when increasing the number of interaction terms. The p-value indicates that we can't reject the exogeneity of the instruments in any of the specifications. % undevelopable is the % of land not developable because under water or with a slope above 15% percent. % developed designates the share of the urban area already built, it is instrumented with the population in 1911 and is never significant Finally refusal is the average number of refusal in the municipality of the urban area, we instrument this index with the % of area covered by the historical monuments and the % covered by the SRU act.

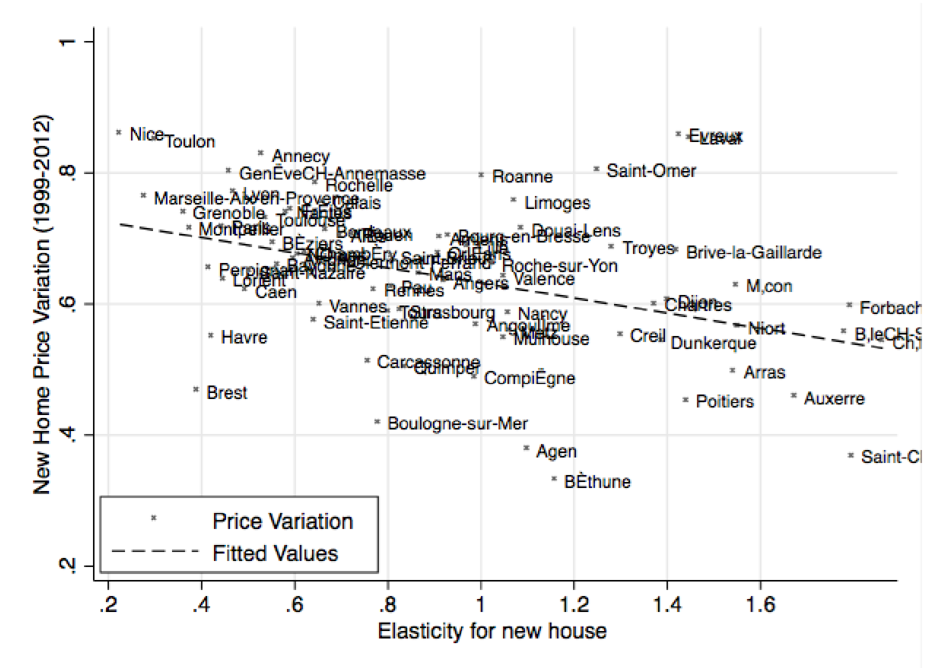
Table 2.D.7: Decomposition of the inverse supply elasticity with new prices (Saiz (2010))

2.D.4 Correlation between the supply elasticity and housing price variation

2.E Robustness check at the department level



(a) Supply elasticity with respect to existing prices



(b) Supply elasticity with respect to new housing prices

Figure 2.D.1: Correlation between the supply elasticity and housing price variation

	(1) $ln(Construction)$	(2) $ln(Construction)$	(3) $ln(Construction)$
$ln(Price_{old})$	0.901***	0.765***	
	(0.202)	(0.236)	
$ln(Price_{new})$			1.016***
			(0.341)
Year & DEP FE	Y	Y	Y
R2	.	.	.
Obs	1439	930	930
N. of DEP	96	62	62
BirthsT-20	Y	Y	Y
F-stat	268.8	180.9	63.14

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Column (1) presents our estimate for all the departments as we have a old price index for all of them, column (2) restricts the sample to the departments for which we have also a price index for new housing units. Column (3) reproduces column (2) but with the new price index. The coefficient for new and old are still statistically different from one another. The difference between column (1) and (2) is easily understandable as the department for which we don't have observations for the new price index are the rural departments more elastic.

Table 2.E.1: Short run estimates of the supply elasticity in the French Departments

	(1) $ln(Price_{old})$	(2) $ln(Price_{old})$	(3) $ln(Price_{new})$
Births T-20	0.694***	0.778***	0.586***
	(0.0421)	(0.0574)	(0.0731)
Year & DEP FE	Y	Y	Y
R2	0.973	0.973	0.948
Obs	1439	930	930
N. of DEP	96	62	62

Standard errors in parentheses

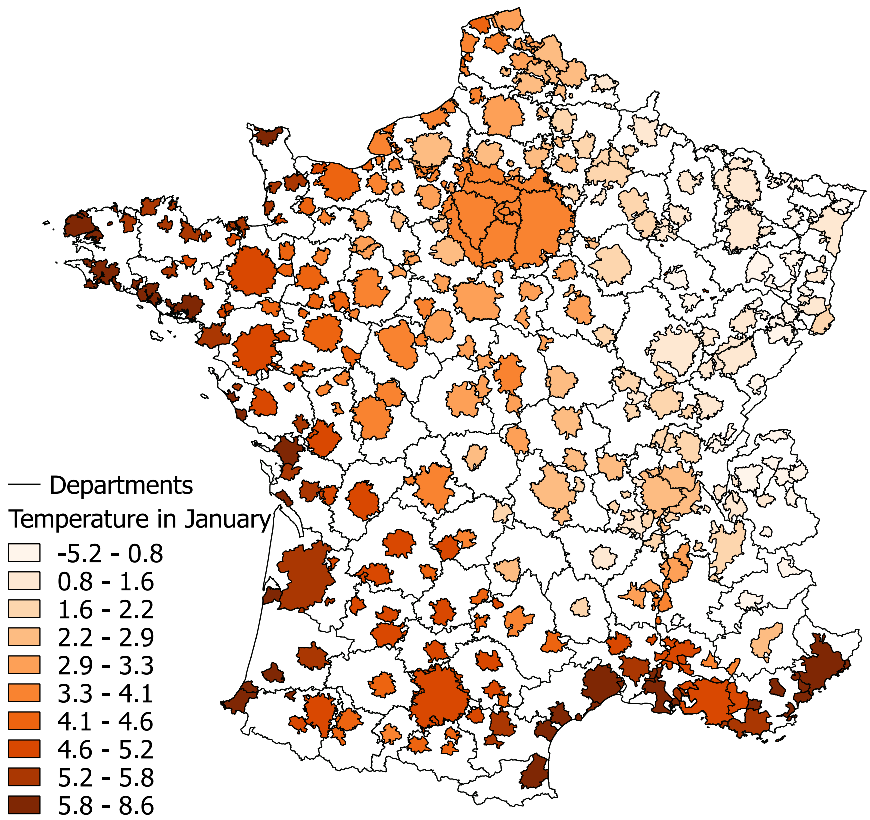
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.E.2: Fisrt Stage of the short run estimates of the supply elasticity in the French Departments

2.F Construction of the variables

2.F.1 The temperature in France

We recover the temperature in January at the barycenter of each urban area using the highly precise data compiled in Hijmans et al. (2005) and available online.

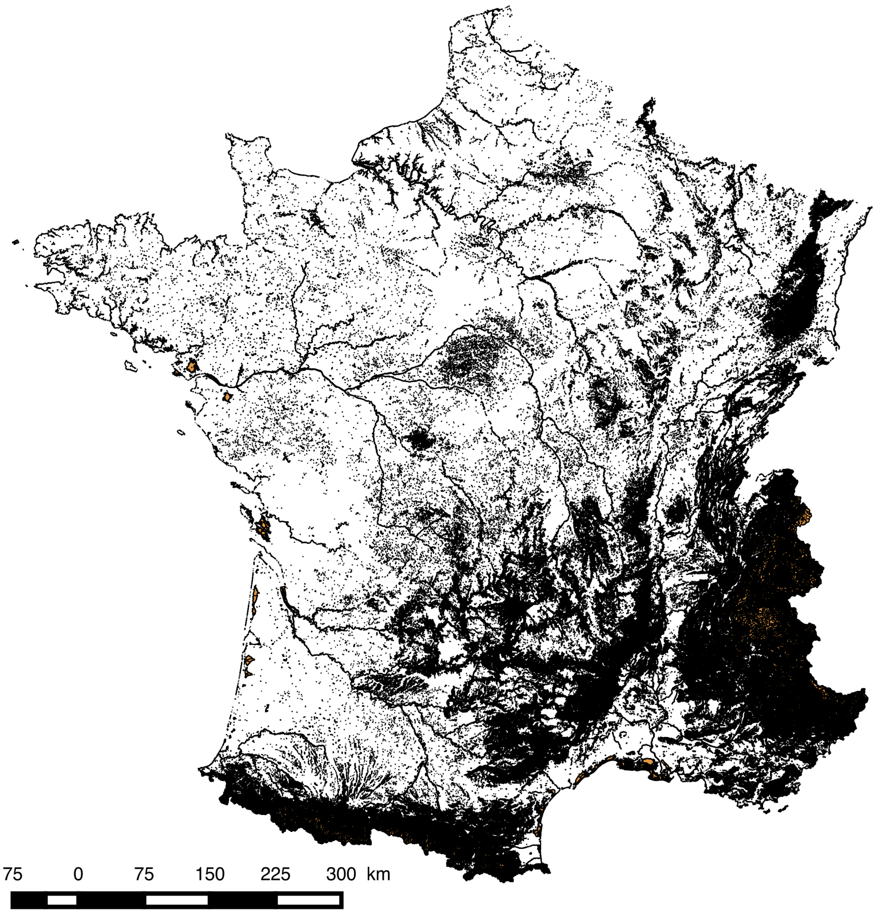


Source : Hijmans et al. (2005)

Figure 2.F.1: The temperature in January

2.F.2 Share of undevelopable land in the Main Urban Areas

As in Saiz (2010) we exploit elevation models computed from the IGN database BD ALTI with a 75m precision (more precise than the previous papers) in order to identify the place where the slope is above 15%. In addition, we use the BD CARTHAGE in order to identify wetlands and water surface. This allows us to build a shapefile describing all the places where constructions can only hardly take place as illustrated in Figure 2.F.2.



Authors' computation from the IGN databases
(GEOFLA, BD ALTI and BD CARTHAGE)

Figure 2.F.2: Geographical Constraint in France

Finally we build a shape file corresponding to the oceans surrounding France that we merge with the continental constraint. This allows us to compute the share of unavailable land. We try different ways to compute this constraint using the unavailable continental area on the territory of the urban area or the global constraint (ocean + continental constraint) within a 25km and 50km radius around the barycenter of the Area. We report in Table 2.F.1 the share of undevelopable land for the main French Urban Area.

Urban Area	Alt. Max. (Meters)	Alt. Min. (Meters)	Range	Continental constraint (in %)	Constraint (25km ring) (in %)	Constraint (50km ring) (in %)
Paris	236	9	227	1	1.9	1.1
Lyon	929	145	784	7.9	6	10.5
Marseille-Aix-en-Provence	1148	0	1148	12.2	37	44.8
Lille	107	9	98	.2	1.5	1
Toulouse	523	85	438	1.3	1.3	1.1
Nice	2649	0	2649	56.1	62.9	72.4
Bordeaux	118	0	118	2.3	3.8	4.7
Nantes	101	0	101	4.7	5.3	5.1
Strasbourg	964	120	844	4.4	2.3	8.9
Toulon	827	0	827	21.4	51.1	59.1
Douai-Lens	188	16	172	1.1	.7	.8
Rennes	191	5	186	.7	.6	.4
Rouen	236	0	236	3	.2	.8
Grenoble	2969	176	2793	55.8	56	49.6
Montpellier	641	0	641	8.6	24.3	36.3
Metz	403	150	253	2.4	2.9	2.4
Nancy	541	179	362	2.3	2.2	1.8
Clermont-Ferrand	1465	288	1177	5.6	5.8	8.5
Valenciennes	135	10	125	1	3.4	1.2
Tours	182	37	145	1.4	1.5	1
Caen	334	0	334	.8	14.9	27.7
Orléans	152	78	74	1.5	1.6	1.5
Angers	104	0	104	2.1	2	1
Dijon	636	176	460	4	3.8	2.8
Saint-Etienne	1308	360	948	16.1	17.3	15.2
Brest	179	0	179	1.5	29.3	53.8
Havre	147	0	147	6.2	42.8	44.5
Mans	182	31	151	.5	.5	.3
Reims	276	45	231	.2	.3	.7
Avignon	891	10	881	5	4.6	8.8
Mulhouse	456	221	235	1	7.8	13.7
Amiens	194	6	188	.7	.6	.4

Urban Area	Alt. Max. (Meters)	Alt. Min. (Meters)	Range	Continental constraint (in %)	Constraint (25km ring) (in %)	Constraint (50km ring) (in %)
Béthune	193	14	179	.7	.4	.8
Dunkerque	54	0	54	1.6	2.7	1.6
Perpignan	784	0	784	8.8	30.5	49.7
Limoges	701	172	529	2.2	2	1.8
Besançon	734	189	545	5.3	6.7	5.1
Nîmes	274	1	273	1.4	2.6	14.9
Pau	1848	90	1758	7	4.1	19.8
Bayonne	883	0	883	10.2	42	42.2
GenèveCH-Annemasse	1840	326	1514	20.6	21.6	34.8
Poitiers	187	55	132	.2	.4	.4
Annecy	2338	320	2018	31.6	35.1	41.9
Lorient	158	-1	159	3	34.7	41.4
Montbéliard	836	277	559	6.4	8.4	11.4
Troyes	303	84	219	1.7	1.9	1.2
Saint-Nazaire	70	0	70	20	43.3	44
Rochelle	56	0	56	1.2	42.6	38.2
Valence	1148	93	1055	12.8	19	30.4
Thionville	423	147	276	5	3.1	2
Angoulême	225	20	205	.3	.3	.3
Boulogne-sur-Mer	202	0	202	.9	46	55.5
Chambéry	1845	222	1623	41	40.1	44.5
Chalon-sur-Saône	502	167	335	1.7	1.9	2.4
Chartres	248	106	142	.3	.3	.2
Niort	200	0	200	0	.1	.2
Calais	181	0	181	.8	45.4	54.9
Béziers	204	0	204	4.9	19.8	42.2
Arras	178	42	136	.1	.4	.5
Bourges	348	107	241	.4	.4	.7
Saint-Brieuc	246	0	246	1.6	22.5	26.7
Quimper	286	-5	291	1.6	15.8	42.4
Vannes	154	-1	155	3.3	21.4	31.1
Cherbourg-Octeville	179	0	179	1	42.5	71.8

Urban Area	Alt. Max. (Meters)	Alt. Min. (Meters)	Range	Continental constraint (in %)	Constraint (25km ring) (in %)	Constraint (50km ring) (in %)
Maubeuge	229	83	146	.2	4.6	1.6
Blois	147	56	91	1.5	1.5	1.4
Colmar	1240	175	1065	14.6	20.8	19.3
Tarbes	579	189	390	1.8	11.8	25.1
Compiègne	188	30	158	.9	1.2	.9
Charleville-Mézières	396	132	264	2.2	5.6	2.7
Belfort	1244	331	913	14.1	16.2	16
Roanne	1155	253	902	8.3	7.5	10
Forbach	388	190	198	3.6	2.5	2.6
Saint-Quentin	156	49	107	.4	.5	.5
Laval	199	32	167	.7	.6	.4
Bourg-en-Bresse	681	182	499	3.7	8.7	12.3
Beauvais	236	50	186	.5	.4	.5
Nevers	441	155	286	1.8	1.6	1
Creil	150	23	127	3.1	1.3	1
Roche-sur-Yon	112	5	107	.6	.6	16.6
Evreux	182	26	156	.6	1.1	1.7
Agen	246	30	216	3.7	3.2	1.9
Saint-Omer	211	0	211	.8	.5	13
Périgueux	271	65	206	1.5	1.2	2
Châteauroux	259	107	152	.8	.7	1.4
Epinal	586	280	306	1.1	4.2	10.7
Alés	692	79	613	18.7	25.1	26
Brive-la-Gaillarde	509	82	427	7.2	6.6	7.6
Mâcon	747	167	580	5.3	5.5	6.7
Elbeuf	179	2	177	3.9	4.5	2.2
Albi	526	130	396	4	7.8	11.8
Auxerre	346	81	265	1.5	1	.9
Saint-Chamond	1396	208	1188	32.8	17.2	13.2
Fréjus	616	0	616	24	49.5	58.4

Urban Area	Alt. Max. (Meters)	Alt. Min. (Meters)	Range	Continental constraint (in %)	Constraint (25km ring) (in %)	Constraint (50km ring) (in %)
Bélech-Saint-Louis	831	222	609	3.6	1.8	4.1
Carcassonne	945	52	893	6.7	12	16.9
Dieppe	216	0	216	1.9	36.9	39.8
Vichy	608	234	374	2.9	3.4	4.7
Châlons-en-Champagne	214	72	142	.5	.4	.9

Table 2.F.1: Geographical features of the Main French Urban Areas

2.F.3 Construction of the new price index and scraping of the old price index

We take advantage of the dataset Enquête sur la Construction des Logements Neufs realized by the Statistical Division of the French Ministry for Housing and sustainable development in order to design price index at the urban area. There are two methods used in France to compute price index. Both are based on hedonic regression but go through different steps. We test both in order to insure that the method does not bias our results :

The first method is based on Gouriéroux and Laferrère (2009) and is composed in several steps :

First, the method estimate correction coefficient using an hedonic regression on an estimation stock of transaction. We thus estimate at the beginning of the period the coefficient of this equation for each urban area:

$$ln(p_i) = log(p_{0,s}) + \sum_{k=1}^{K} \beta_{k,s} X_{k,i} + \sum_{a=1}^{2} \alpha_{a,s} Y_{a,i} + \epsilon_i \tag{2.18}$$

where $ln(p_i)$ is the price per square meter of the project and the intercept $log(p_{0,s})$ is interpreted as the price per square meter of the reference good at the beginning of the period. $Y_{a,i}$ is a year dummy, $X_{k,i}$ are the unit characteristics (here the number of rooms, the type of units (flats or single units[20]), the surface of the project, the number of dwellings in the project and the distance from the barycenter). Second, the parameters $\beta_{k,s}$ are recovered and are used in order to correct the value of the transaction in terms of the reference good. We then follow the average price of the reference good for every year in order to build the new price index.

The second method is based on Balcone and Lafferrère (2015) and is simpler, we pool all the observations and estimate a rather similar equation :

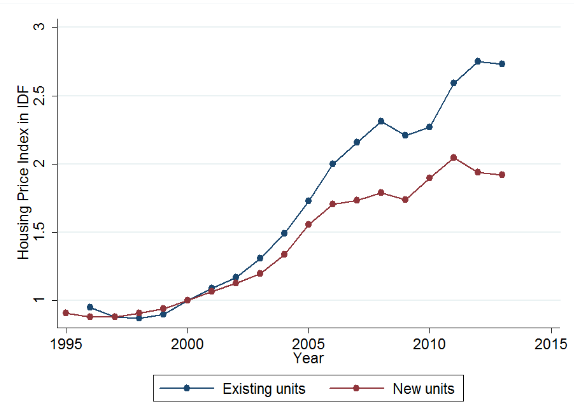
$$ln(p_i) = log(p_{0,s}) + \sum_{k=1}^{K} \beta_{k,s} X_{k,i} + \sum_{a=1996}^{2014} \alpha_{a,s} Y_{a,i} + \epsilon_i \tag{2.19}$$

where the $e^{\alpha_{a,s}}$ is the index for each year a with respect to the reference year which is here 1995 (the year dropped). As in Balcone and Lafferrère (2015), we find very close results using both methods.

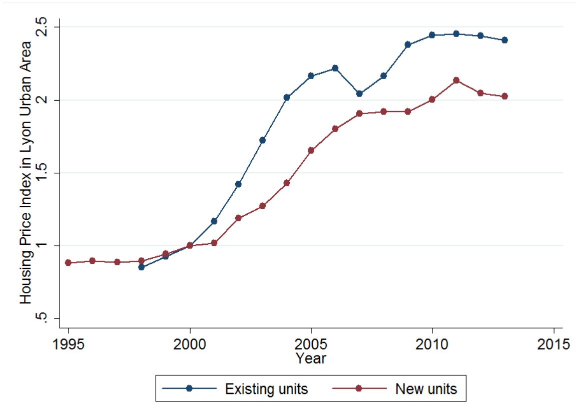
These models are estimated for each Urban Area where we have enough observations for each year. We thus have 56 Urban Areas for which we have enough observations to compute a yearly index for flats. We conducted some robustness checks including single units: the re-

20. In the main table the index is the one for flat only as we have the existing unit price index for flats, including new units does not affect our results

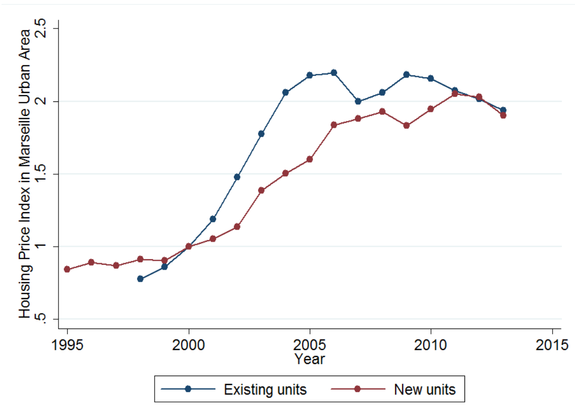
sulting index does not change our results.
We were also able to recover online the strata-level components of the INSEE-Notaires price index for existing unit transactions for flats. We are thus able to get index covering approximately the urban area and the index for French departments. We can compare the dynamics of new dwellings and of existing dwelling. We thus represent both index for the urban area as illustrated in Figure 2.F.3.



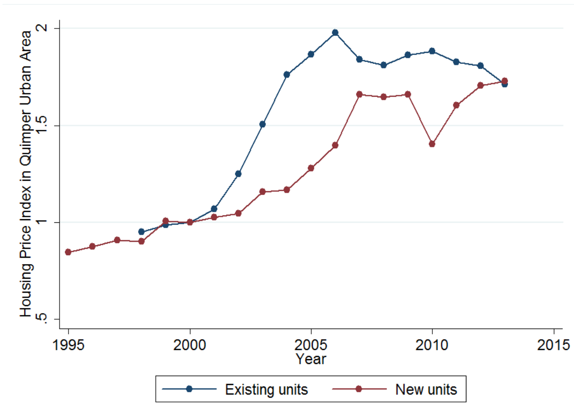
(a) Paris



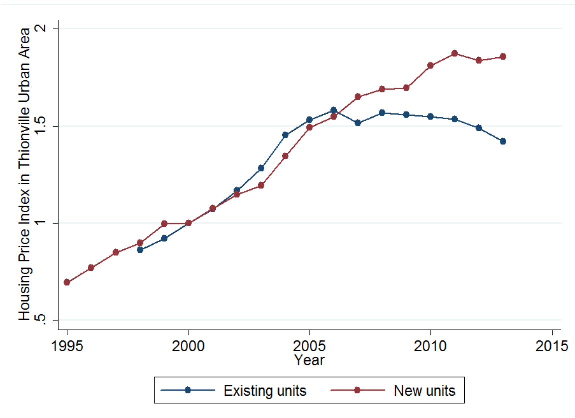
(b) Lyon



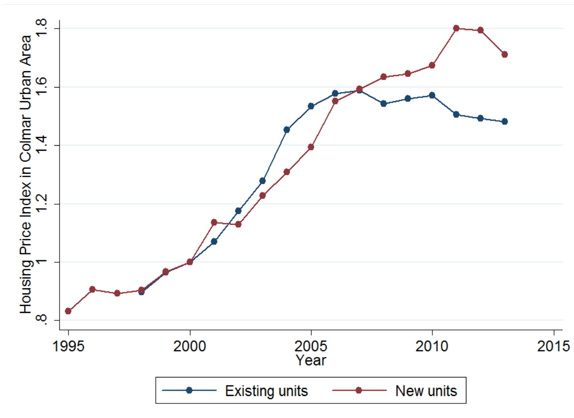
(c) Marseille



(d) Quimper



(e) Thionville



(f) Colmar

Figure 2.F.3: Price series for several Urban Areas

2.F.4 Construction of the Bartik Instrument

We build the bartik instruments thanks to the INSEE dataset on employment categories, which are available for four categories of employment in the census at the municipal level[21] and from 5 to 38 categories at Employment Area[22] or Department level [23]. We thus build bartik predicting the evolution of the employment in the department or the employment area of the Urban Area under study starting from their initial composition in 1990. Alternate reference years can be taken however, one might think that exogeneity will be strengthen taking the largest time span. We illustrate the different shocks in Figure 2.F.4. We can clearly see that there has been a major decline of the industrial employments and of agricultural activities while tertiary activities have been constantly increasing. We build two bartiks based on the 5 and 17 sectors illustrated in both aforementioned figures, both are closely correlated and does not change our results.

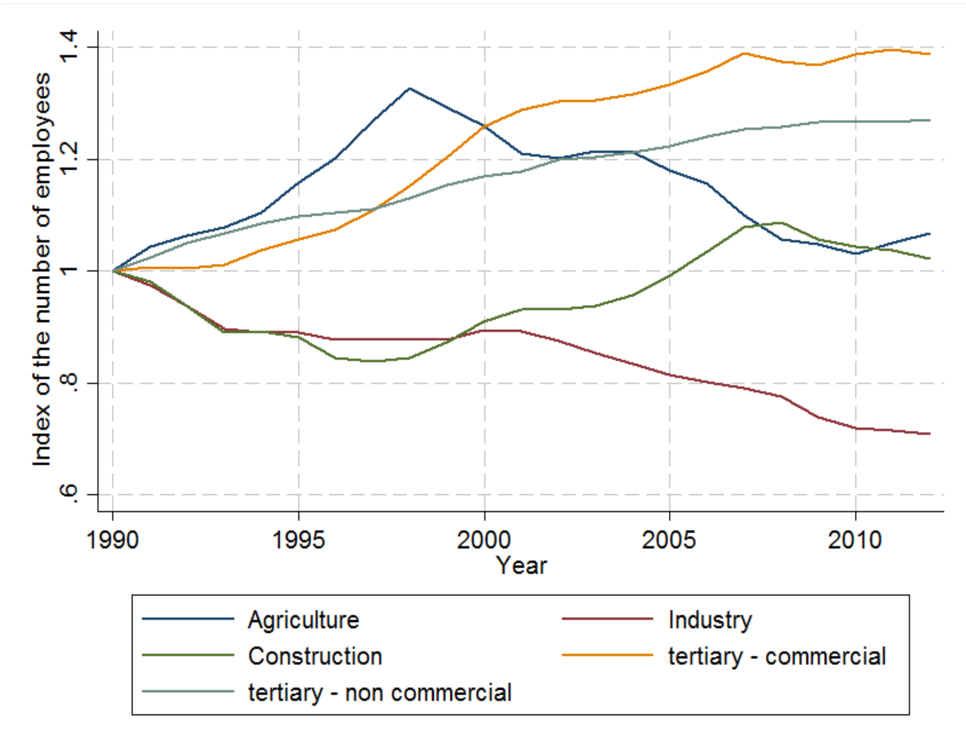
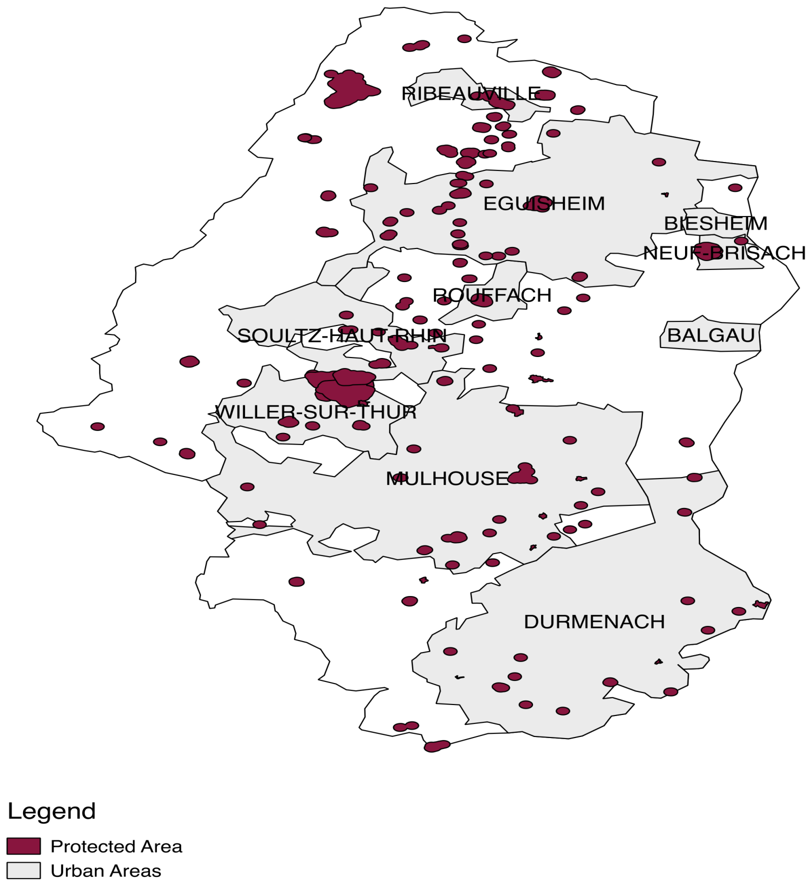


Figure 2.F.4: National Employment shocks : 5 sectors

21. https://www.insee.fr/fr/statistiques/1893185
22. https://www.insee.fr/fr/statistiques/1893177
23. https://www.insee.fr/fr/statistiques/1409895?sommaire=1409948

2.F.5 The historical monuments areas



Authors' computation from wikipedia compared with Bas Rhin Dataset

Figure 2.F.5: Protected Areas around Historical Monuments : the example of Bas Rhin

Chapter 3

Studying rental market with online data

This paper is jointly written with Guillaume CHAPELLE

3.1 Introduction

The private rental sector plays an important role in the economy and is supported by various public policies. In France, 33% of the 40 billions euros spent on housing subsidies are directed toward the private rental sector through housing allowances or direct support to landlords. While several recent contributions pointed the limits of these programs, one can regret the fact that access to statistics on the private rental market remains limited when compared with the social housing sector or housing transactions. Indeed, while transactions prices are usually systematically recorded by the fiscal administration or the solicitors, access for researchers to rental data remains limited, in particular at the local level. In this paper, we propose to fill this gap taking advantage of the relevance of real estate websites in the matching process between landlords and their tenants.

The objective of our work is threefold. First, we aim at providing a reliable database on French local rental market to scholars and other people interested in the housing market. Second, we want to highlight the strong complementarity between administrative data and online data: scraped data reveal their potential only when they are used with external data. Third, in a period where Internet is increasingly used for economic transactions, we want to share a methodology to extract and use online data in economics.

Building on the recent literature on webscraping (Boeing and Waddell (2016), Laouénan and Rathelot (2016), and Laouénan et al. (2018)), we have periodically collected, cleaned and analyzed housing posts coming from the two largest French rental websites between December 2015 and June 2017. Each post provides the features of the housing good as well as its precise location. In this paper, we argue that web activity provides a faithful picture of the rental market as websites gather millions of ads and are almost exhaustive. Web scraping can thus be used in order to follow housing market dynamics. Indeed, we show that web activity is involved in a large part of the transactions of the rental sector, where few negotiations on the rent takes place even in loose markets. To show this point, we compute the value of a comparable good in French regions and departments thanks to our data and confront our results with the same exercise based on the French housing survey which record signed contracts. We show that no systematic bias appears when comparing both databases. Finally, we use our dataset in order to compute the market value and the rent savings of tenants in the French social housing sector. We find that the median implicit subsidy represents about 42% of the rental value of the unit which is close to Trevien (2014). On the other hand, the use of an exhaustive dataset on the social housing stock allows us to carefully document the distribution and the heterogeneity across space of the implicit subsidy represented by the access to a social housing unit. Our findings confirm that the benefits of place based policies are very unevenly distributed between their tenants. This is illustrated by the strong discrepancy between the average and the median subsidy, the average subsidy is much higher as some very well located units, in particular in Paris, have a very low controlled rent.

The paper is structured as follows: Section 2 reviews the economic literature highlighting the opportunity given by online data for urban economics. It emphasizes the academic need for more precise knowledge of local rents and summarizes the different sources currently available for such a purpose. In Section 3, we briefly present our methodology to build an important database from posts on the web. Section 4 briefly presents our dataset providing some descriptive statistics of our database. We discuss the potential strengths and drawbacks of observing web activity in order to increase our knowledge of the rental market. In Section 5, we provide an estimate of the price of a similar good for French departments and regions using our dataset and the French housing survey in order to assess the negotiation bias. In Section 6 we estimate the implicit rent savings of households in the social housing sector and its distribution across space.

3.2 Understanding the rental market

3.2.1 What can information technology tell us about cities ?

Most of the urban economics literature has been built on aggregate statistics and surveys. However, the digitalization revolution starts to provide data at a very fine resolution. As highlighted by Glaeser, Kominers, et al. (2016) this will *fundamentally change urban science* for two reasons.

First, from a policy maker perspective, it will provide tools to improve city management.

Citizens leave an increasing number of comments about the quality of areas or restaurants, on various Internet applications such as Tripavisor.com, LaFourchette.com or Google.com. This data could be used to assess city management by looking, for instance, at the hygiene of restaurants (Glaeser, Hillis, et al. (2016)) or the spread of diseases (Polgreen et al. (2008), Ginsberg et al. (2009)). Second, from a more academic perspective, it will provide new source of data to better assess unmeasured variables. As an example, Glaeser, Kominers, et al. (2016) show that Google Street images are a good predictor of median income of New York City blocks suggesting that such a method could be used in developing cities to follow the urbanization process.

The power of online data relies on the fact that most of the observations are geocoded or observable at a fine scale. This last characteristic is fundamental in urban economics. For example, a large part of the urban economics literature focuses on the link between density and productivity. In this context, local unobserved heterogeneity matters and being able to carefully locate variables could lead to a better understanding of agglomeration forces in particular to show how density has an effect on productivity (Arzaghi and Henderson (2008)). Thus, exploiting web data could improve our understanding of this complex phenomenon. That being said, exploiting large database is not a magic wand. Online data are very messy and need to be carefully cleaned and checked before any empirical study. On this point, administrative databases play a fundamental role by providing a great tool to check the quality of the data. Moreover, increasing the size of the database will not solve the classical problems of causal inference per se: one still needs to find and exploit exogeneous shocks.

Nevertheless, online data have been increasingly used by urban economists. In particular, it has been used to investigate various topics such as urban discrimination, consumption patterns or competition. For instance, Davis et al. (2016) use data from Yelp.com to study the role of spatial and social frictions on restaurant choice in New York City. They join several papers which study Yelp's comments to study discrimination and competition (Anderson and Magruder (2012), Luca (2016)). User-generated content is also increasingly use to study discrimination. Among others, Laouénan and Rathelot (2016) build a panel of scraped posts on an online platform in order to disentangle the existence of a taste-based or statistical discrimination on the vacation rental sector. Edelman and Luca (2014) infer racial identities from profile photos to study discrimination on Airbnb.com.

Interestingly, online data has not really been used to study the housing market per se. Among the studies that use them, we are close to the work of Bricongne, Pontuch, and Turrini (2017) who develop a new international database for housing prices based on several sources and exploiting the complementarity between standard surveys and innovative methods such as webscraping. Mense, Michelsen, and Cholodilin (2017) also develop a similar database in order to assess the impact of rent control in Germany. Boeing and Waddell (2016) who use Craiglist rental housing listings to study the rental housing market in the US. Other researches use these kind of data provided by the websites without scraping. Brülhart et al. (2017) also use rental data collected by a website in order to measure the housing supply and demand elasticities in Switzerland. Ads were also exploited in Basten, Von Ehrlich, and Lassmann (2017) to investigate spatial sorting on the Swiss market while Kholodilin, Mense, and Michelsen (2017) and Hyland, Lyons, and Lyons (2013) use these types of data to investigate the impact of energy efficiency labels on housing prices. Moreover, Chapelle and Wasmer (2017) or Ortega and Verdugo (2016) use the present dataset in order to measure the rent gradient in Ile-de-France or to investigate workers' mobility patterns. The closer contribution to our work is Loberto, Luciani, and Pangallo (2018) who use similar data on housing price to describe the Italian Market but do not collect the dataset themselves and thus only rely on one single web site.

3.2.2 The academic and administrative demand for rental data

While the support to the rental sector and its tenant represents an important share of public spending[1], rising an important amount of questions on their efficiency (see Grislain-Letrémy, Trevien, et al. (2014) or Fack (2006)), our knowledge of the rental sector remains limited due to the lack of large-scale micro-level datasets providing information on rents. This is of particular importance in order to prevent windfall profit when conditioning some subsidies for landlords under rent ceiling below the supposed market rent as it is the case with the *Scellier Tax Credit*. A precise knowledge of the rent is also desirable in order to measure the market tightness of the rental sector when designing public policies. Finally, evaluation of urban policies might also require to follow rent prices in order to measure the capitalization of amenities, potential inflationary effects or the respect of a rent ceiling.

Having an accurate knowledge of the rental market could also be important for taxation purposes. Indeed, a growing literature emphasizes the need to tax homeowners' imputed rents or at least to update local fiscal bases (Trannoy and Wasmer (2013)): while housing accounts for the most important share of households savings, returns to homeownership are not included in the tax base of income taxation. For many scholars, this could lead to important distortions in investments and decrease the redistributive impact of income taxation (see Landais, Piketty, and Saez (2011), Artus, Bozio, and Garcia-Penalosa (2013) or Bonnet et al. (2016)). A fiscal reform as a revision of the taxable base of local taxes or the inclusion of imputed rent into the income tax base would thus require a precise knowledge of the potential rent of a house. The revision of the taxable base (*Valeurs Locatives*) appears to be an important reform since the current taxable base were computed in the 1970s and have only been marginally updated so

1. Housing allowances and fiscal subsidies to the private rental sector represents about 31% of the Housing Subsidies. The latter represent a total amount of more than 40 Billions euros.

far. The data required for such purpose remains unclear: if some suggest that such a fiscal base could be set using housing prices (see Vignolles (2016)), one might also think that rents represent a more accurate measure of the implicit income connected with the use of one's own house (see Bonnet et al. (2016)). Indeed, one can remark that rents and housing prices do not systematically follow equivalent temporal or spatial patterns. For example, we can notice an important divergence between housing prices and rent during the 2000s in France and Chapelle and Wasmer (2017) find that price and rent gradients are not the same across Paris Urban Area.

The knowledge of local rents could also be important when studying the social housing sector and the redistributive impact of such in kind benefit. While Le Blanc, Laferrere, and Pigois (1999) find that social housing increases households consumption, Trevien (2014) finds that such a unit confers a subsidy equivalent to 261 euros per month, which tends to be higher for the highest income deciles. This leads Cazenave, Domingues, and Vicard (2016) to simulate the potential impact of taxing such implicit subsidy in the same spirit as the implicit rent taxation of homeowners aforementioned. The authors emphasize that the implementation of such reform would also require a precise knowledge of local rents.

3.2.3 Access to rental data at a fine geographic level remains limited

The French Housing Survey[2] or the Survey on Rents and Housing Expenditures[3] provide good quality data on the rental sector but have two drawbacks. On the one hand, they are only representative at the national level as they have a limited number of observations[4]. Thus, one cannot use them to follow the rental dynamics of a city or an urban area. On the other hand, they do not allow to follow the housing market on a monthly basis as they are published every four years (French Housing Survey) or every quarter (Survey on Rents and Housing expenditures).

The lack of information at the local level led to two private initiatives: the Observatoire des Loyers de l'Agglomération Parisienne (OLAP)[5] and Connaître Les Loyers et Analyser les Marchés sur les Espaces Urbains et Ruraux (CLAMEUR)[6]. The first one, the OLAP, is publicly supported and was first in charge of observing rents in the urban area of Paris while progres-

2. Enquêtes logements de l'INSEE, see http://www.insee.fr/fr/methodes/default.asp?page=definitions/enquete-logement.htm

3. Enquête Loyers et charges see http://www.insee.fr/fr/methodes/default.asp?page=sources/ope-enq-loyers-et-charges.htm

4. The French housing survey has 36 000 households but only 2 947 tenants in the private sector, the Survey on Rents and Housing Expenditures 4300 households.

5. http://www.observatoire-des-loyers.fr/

6. http://www.clameur.fr/

sively extending its survey to the main French urban areas. This observatory has two main micro level datasets: a panel dataset and a serie of yearly cross sectional observations from 1990 until nowadays. Even though this dataset is of good quality, it also presents two main limits: it only covers a limited share of the French territory and its access to researchers appears relatively difficult. So far, to our knowledge, there exists only a single published study based on this dataset (see Gregoir et al. (2012)). The second one, CLAMEUR, collects rental data from real estate agents and insurance. Its provides quarterly average of the rent per square meters for many French Municipality and groups of Municipalities (EPCI). If such a source provides useful information on an important share of the territory, few details concerning the variables available in their database were provided. To our knowledge, no academic paper has ever used their micro-level dataset.

Finally, it is worth noting that if the French Statistical Agency has no particular project to collect rent besides the National Survey already mentioned, the Family Branch of the Social Security is actually collecting about 50% of the rents paid in the private sector. Indeed, about 50% of the tenants in the private sector receive a housing allowance and provide information on the rent and the municipality but no characteristics of the unit.

These three aforementioned sources might present some leads to deal with the limited knowledge of local rental markets. However, such surveys or administrative database requires an important and potentially costly treatment to increase the number of observations (for the survey based data) or the number of variables (for the administrative data) and as mentioned might just not be available for researchers. To us, exploiting online data can provide an interesting and complementary way to survey local housing markets for a moderate cost.

3.2.4 Online ads can help to follow the evolution of new leases

Nowadays a vast majority of private landlords or real estate agencies use internet to find tenants as illustrated in Table 3.1. Even if these channels do not constitute the whole market, as 22% of the tenants found their flat by alternate channels[7], one can think that we are able to observe the vast majority of the market. Ads posted online can thus be an interesting way to follow the rental sector dynamics.

7. Namely 19% by word of mouth, 1% from the employer and 2% from social services.

	Not Furnished	Furnished	Total
Privately (adds on internet or Newspapers)	37	42	37
Real Estate Agency	41	22	39
by word of mouth	19	20	19
From the employer	1	3	2
Social Services	2	10	3
Others	0	3	1
Total	100	100	100

Source: Author's computation from the French Housing Survey 2013 (INSEE)
Households in the private rental sector installed for less than 4 years.

Table 3.1: Method used to find a Flat in the rental sector (%)

This source of information has special features. First, it allows to measure the level of the rent for new tenants who represent 18% of the Rental Sector as illustrated in Table 3.2. This fact is of particular importance given the regulation of the French Housing Market. Indeed, once the contract is signed, yearly revision of the rent level cannot exceed an official index : the Rent Revision Index[8] which is a price index from which tobacco and rental prices were removed. Such a regulation is defined as Rent Control of Type 2 in Arnott (1995). As a consequence, such transactions can only provide information about the change on the flow of rental housing as when observing housing price transaction. The rent we follow corresponds to the rent for new rentals while the INSEE rent index corresponds to an index for the stock of rentals. Following new leases can provide us additional information.

	Not Furnished	Furnished	Total
Less than 1 year	18	39	19
1 to 4 years	28	36	28
4 to 8 years	18	15	18
8 to 12 years	9	5	9
more than 12 years	27	5	26
Total	100	100	100

Source: Author's computation from EL 2013 (INSEE)
Households in the private rental sector

Table 3.2: Time of occupation of the housing unit (%)

8. Indice de Référence des Loyers (IRL)

3.3 Methodology

3.3.1 Scraping process

There are several rental websites in France. To get access to the biggest source of data we decided to focus on the two largest. The first has about half of its posts from landlords and half from real estate agents. The second has mostly his post from real estate agents. The information we want to extract consists of a set of posts that are available on the rental websites. Each post is a Volunteered Geographic Information (VGI) as it is both user generated and geolocated (Jiang and Thill (2015)). It has a unique identifier, pictures, a short text describing the offer and a standardized table presenting the most important characteristics as the surface, the number of rooms, the monthly rent or the type of contract (furnished or not). It is also localized thanks to the name of the municipality, a zip-code and a map indicating the geographic coordinates which can be more or less precise (city level, neighborhood or address). The non-structured part of the post (description) allows to identify key words in order to find additional information as the presence of an elevator, the floor, the amount of extra expenditures.

To get the data from the two websites, we use Python to create programs that mimic a web browser request. The first step consists in finding the Uniform Resource Locator (URL) of each post which concerns the rental market in France. In a second step, we extract the Hypertext Markup Language (HTML) of each page from the server. In a third step, we clean it and structure it so as to get a structured format for each post. Finally, we save the database in comma separated values format. Overall, the operation takes between 10 hours and two days depending on the Website and the period of time. We repeat the process of scraping every month for each website from December 2015 until January 2018 and end up with a database of 4.2 millions posts in the rental sector.

The database we create belongs to the Big-Data family as defined by Laney (2001) as it is characterized by the three Vs: volume, variety, and velocity. Or as Jiang (2015) describes it, "Small data are mainly sampled (e.g., census or statistical data), while Big Data are automatically harvested [...] from a large population of users.". Therefore, it has Big Data benefits such as the mass of data or the precision which allows to observe economic phenomena at a small scale. Still, it also has its drawbacks: the posts can be messy and misreported. Even if the websites try to keep only correct posts, one should pay attention to get clean data.

3.3.2 Cleaning the data

The cleaning procedure starts by identifying the repeated posts which have the same identifier between each wave. We also identify similar posts between both sites using the post's description. We keep only one observation by post and keep the number of occurrences of the post. our approach is different from that use a Machine Learning algorithm to identify similar ads with different Identifier. In our approach, we generated a full set of variables describing each unit (see below) and consider that a unit with the same price and the same characteristics (rent, surface, number of rooms, amenities and geocoding) posted in the same month are duplicates. We keep only the posts that have a price per square meter which is strictly positive and lower than 100[9] and above 2. This procedure creates the final database that we describe in the next section. For each post, we compute the price per square meter dividing the price per month by the surface of the housing good. The main point of our study is to have geolocalized data. Consequently, we decide to drop observations which do not provide a city name or a precise geographic location.

Overall, our cleaning procedure decreases the number of observations by 12.87%. The largest part of this decrease is explained by observations which don't report the surface of the good. We believe that the price per square meter is the relevant statistics to characterize the housing market for several reasons. First, it provides a rental value which is used in other countries and is easily comparable. Second, it is used in the hedonic regression framework that we use in a second part of the study (see Musiedlak and Vignolles (2016))

3.4 The database

In this section we present extensively the database by reviewing the most important variable available. Overall our cleaned database has about 4.2 millions observations collected between December 2015 and January 2018.

3.4.1 The representativeness of the database

In order to assess the representativeness of the dataset coming from our collection process, we consider that housing units observed are a subsample of the exhaustive rental market which is observed in the French Census.

1. From the census, we create many strata crossing the location of the rental units (municipality) and their number of rooms. Each strata contains a number of observation in the census noted N^c.

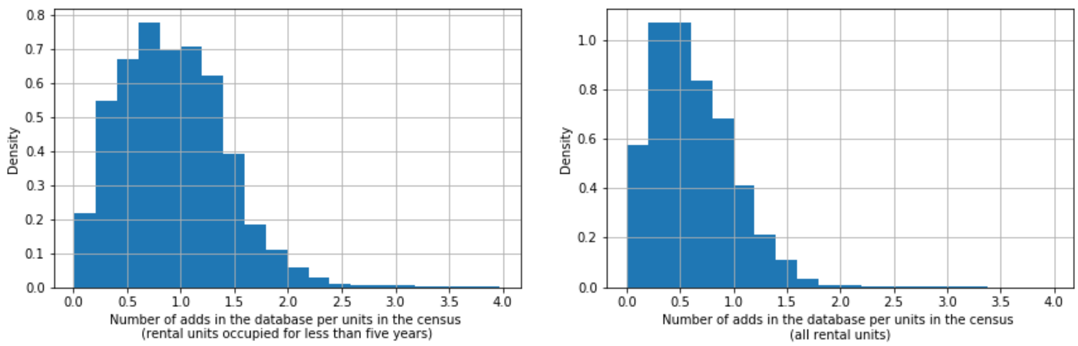
2. In a second step we assign our posted scraped to each strata. The number of scraped posts in each strata is noted n^s.

9. The 99th percentile of the price per square meter variable is 38.8 euros, the 99.9th percentile 63.5 euros, and the 99.95% 111.1 euros.

3. The respresentativeness (i.e. number of post for each unit) is simply defined as $\frac{n^s}{N^c}$.

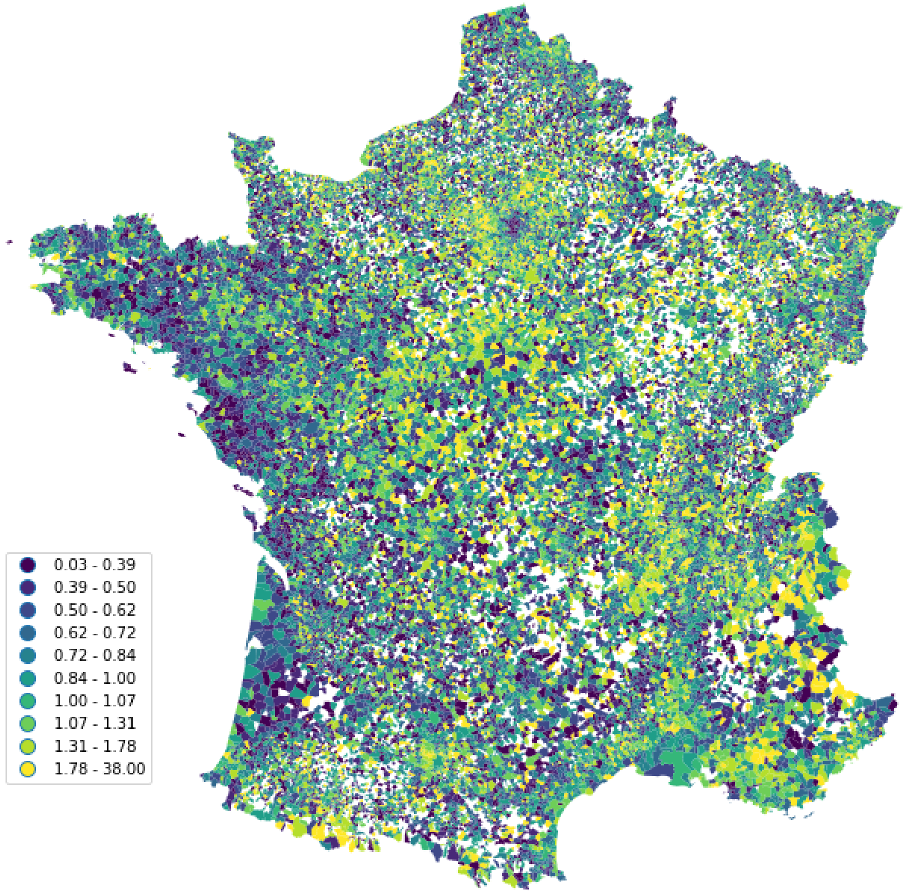
We can thus measure the representativeness of each types of goods following two dimensions: their location and the number of rooms. For example: we can know how many flats a post with two bedrooms in the Ist district of Paris will represent.

We use two different subsamples of the census to create two alternate measures. First, N^c is defined using all the rental units. Second, N^c is defined using the rental units occupied for less than five years used to proxy the flow of rental units on the market over our period of study. Figure 3.1 represents the distribution (weighted by the number of units) of the coverage of our strata. One can observe that On average each strata has 1 post per units rented for less than five years and 0.66 post per rental unit. Area with no coverage are rural municipalities with a residual rental sector. The coverage is usually very high in rural places where the number of tenants is low and in the suburbs while it is lower in city center where the number of tenants and the turnover in the private sector is very high. For example, within Paris the average coverage among strata is around 0.5 ads per rental units occupied for less than five years. This coverage is expected to grow over time as we only have been scraping for 2 years.



Each observation is a strata weighted by its number of rental units (N_c)

Figure 3.1: Representativeness of the database



This map gives the average number of ads per unit in all strata of a Municipality

Figure 3.2: Representativeness of the database through space

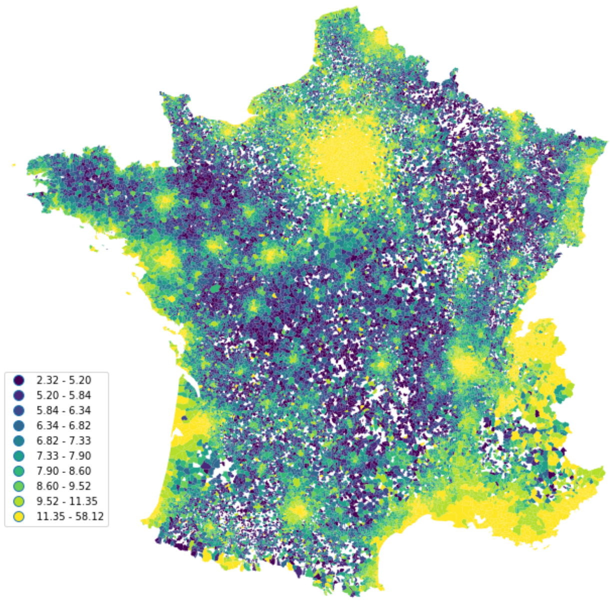
3.4.2 The geocoded location and the granularity of the dataset

One important variable is the location of each post. Both websites provide geocoded information for each good. However, some realtors or households might not be willing to disclose too precisely the address even if platforms usually provide financial incentives to disclose the true location of the good. The HTML code informs directly to what level of precision the geolocation corresponds. Table 3.1 summarizes the level of geocoding in our database. 60% of the ads are located at the broadest level: French Municipalities while 40% remaining are precisely geocoded at the address or neighborhood level using the information provided by the user or the location of the device used by the user when creating the add. This database provides thus fine grain data as even municipalities remain quite small.

This allows us to compute an average rent for the majority of the municipalities in France as illustrated in Figure 3.3 where one can easily identify the main urban areas and the places close to the frontiers where rents are usually higher.

	Count	Mean	Std	Min	25%	50%	75%	Max
Geocoding (%): unknown	4225887.0	0.0	1.1	0.0	0.0	0.0	0.0	100.0
Geocoding (%): address	4225887.0	17.9	38.3	0.0	0.0	0.0	0.0	100.0
Geocoding (%): city	4225887.0	59.0	49.2	0.0	0.0	100.0	100.0	100.0
Geocoding (%): neighborhood	4225887.0	12.8	33.4	0.0	0.0	0.0	0.0	100.0
Geocoding (%): user	4225887.0	10.0	30.1	0.0	0.0	0.0	0.0	100.0

Table 3.1: Precision of the geocoding



This map represents the gross average rent per square meter of online ads

Figure 3.3: Average rent in French Municipalities

3.4.3 The type of units, the surface and the number of rooms

Each website has a specific part of the webpage dedicated to the type of unit, the surface and the number of rooms. No treatment is thus required and these variables are taken directly from the HTML code.

	Count	Mean	Std	Min	25%	50%	75%	Max
Surface	4225940.0	55.9	31.1	1.0	34.0	50.0	70.0	1080.0
Single unit (%)	4225940.0	15.8	36.4	0.0	0.0	0.0	0.0	100.0
Rooms (%): 01	4225940.0	20.7	40.5	0.0	0.0	0.0	0.0	100.0
Rooms (%): 02	4225940.0	32.5	46.9	0.0	0.0	0.0	100.0	100.0
Rooms (%): 03	4225940.0	26.2	44.0	0.0	0.0	0.0	100.0	100.0
Rooms (%): 04	4225940.0	12.6	33.2	0.0	0.0	0.0	0.0	100.0
Rooms (%): 05	4225940.0	5.5	22.8	0.0	0.0	0.0	0.0	100.0
Rooms (%): 6+	4225940.0	2.5	15.7	0.0	0.0	0.0	0.0	100.0

Table 3.2: Type of units, number of rooms and surface

As one can observe in Table 3.2, most of the units are flats as single units only represent about 16% of the sample. Units are of a relatively small size as their vast majority have one or two rooms while the average surface is about 56 square meters. These characteristics are typical from the French rental market that is dedicated to younger people with usually few children in urban areas.

3.4.4 The rent, type of lease and the expenditures

Another important variable is the rent. This variable is also directly coded and easy to recover. The average gross rent is about 650 euros while the rent per square meter is around 13 euros. Both websites also provide additional information specifying whether the rent displayed includes extra expenditures (as waste collection, water, heating). 70% of the rent displayed includes some kind of extra expenditures. Unfortunately, the share of the rent attributed to these is not directly coded and is recovered from the text using regular expressions. The algorithm identifies whether the word ”charges” is in the text and recover the amount in euro around this word that is inferior to the rent. About 30% of the ads inform the amount of extra expenditures. The average estimated amount of extra expenditures on the subsample is around 58 euros which represents 9% of the average rent. From the text it is also possible to infer which type of expenditures are included as collective heating or trash collection. Finally, a second important information is the type of lease indicating whether furnitures are included in the lease or not. This variable is of particular importance as the minimal length of the lease is 1 year when the flat is furnished while it will be 3 years when not. Once again, if this information appears in the code of the web page for the most recent period, this was not systematically filled in the first waves. Consequently it is also coded from regular expressions identified in the description. About 20% of the flats are offered as furnished.

	Count	Mean	Std	Min	25%	50%	75%	Max
Rent	4225940.0	646.2	396.7	8.0	445.0	561.0	730.0	65000.0
Rent per square meter	4225940.0	13.3	6.7	2.0	8.9	11.7	16.0	100.0
Expenditures : Included	4225940.0	72.3	44.8	0.0	0.0	100.0	100.0	100.0
Expenditures : Not Included	4225940.0	5.9	23.6	0.0	0.0	0.0	0.0	100.0
Expenditures : Unknown	4225940.0	21.8	41.3	0.0	0.0	0.0	0.0	100.0
Expenditures	1594691.0	58.3	51.9	0.0	30.0	45.0	72.0	3705.0
Collective heating (%)	4225940.0	3.5	18.4	0.0	0.0	0.0	0.0	100.0
Hot water (%)	4225940.0	0.2	4.1	0.0	0.0	0.0	0.0	100.0
Trash collection (%)	4225940.0	4.7	21.1	0.0	0.0	0.0	0.0	100.0
Furnished (%): No	4225940.0	81.1	39.2	0.0	100.0	100.0	100.0	100.0
Furnished (%): Yes	4225940.0	18.9	39.2	0.0	0.0	0.0	0.0	100.0

Table 3.3: Price, expenditures and type of lease

3.4.5 Floors and other amenities

It is also possible to identify in the description what is the floor and the amenities of the building. As one can see in Table 3.4, the floor can be recovered for 40% of the ads while 14% of the ads announce the presence of an elevator. 36% have a balcony or a kitchen with some equipment. Finally, 46% offer some possibilities to park a car.

	Count	Mean	Std	Min	25%	50%	75%	Max
Floor								
Floor (%): 0.0	4225940.0	8.9	28.5	0.0	0.0	0.0	0.0	100.0
Floor (%): 1.0	4225940.0	10.8	31.1	0.0	0.0	0.0	0.0	100.0
Floor (%): 2.0	4225940.0	7.9	27.0	0.0	0.0	0.0	0.0	100.0
Floor (%): 3.0	4225940.0	4.1	19.9	0.0	0.0	0.0	0.0	100.0
Floor (%): 4.0	4225940.0	2.0	13.9	0.0	0.0	0.0	0.0	100.0
Floor (%): 5.0	4225940.0	0.9	9.7	0.0	0.0	0.0	0.0	100.0
Floor (%): 6+	4225940.0	1.0	10.0	0.0	0.0	0.0	0.0	100.0
Floor (%): unknown floor	4225940.0	59.6	49.1	0.0	0.0	100.0	100.0	100.0
Floor (%): last floor	4225940.0	4.7	21.1	0.0	0.0	0.0	0.0	100.0
Amenities								
Elevator (%)	4225940.0	14.0	34.7	0.0	0.0	0.0	0.0	100.0
Double glazing (%)	4225940.0	9.5	29.3	0.0	0.0	0.0	0.0	100.0
Kitchen with equipment (%)	4225940.0	35.5	47.9	0.0	0.0	0.0	100.0	100.0
Garage (%)	4225940.0	46.1	49.8	0.0	0.0	0.0	100.0	100.0
Garden (%)	4225940.0	17.4	37.9	0.0	0.0	0.0	0.0	100.0
Balcony (%)	4225940.0	35.6	47.9	0.0	0.0	0.0	100.0	100.0

Table 3.4: Floors and other amenities

3.4.6 Energy consumption and Greenhouse Gas emission

Since July 2007, each landlord should realize a diagnosis of the energy efficiency to rent their unit. This information was already used in previous work in order to investigate the impact of energy efficiency of buildings on real estate prices (Kholodilin, Mense, and Michelsen (2017) and Hyland, Lyons, and Lyons (2013)). These previous work emphasize the importance of these indicators showing a positive correlation between rent, prices and the energy efficiency displayed. The energy efficiency and GES consumption category are directly embedded inside the HTML code and can be easily recovered. As illustrated in 3.5, the problem of selection for this variable appears very limited provided that only 10% of the ads do not display this information. This information appears as an interesting proxy in order to control for the housing unit quality.

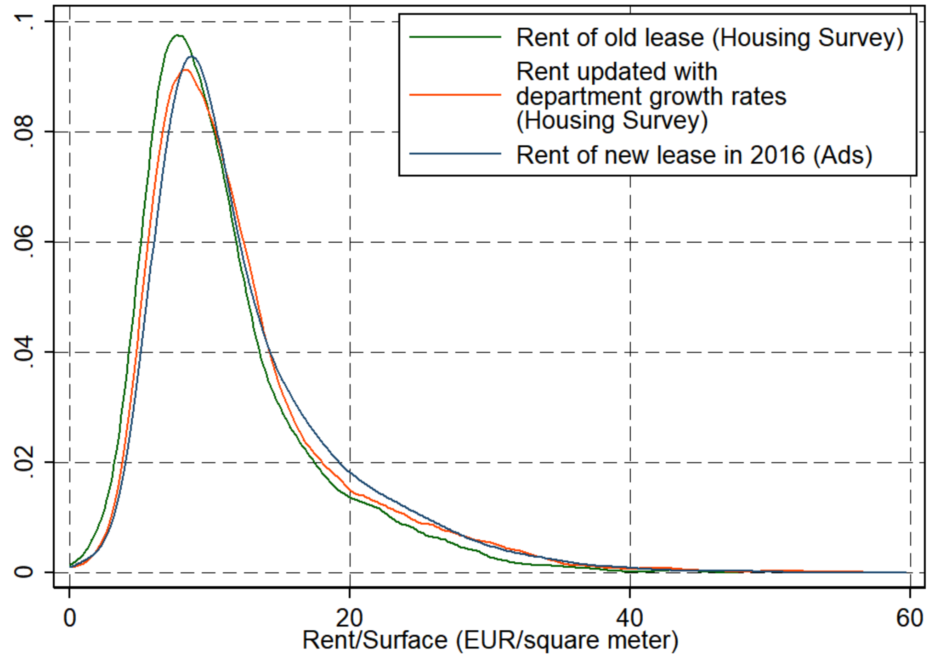
	Count	Mean	Std	Min	25%	50%	75%	Max
Energy (%):A	4225940.0	3.6	18.5	0.0	0.0	0.0	0.0	100.0
Energy (%):B	4225940.0	5.8	23.4	0.0	0.0	0.0	0.0	100.0
Energy (%):C	4225940.0	13.2	33.8	0.0	0.0	0.0	0.0	100.0
Energy (%):D	4225940.0	25.6	43.6	0.0	0.0	0.0	100.0	100.0
Energy (%):E	4225940.0	17.8	38.3	0.0	0.0	0.0	0.0	100.0
Energy (%):F	4225940.0	6.2	24.2	0.0	0.0	0.0	0.0	100.0
Energy (%):G	4225940.0	2.4	15.4	0.0	0.0	0.0	0.0	100.0
Energy (%):H	4225940.0	0.0	1.8	0.0	0.0	0.0	0.0	100.0
Energy (%):I	4225940.0	0.0	1.5	0.0	0.0	0.0	0.0	100.0
Energy (%):None	4225940.0	8.9	28.5	0.0	0.0	0.0	0.0	100.0
Energy (%):V	4225940.0	4.8	21.4	0.0	0.0	0.0	0.0	100.0
GES (%):A	4225940.0	4.3	20.4	0.0	0.0	0.0	0.0	100.0
GES (%):B	4225940.0	13.6	34.3	0.0	0.0	0.0	0.0	100.0
GES (%):C	4225940.0	21.3	40.9	0.0	0.0	0.0	0.0	100.0
GES (%):D	4225940.0	13.9	34.6	0.0	0.0	0.0	0.0	100.0
GES (%):E	4225940.0	10.4	30.6	0.0	0.0	0.0	0.0	100.0
GES (%):F	4225940.0	4.8	21.5	0.0	0.0	0.0	0.0	100.0
GES (%):G	4225940.0	1.9	13.8	0.0	0.0	0.0	0.0	100.0
GES (%):H	4225940.0	0.0	2.1	0.0	0.0	0.0	0.0	100.0
GES (%):I	4225940.0	0.0	1.7	0.0	0.0	0.0	0.0	100.0
GES (%):None	4225940.0	11.2	31.5	0.0	0.0	0.0	0.0	100.0
GES (%):V	4225940.0	4.4	20.4	0.0	0.0	0.0	0.0	100.0

Table 3.5: Energy consumption and greenhouse gas emission

3.5 Is there a negotiation bias ?

If the type of housing unit observed and the channel used to find the flat appear fairly representative, one can fear that the posted rent might be different from the real one. Nevertheless several important observations lead us to believe that this bias remains limited. From a theoretical standpoint, if we model the housing market as a frictional market where a landlord and a tenant meet (Wheaton (1990)), the bargained rent is a weighted sum of the landlord's and the tenant's surpluses. The rent crucially depends on the relative bargaining power of the landlord / tenant. However, Desgranges and Wasmer (2000) show that when the bargaining power of the tenant is close to zero the rent converges toward the posted rent when we assume a price competition among landlords. Moreover, Binmore, Rubinstein, and Wolinsky (1986) show that the bargaining power in Nash bargaining process can be seen as a factor of relative impatience where the impatient party has a lower bargaining power. The lack of housing supply in France, particularly in large cities, leads us to believe that prospecting people have a relatively small bargaining process at least in the major urban areas. Moreover, for other markets, one can expect that the transparency of the the online ads where landlords can observe at a reduced cost the prices and movements of their competitors offering a similar unit in the same area can also drive the posted rent close to the market rent.

These reasons lead us to believe that posted rents are not likely to differ too much from the signed ones. To evaluate the importance of such a concern we confront our dataset with a standard survey based dataset: the French Housing Survey of 2013. The French housing survey is a series of survey representative at the national level performed every five years from a random sample of the French census. Its sample size is limited and contains information about 36 000 households and their housing conditions. It is only considered as representative for France, Ile-de-France (Paris region) and the North of France. Moreover, the number of tenants is relatively small as the sample only contains about 4 400 households in the private rental sector. In addition, the direct comparison with our dataset is limited as it only contains mostly old lease signed over the previous year. After deflating the rent with the Rent Revision Index in order to proxy for the signed rent, we update the rents of this survey with the corresponding departmental growth rate of new lease between the date the signature of the lease and 2016 published on the website Clameur. As these growth rates are only published since 2000, this restricts the sample to 3 818 households. The change in the rent distribution is displayed in Figure 3.1.



Source: Authors' computation from the French Housing Survey, updated with Clameur's department growth rates.

Figure 3.1: Distribution of the rent per square meter

To assess the negotiation bias comparing both dataset, we estimate an hedonic regression model for each database in order to obtain an estimate of the rental value of a similar reference good for each region or department. We define this reference good as follows :

1. A flat with two rooms
2. with a surface of 50 square meters
3. located on the second floor
4. with no extra expenditures included in the rent

Formally, we follow a methodology close to Gouriéroux and Laferrère (2009), Musiedlak and Vignolles (2016) or Poulhès (2015) for housing price estimating the following model for the rent per square meter:

$$ln(p_{i,s}) = ln(p_s^{ref}) + X_{i,s}\beta + u_{i,s} \tag{3.1}$$

Centering the variables X_i around the reference good characteristics allows us to interpret the intercept ($ln(p_s^{ref})$) as the log of the rent per square meter of the reference good in the department (or region) s (see Musiedlak and Vignolles (2016) or Combes, Duranton, and Gobillon (2012)). We control for the variables that are common to the two datasets: the log of the surface and its square, the number of rooms, the floor. The dependant variable is the log of the rent per square meter in the ads and the updated rent for the housing survey.

Results of the hedonic regressions are reported in Table 3.1, one can notice that the coefficients between both database are fairly close in particular for the surface and its square. Moreover, when we confront our estimates of the rent per square meter of a representative good at the department or regional level with those based on the French housing survey, the correlation is higher than 90% in Figure 3.2 and 3.3. When plotting the 45 degree line, one does not observe any systematic bias in the market where the market is not tight; this should relieve our concerns about the negotiation bias. Even if the French Housing survey is only representative within Ile-de-France and the North of France, the strong correlation between these fixed effects can be considered as an important evidence of the limited bias in our scraped data when compared with standard surveys.Our estimates are only higher for Paris (department 75) and Hauts-de-Seine. However, our estimates for Paris are not very different from an alternate database dedicated to Paris area the OLAP. Here the average and median rent for new lease for a flat with 2 bedrooms in 2016 are respectively 24.8 and 25.1 euros per square meters for 1003 observations [10] which corresponds to our estimates for our reference good in Paris.

10. http://www.observatoire-des-loyers.fr/annees-precedentes/donnees-annee-2016

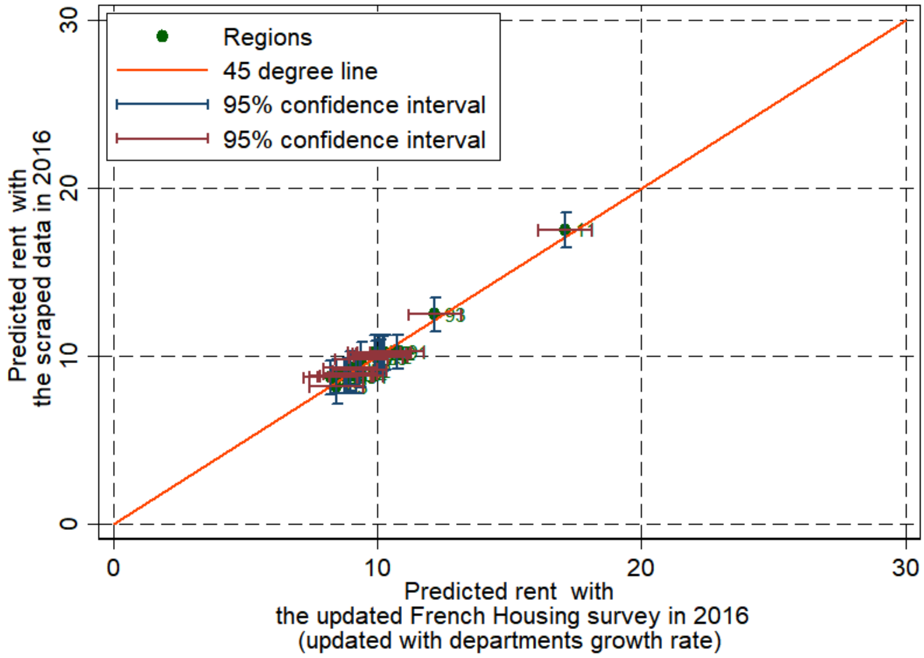


Figure 3.2: Predicted rent for a similar flat at the Regional level

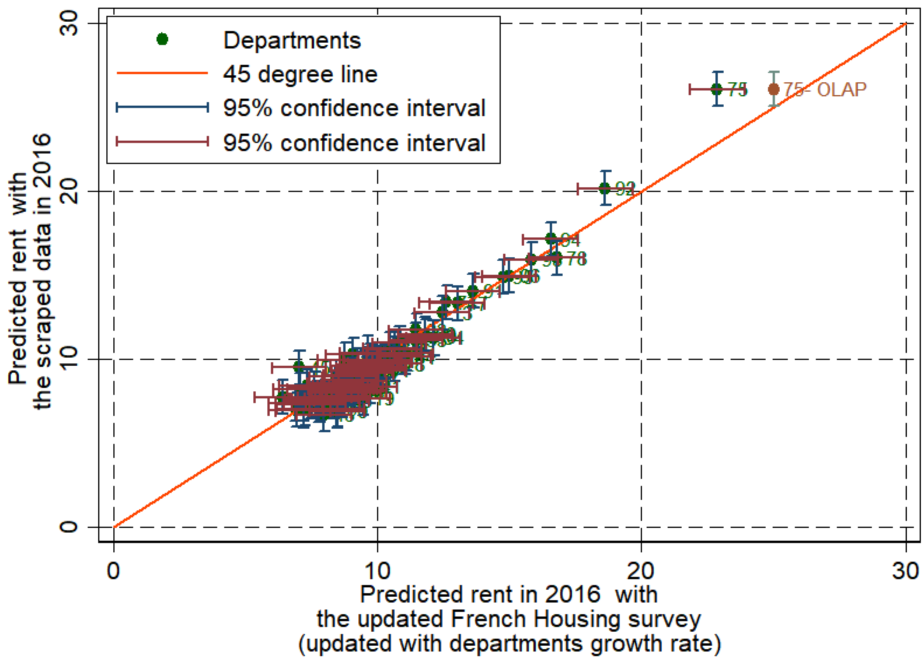


Figure 3.3: Predicted rent for a similar flat at the Department level

	(1) ln(Price/Surface)	(2) ln(Price/Surface)	(3) ln(Price/Surface)	(4) ln(Price/Surface)
ln(surface)-ln(50)	-0.425***	-0.461***	-0.452***	-0.449***
	(0.000920)	(0.0211)	(0.000800)	(0.0195)
(ln(surface) - ln(50))^2	0.124***	0.106***	0.0833***	0.0711***
	(0.000754)	(0.0210)	(0.000657)	(0.0194)
1 room	-0.0131***	-0.00716	-0.0283***	0.0100
	(0.000779)	(0.0189)	(0.000676)	(0.0173)
2 rooms (ref.)	0	0	0	0
	(.)	(.)	(.)	(.)
3 rooms	-0.0269***	-0.0209	0.00397***	0.00261
	(0.000664)	(0.0169)	(0.000577)	(0.0156)
4 rooms	-0.0596***	-0.0438*	-0.00410***	-0.0198
	(0.000979)	(0.0229)	(0.000852)	(0.0212)
5 rooms	-0.0671***	-0.0175	-0.00307**	0.0177
	(0.00155)	(0.0376)	(0.00135)	(0.0347)
6+ rooms	-0.113***	0.110***	-0.0453***	0.118***
	(0.00260)	(0.0399)	(0.00225)	(0.0366)
Street level	-0.0180***	-0.0552***	-0.00532***	-0.0603***
	(0.000760)	(0.0157)	(0.000659)	(0.0144)
Floor 2 (ref.)	0	0	0	0
	(.)	(.)	(.)	(.)
Floor 3 and 4	0.0934***	0.0463***	0.0456***	0.0168
	(0.000923)	(0.0150)	(0.000803)	(0.0139)
Floor > 4	0.164***	0.109***	0.0483***	0.0392**
	(0.00130)	(0.0212)	(0.00114)	(0.0197)
Floor not available	-0.00622***	0	0.00589***	0
	(0.000569)	(.)	(0.000495)	(.)
Constant	2.539***	2.460***	2.533***	2.462***
	(0.000601)	(0.0250)	(0.000521)	(0.0228)
R2	0.652	0.623	0.739	0.699
Obs	2116617	2947	2116625	2947
Weights	Y	Y	Y	Y
Fixed Effects	REG	REG	DEP	DEP
Length of stay	No	Yes	No	Yes
Estimator	OLS	OLS	OLS	OLS
Data	Adds	Survey	Adds	Survey

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Authors computation online ads and the French Housing survey 2013

Table 3.1: Estimate of the value of the reference flat for departments and regions

3.6 Real estate appraisal using Big Data: Estimating the market value of social housing in France

The previous section confronts the average prediction of online data for a given area with the prediction of standard survey and suggests that online ads remain close to the market rent. Such data can thus be used in order to predict the rental value of a specific housing unit. In economics assessing the rental value can be useful in order to assess the income associated with homeownership: the imputed rent. This might be important for taxation purpose or to assess the living standard of homeowners and improve the accuracy of income inequality measures in a context where housing prices and rents have been dramatically diverging (see Bonnet et al. (2016)). In the present section, we use our data and alternate statistical models in order to predict the market value of social housing units. The underlying idea is to present a simple application of our database which exploits its geographical granularity.

	PLA-I	PLUS	PLS	PLI
Subsidized interest rate (with respect to livret A)				
	-0.2pp	+0.6 pp	+1.1 pp	+1.4 pp
Other State Subsidies				
Brick and Mortar	<20%	<5%	No	No
Reduced VAT	Yes	Yes	Yes	No
Property Tax exemption (25 years)	Yes	Yes	Yes	No
Local Subsidies				
loan guaranty	Yes	Yes	Yes	No
Maximum Rent Per square meter				
Ibis (Paris for PLI)	5.42	6.09	9.14	16.82
I (A for PLI)	5.09	5.73	8.60	14.01
II (B for PLI)	4.46	5.03	7.54	9.74
III (C for PLI)	4.14	4.67	7.01	7.01
Share of households eligible in 2005				
	30%	65.5%	80.7%	87.4%

Table 3.1: Characteristics of the four main type of social housing units

Social housing units, often called "Habitations à Loyers Modérés" (HLM) represent about half of the rental market. They are mostly owned and managed by non-profit and public landlords. Contrarily to the private sector, their rent is controlled and set administratively following the regulation in place when the unit is built. Moreover, there is no market to access these units which are allocated administratively. Households under specific rent ceilings have to be registered on a waiting list to access these units. Provided that rent are controlled, access to social housing generates a significant rent saving that might be estimated (Trevien

(2014) and Eerola and Saarimaa (2017)). A social housing program usually combines 3 to 4 types of units which are directed toward different households and associated with different level of subsidies and rent ceiling. The poorer the households, the larger the subsidy and the lower the rent ceilings per square meter as illustrated in Table 3.1. One important feature of the sector arises from the fact that the rent ceiling has no reference to any market rent. It only adjusts moderately (about 50 cents per square meters) accounting for the area where the unit is located: Paris (I Bis), Ile-de-France (I) other large urban areas (II) and the rest of France (III). The rent savings is thus likely to vary dramatically with local market rent and it is thus important to have a precise knowledge of local rental market to evaluate it properly.

Estimating the rent savings connected with the access to a subsidized unit is important to evaluate housing policy programs. Indeed, while housing policies represent a sizable amount of public expenditures, it is still unclear whether place based programs as Social housing should be preferred to tenant based programs as vouchers or allowances. Subsidized housing programs tend to be considered as more expansive and generate important misallocations (Leung, Sarpca, and Yilmaz (2012)) as they reduce households mobility and can sometimes increase the unemployment duration of their tenants (Gregoir and Maury (2018) and Goffette-Nagot and Sidibé (2014)), crowd out private construction (Chapelle, Vignolles, and Wolf (2017) and Eriksen and Rosenthal (2010)) and often fail to reduce segregation (Eerola and Saarimaa (2017) and Laferrère (2013)).On the other hand, welfare can be increased by the important rent savings granted to their tenants. In partial equilibrium, when not accounting for the impact of these unit on the private rent, the net benefit of a program will thus depend on the rent savings generated by the unit. It is thus necessary to have an accurate measure of the market value of these units which strongly depends on local market conditions as emphasized in Eerola and Saarimaa (2017). Exploiting our fine resolution dataset should thus be an interesting way to estimate more precisely the market value of these units.

We thus propose to compute the rent saving associated with all social housing units in France combining our original dataset with: the Répertoire Locatif du Parc Social (RPLS). The RPLS is an exhaustive census of every social housing unit in France and contains many variables as the rent of the unit, its surface, the number of rooms, the floor, the period of construction or the energy efficiency of the apartment and its precise location. We can thus use these variables to predict the market rent of these units thanks to model estimated thanks to our dataset on the private rental sector. In a first step, we closely follow Trevien (2014) and Eerola and Saarimaa (2017) using hedonic regression but also use machine learning algorithms as Random Forests.

3.6.1 OLS Hedonic Regression

To predict the rental value of social housing units, one can estimate an hedonic regression model with Ordinary Least Squares. We thus propose to estimate the following model:

$$ln(p_i) = \theta_{k(i)} + X_i\beta + u_i \tag{3.2}$$

Where $ln(p_i)$ is the log of the rent per square meter of a flat located in the housing block k in municipality m, X_i are the property characteristics also available in the exhaustive census of social housing units (surface and its square, number of rooms, floor, energy consumption and greenhouse gas emission) and $\theta_{k(j)}$ is a housing block fixed effect. It is worth noting that the use of very precise local fixed effects at the housing block level can allow us to avoid using contextual variable as the neighborhood characteristics. Nevertheless, as fine grain fixed effects might lead to ovefit the data when the number of observations is small, an alternate specification substitutes housing block fixed effects with $Z\lambda_{k(j)} + \theta_{k(j)}$ where $\theta_{k(j)}$ is a municipality fixed effect and $\lambda_{k(j)}Z$ are housing blocks controls from the Filocom dataset described in Chapelle, Vignolles, and Wolf (2018). Moreover, in order to limit overfitting issues, we cross validate the model on subsamples of our dataset. Provided the large amount of data, one can estimate the model either with for the whole French territory, in such a case the vectors β and Z are unique or for each department separately. These two alternate approaches do not change our results, we thus present the results where hedonic regressions were performed separately for each department, d, β_d and Z_d will thus be department specific. The predicted price is then corrected following Wooldridge (2003), pp. 207-210.

3.6.2 Random Forest

A well-known problem of linear methods is their inability to deal with complex phenomena. Non linearities are generally model with interactions of dependent variables and reflect arbitrary choices. If this is acceptable in simple frameworks with few dependent variables, it becomes a salient problem when the number of depend variable becomes large or when the dataset contains qualitative variables. Interacting all variables become impossible and arbitrary restrictions need to be set. Tree based methods overcome the non-linearity problem by searching these interactions automatically.

In this paper, we use linear combination of trees known as the random forest algorithm to predict the price of social housing. The random forest algorithm uses many decision trees to combine them into a single ensemble: the random forest. The idea is to exploit the statistical flexibility of the tree without suffering from its overfitting issues. To avoid the overfitting problem, the random forest draws subsamples of observations that are used to build the trees.

It also randomly draws subsets of predictors used to construct the branches of tree. Overall, the algorithm furnishes a decision tree which takes into account all form of non linearities.

One crucial parameter is the depth parameter of the random forest. Following the literature, it was chosen using a k-fold validation procedure. For sake of comparability, the variables used to predict the housing price with the random forest are the same than the one used in the Hedonic model.

3.6.3 Results

Models cross validation

In this section, we aim at providing precise market rent estimates for social housing units. It is thus important to assess the predictive capacity of the different models proposed. We thus assess the relative performance of the models estimating the models on a subsample to predict the rent of another one to avoid the risk of over fitting.

Figure 3.A.3 reports the distribution for out of sample predictions in both models. The average errors is -0.0002 for both models, this represents about 1 euro per square meters. The root mean square error are around 0.16 (1.2 euros) and are reported in Columns (1) and (2) in Table 3.A.1 for each model and each department. When regressing the error on the characteristics of the flat, no coefficient turn significant, this thus means that our model performs relatively well for flats whatever their size, location and energy consumption level. In others words, no systematic bias arises from our specification.

Nevertheless, it is worth noting that the prediction error remains relatively high when using linear models. We thus turn to the random forest model.

The Implicit subsidy

We obtain several estimates of the market rent for each social housing unit and thus an estimate of the rent savings for each occupied unit. We represent the distributions of the rent savings in Figure 3.1. One can notice our hedonic regression models and the random forest algorithm yield very close results and distributions of implicit subsidy. In relative terms, the implicit subsidy represents about 46.6% of the rental value of the unit (which is relatively close to Trevien (2014)). In absolute terms, the average subsidy is between 370 and 390 while the median is around 300 euros. The average subsidy is 110 euros larger than in Trevien (2014), three reasons might be invoked to explain such a result. First rents have been increasing since 2006 and thus the subsidy should be at least around 306 euros by the sole effect of inflation of both rents, a level close to our median estimates. Second, Trevien (2014) estimates are based on former lease (in stock) while we estimate it in flow, if Trevien (2014) controls for the length of stay, this might brings some discrepancy. Third, and more importantly, the dataset used in Trevien (2014) is a survey and is probably not representative of the whole distribution of rents in the social housing sector. This is a concern for Paris which represents about 5% of the social housing units. The implicit subsidy for the French capital appears extremely high for a large number of units and increases dramatically the average. Indeed, the right tails of the distribution of the subsidy is exclusively composed of housing units located in Paris where the subsidy can be well above 1000 euros. Typically, a social housing units in the center of Paris with a surface above 80 square meters and a controlled rent below 600 euros while its market rent should be above 2500 euros. The absence of these units from the French housing survey might bias the average subsidy in Trevien (2014). This is easily perceptible by the large discrepancy (80 euros) between the average and the median subsidy in our results. When excluding Paris from our dataset, the average subsidy declines dramatically to 235 euros. Finally when excluding Paris Urban Area, it drops to 255 euros. However, it is worth noting that the RPLS does not contains any information about the complementary rents (Supplément de Loyer Solidarité) that the wealthiest households should pay when occupying some social housing units in desirable Areas. This might decrease the rent savings for some desirable units even if many administrative reports estimate that these additional rent are only mildly applied. In a nutshell, our results, in particular the median subsidy estimated confirm the previous estimates of Trevien (2014) while getting access to the whole distribution of the social housing units confirms that place based policies might generate a very uneven subsidy between tenants. In the next section, we investigate what generates the important discrepancies between units.

	Count	Mean	Std	Min	25%	50%	75%	Max
Hedonic (Blocks FE)	4166360	385.6	282.6	-1948	203	308	491	7177
Hedonic (Blocks controls)	4166360	382.3	268.0	-2079	206	306	488	4625
Random Forest	4166360	377.4	271.6	-1781	202	303	480	6876

Table 3.2: Distribution of the estimated rent savings

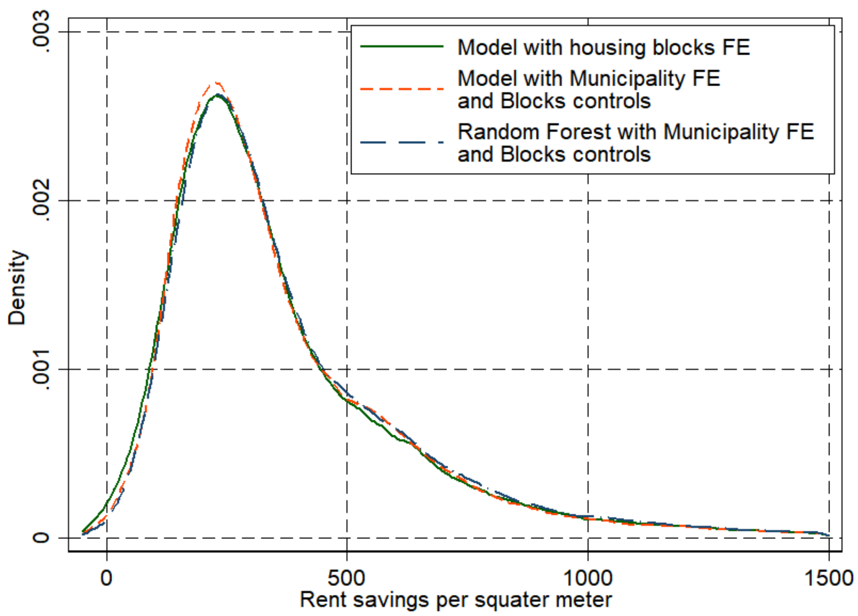


Figure 3.1: Estimated distribution of the implicit subsidy received by social housing tenants

Where is the subsidy higher ?

Our method also allows us to investigate the variation of the subsidy between units and geographically. To do so we first regress the implicit subsidy of each unit on the units characteristics and geographic fixed effects as follows:

$$ln(\hat{p_m} - p_s)_i = X_i\beta + \delta_m + \epsilon_i \tag{3.3}$$

The β will inform us about the individual units features (type of loans, age, surface etc..) on the magnitude of the subsidy. In a second step, geographical fixed effects δ_m will be regressed on the Municipality's or housing block's characteristics:

$$\delta_m = X_m\beta + \epsilon_m \tag{3.4}$$

Results of the individual regression are displayed in Table 3.3. One can notice that social housing unit's characteristics explain a relatively low share of the size of the implicit subsidy associated with the unit. Indeed, if the characteristics as surface, date of construction, type of loan used have a direct influence both the market value of the good and the rent ceiling of the social unit, most of the variation an discrepancy between the social rent and its market value comes from the location of the unit as illustrated by the very strong correlation between the average subsidy per square meter and the average rent in the private sector displayed in Figure 3.2. Indeed, the social housing sector shares very similar rent caps across the whole French territory (see Chapelle and Wasmer (2017) for a discussion on the spatial implications of this phenomenon). Nonetheless, it is worth noting that our results illustrate the strong discrepancy between the social and the private sector. First, one can note that the subsidy tends to be higher in smaller apartments, this is caused by the fact that the rent cap per square meter is very similar whatever the size of the flat in the social sector while the rent per square meter decreases significantly with the size of the flat in the private sector. Second, the subsidy appears to be higher for the appartments built between 1960 and 1980. Apartments built more recently tend to have a higher rent cap. The order of magnitudes remains limited, of the order of 10 cents per square meter. Finally, tenants in the most subsidized units (PLA-I) save a rent relatively close to the the most common type of social housing (PLUS). They save about 50 cents per square meters which is in line with the rent cap which is of 5.40 euros in the PLA-I and 6.09 euros in the PLUS. Single units provide a lower benefit but most of the effect seems to arise from the fact that they are mostly located in less expensive municipalities as the effect vanishes when controlling for municipalities fixed effects.

Table 3.4 investigates the geographical disparities of the subsidy. As already discussed, the subsidy is mostly explained by the level of the private rent. In a nuthsell, on can say that units in the most expansive areas provide the highest subsidy. Moreover it is also higher in wealthier areas where the median income is higher, in denser areas closer to the City Business District of the Urban Area and where the share of empty units is lower. Finally column (6) investigates the correlation between the median income of social tenants and the magnitude of the subsidy within Urban Units. One can note a positive correlation in line with the fact that tenants are granted a lease for life whatever the evolution of their income tends to generate sorting (Laferrère (2013)): wealthier tenants being the best units in the most attractive areas. This confirms also the findings of Eerola and Saarimaa (2017) who argues that social housing re distributive performance is lower than monetary benefits as it tends to be unevenly distributed and is harder to focus on the poorest households.

	(1) ln(Subsidy)	(2) ln(Subsidy)
Single unit	-0.593***	-0.0728***
	(0.174)	(0.0118)
1 room (ref.)	0	0
	(.)	(.)
2 rooms	-0.288***	-0.193***
	(0.0148)	(0.0235)
3 rooms	-0.435***	-0.305***
	(0.0161)	(0.0398)
4 rooms	-0.509***	-0.396***
	(0.0190)	(0.0533)
5 rooms	-0.574***	-0.508***
	(0.0281)	(0.0667)
6+ rooms	-0.707***	-0.709***
	(0.0300)	(0.0539)
Street level (ref.)	0	0
	(.)	(.)
Floor 1	-0.0116	-0.0111**
	(0.0104)	(0.00499)
Floor 2	0.0152	-0.0307***
	(0.0102)	(0.00833)
Floor 3 and 4	0.122***	-0.0264***
	(0.0279)	(0.00849)
Floor 5+	0.351***	-0.0493***
	(0.0712)	(0.00695)
Floor not available	0.0874	0.00436
	(0.0705)	(0.00774)
Before 1900 (ref.)	0	0
	(.)	(.)
1900-1949	0.0334	0.166***
	(0.166)	(0.0424)
1950-1959	-0.0676	0.291***
	(0.231)	(0.0546)
1960-1979	-0.308	0.200***
	(0.277)	(0.0488)
1980-1999	-0.494**	-0.146***
	(0.192)	(0.0205)
After 2000	-0.532**	-0.141***
	(0.241)	(0.0179)
PLAI (ref.)	0	0
	(.)	(.)
PLUS	-0.227***	-0.191***
	(0.0279)	(0.0274)
PLS	-0.289***	-0.545***
	(0.106)	(0.0800)
PLI	-0.299**	-0.533***
	(0.136)	(0.0779)
R2	0.250	0.845
Obs	3893496	3893496
Municipality Fixed Effects	N	Y
Estimator	OLS	OLS

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Authors computation online ads and the French Housing survey 2013

Table 3.3: Drivers of local subsidy

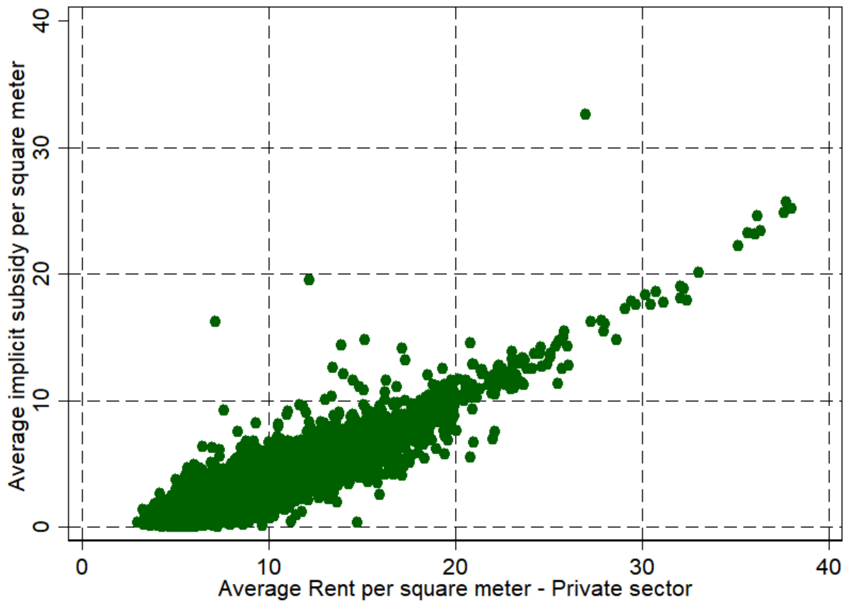


Figure 3.2: Average subsidy in the main French Municipalities

	(1) ln(Subsidy)	(2) ln(Subsidy)	(3) ln(Subsidy)	(4) ln(Subsidy)	(5) ln(Median income social tenants)
ln(Rent)	2.128^{***}	2.020^{***}	1.910^{***}	1.812^{***}	
	(0.116)	(0.114)	(0.0998)	(0.0913)	
ln(Median income)		0.445^{***}	0.286^{***}	0.630^{***}	
		(0.0746)	(0.0809)	(0.117)	
ln(Population)			0.0134	0.0680^{***}	
			(0.0140)	(0.0155)	
ln(Surface)			-0.0306^{**}	-0.0389^{***}	
			(0.0153)	(0.0129)	
Share of empty units (%)			-1.667^{***}	-1.348^{***}	
			(0.300)	(0.298)	
ln(Distance from CBD)				-0.0188^{***}	
				(0.00642)	
ln(Subsidy)					0.101^{***}
					(0.0243)
Constant	-5.214^{***}	-9.403^{***}	-7.470^{***}	-10.98^{***}	9.831^{***}
	(0.238)	(0.746)	(0.833)	(1.301)	(0.00801)
R2	0.607	0.612	0.618	0.695	0.580
Obs	12785	12557	12415	12415	4406
UU Fixed Effects	N	N	N	Y	Y
Estimator	OLS	OLS	OLS	OLS	OLS

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Authors computation online ads and the French Housing survey 2013

Table 3.4: Drivers of local subsidy

3.7 Conclusion

In this paper, we describe a data collection technique in order to provide accurate data on local housing markets for researchers and statisticians thanks to online data. As we show, this can provide a relatively cheap and precise way to collect an important amount of micro data in order to answer research questions related to market dynamics or to evaluate public policies. If these online data correspond to posted rents and not to signed contracts, one can think that the relative transparency of online platforms tends to force landlords to reveal the market price. The comparison between our dataset and standard surveys as the French housing survey supports this intuition. Indeed, one can observe that the predicted rents using both dataset are extremely close.

Moreover, we use these data to estimate the market value of social housing units thanks to standard hedonic regression models and machine learning algorithms. Both methods tend to yield very similar results while the precision of our dataset allows us to investigate the whole distribution of the rent savings in the social housing sector. Overall our findings suggest that the implicit subsidy connecting with this place based policy is very unvenly distributed. Households benefiting from a social housing unit in city centers of the main urban areas as Paris receive a massive subsidy,sometimes larger than 1000 euros while the majority benefit from a much lower amount. As the location of the unit and not the parameters of the policy remains the main drivers of the size of the subsidy, it is highly likely that such policy increases inequalities between its tenant as the income of social tenants tend to be higher in municipalities where the subsidy is also higher.

As a conclusion, we would like to emphasize that one shouldn't neglect the opportunity offered by alternate data collection methods as webscraping. In our paper, we provide evidence that online rental data can be used in order to build a reliable measure of local rent and predict the rental value of housing units. To us, it is particularly important to collect data on the rental sector in order to deepen our knowledge of the cost of housing. Indeed, if we currently have fairly precise information about selling prices, it is also important to study rents which are an important part of agglomeration costs. For example, reproducing Combes, Duranton, and Gobillon (2012) exploiting rental data would be an interesting application. Indeed, as rents and prices tend to diverge across time (see Bonnet et al. (2016) for an illustration on the implications of the divergence of price and rents since the 2000s) and space (see Chapelle and Wasmer (2017) for an illustration of the difference between the price and the rent gradients in Paris Urban Area), it might be important to investigate also how rent vary with city size. To us, rents could constitute a more accurate measure of housing cost as they do not internalize expectations on future price growth and should equalize the user cost of homeowners.

These are not the only possible applications for such data. It might be also useful to test for spatial equilibrium models in the spirit of Rosen (1979) and Roback (1982) as done in France with the side products of the present paper in Ortega and Verdugo (2016).

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Appendix

3.A General Appendix

3.A.1 Example of Posts and Location

10 photos disponibles

Mise en ligne le 19 septembre à 18:43

HERVEORAIN35

Loyer mensuel	1 285 € Charges comprises
Ville	Noyal-Châtillon-sur-Seiche 35230
Type de bien	Maison
Pièces	6
Meublé / Non meublé	Non meublé
Surface	160 m^2
GES	C (de 11 à 20)
Classe énergie	C (de 91 à 150)

Description :

A LOUER AU 15 décembre prochain

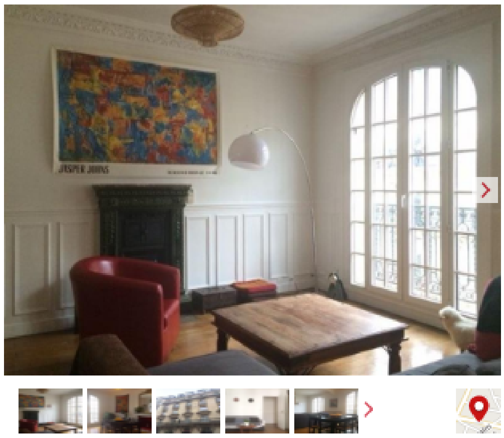
Maison (non mitoyenne) située à NOYAL CHATILLON SUR SEICHE (10 kms de Rennes Sud par 4 voies direction Nantes)
Totalement rénovée en août 2015.
Surface habitable 160 m2 sur terrain de 550 M2.
Orientée sud.
Au calme (en impasse)
Au rez de chaussée : entrée avec placard, séjour salon avec cheminée, cuisine aménagée, une chambre avec salle de bain privative (douche et baignoire) wc suspendu et garage.
A l'étage : 3 chambres sur parquet + une grande pièce sur garage pouvant être utilisée en chambre, salle de jeux, lingerie ou bureau, salle d'eau et wc.
Chauffage au gaz.

Terrasse extérieure orientée ouest.

Périphérique de RENNES à 4 minutes.
Aéroport et gare TGV à 10 minutes.
Bus pour RENNES et station métro Triangle à 100 mètres.
Commerces, écoles et collège à proximité.

Particulier : 0670346882

2 200 € TTC - CC



Description de Appartement à Paris 10ème

Paris 10e, au pied du métro Stalingrad - A proximité du Bassin de la Vilette et du Faubourg St. Martin, rue de l'aqueduc. En étage élevé avec ascenseur d'un bel immeuble pierre de taille bien entretenu, charmant 4 pièces meublé comprenant une entrée galerie desservant un vaste double séjour sur rue, deux grandes chambres au calme sur cour, une cuisine dînatoire entièrement équipée, salle de bains avec baignoire et douche. WC séparés. Parquet, moulures et cheminées. Prestations de qualité. Environnement agréable, bien desservi avec de nombreux commerces à proximité.

Surface de 84 m^2	4 Etage
4 Pièces	2 Chambres
1 Salle de bains	1 Toilette
Toilettes Séparées	Meublé
Parquet	Ascenseur
Cheminée	Chauffage individuel gaz
Cuisine coin cuisine équipé	Interphone
Digicode	Gardien
Entrée	Salle de Séjour
Calme	DPE : D (196)
GES : E (46)	Honoraires ttc : 1260 €
Garantie : 2050 €	Charges : 150 €
Disponibilité : 01/11/16	

Vous désirez en savoir plus ? Contacter L'Agence Téléphone

Réf.: L-95-1509-8482

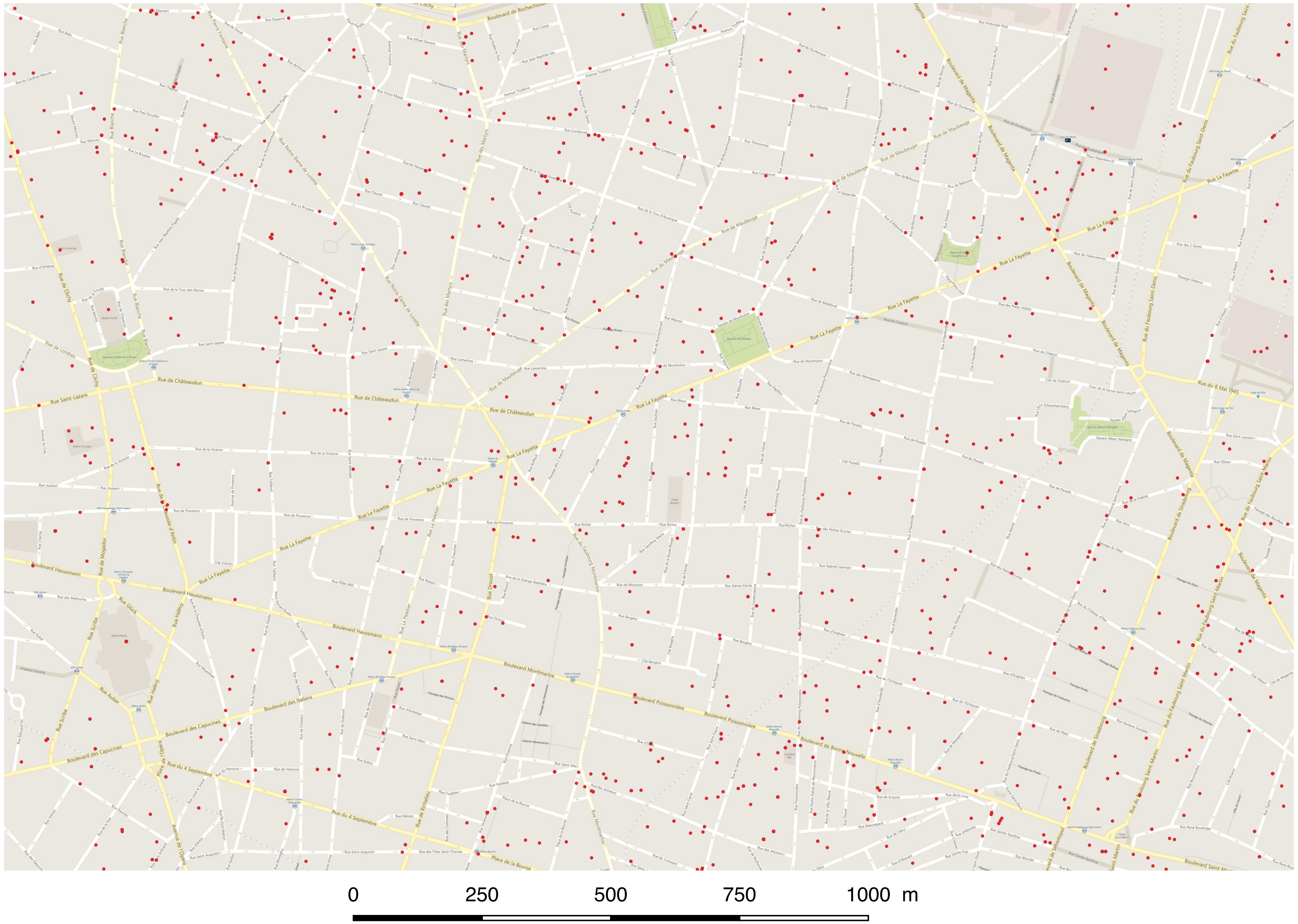


Figure 3.A.1: Posts location around Grands Boulevards area in Paris

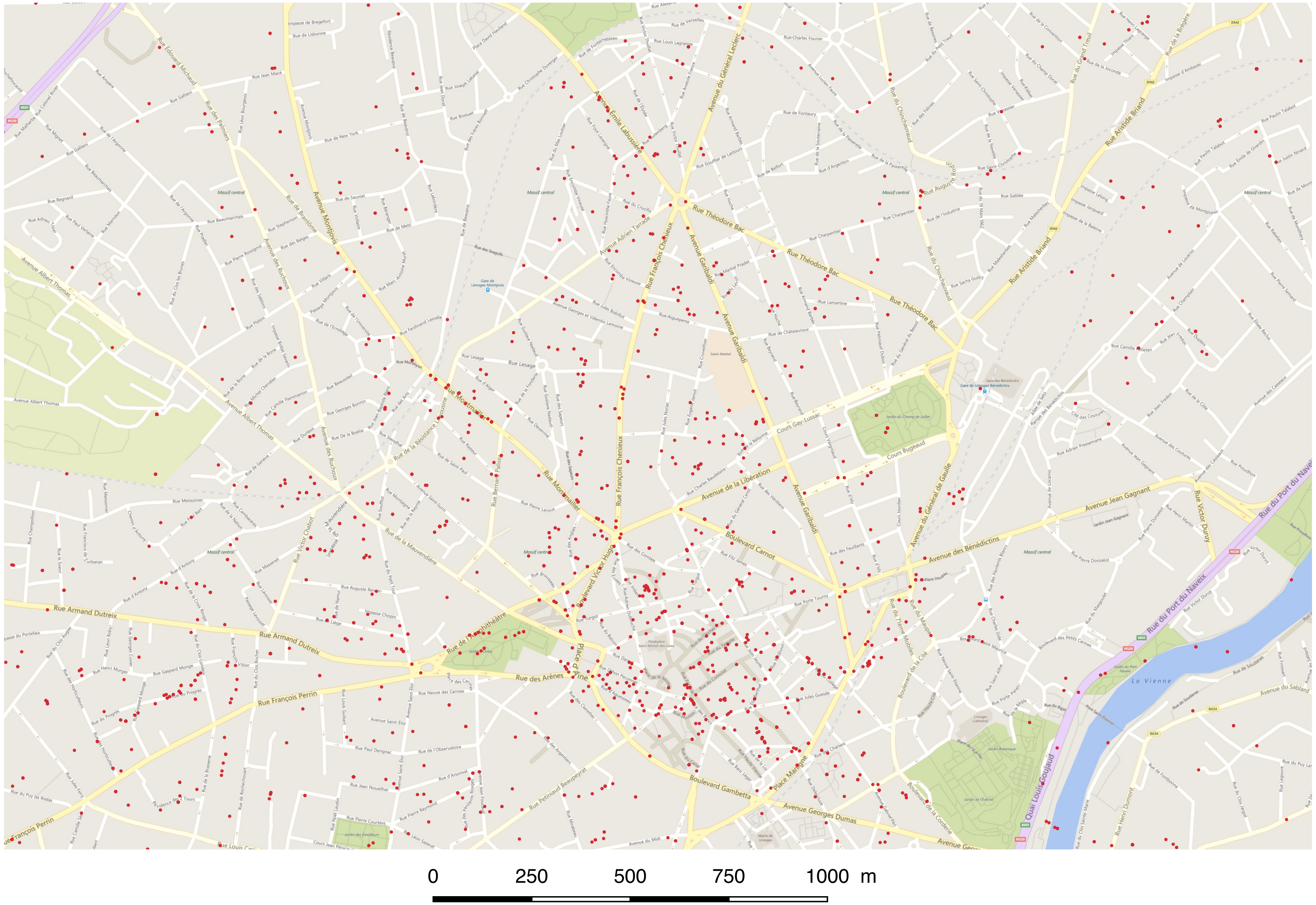


Figure 3.A.2: Posts location for Limoges

3.A.2 OLS errors and Root Mean Square Errors

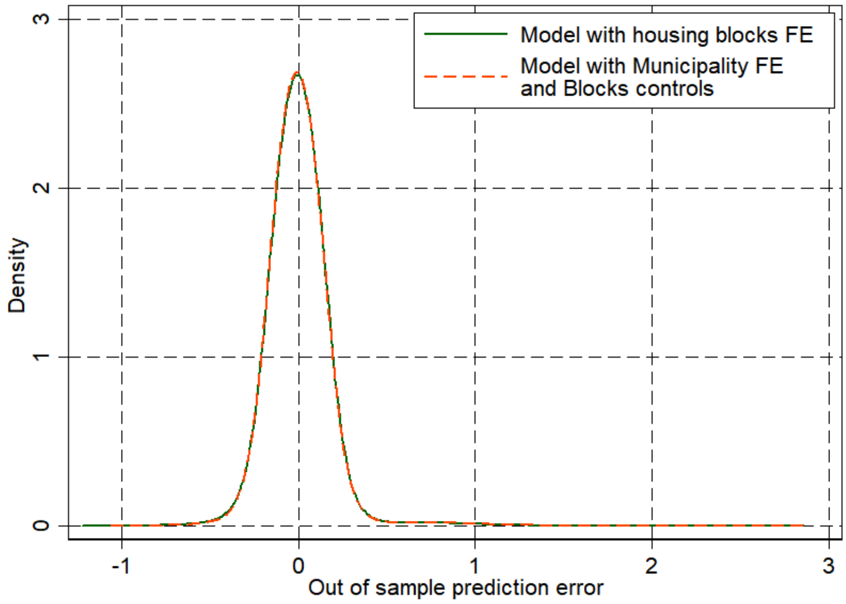


Figure 3.A.3: Distribution of the out of sample errors

Department	OLS - No FE	OLS - FE
1	0.164	0.168
2	0.140	0.140
3	0.175	0.176
4	0.209	0.209
5	0.228	0.232
6	0.221	0.221
7	0.172	0.180
8	0.155	0.154
9	0.183	0.185
10	0.165	0.165
11	0.158	0.158
12	0.163	0.162
13	0.160	0.160
14	0.144	0.144
15	0.167	0.168
16	0.158	0.163
17	0.174	0.177
18	0.154	0.153
19	0.137	0.138
21	0.142	0.141
22	0.164	0.169
23	0.152	0.149
24	0.155	0.156
25	0.155	0.155
26	0.170	0.169
27	0.129	0.128
28	0.125	0.124
29	0.150	0.149
30	0.152	0.154
31	0.149	0.149
32	0.166	0.169
33	0.181	0.180
34	0.180	0.180
35	0.160	0.161
36	0.162	0.161
37	0.145	0.145
38	0.162	0.162
39	0.166	0.165
40	0.182	0.182
41	0.154	0.155
42	0.166	0.166
43	0.169	0.169
44	0.167	0.167
45	0.141	0.140
46	0.150	0.154
47	0.140	0.139
48	0.170	0.172
49	0.156	0.156
50	0.165	0.169
51	0.152	0.151
52	0.149	0.147
53	0.159	0.161
54	0.130	0.129
55	0.145	0.152
56	0.167	0.166
57	0.151	0.152
58	0.152	0.148
59	0.159	0.158
60	0.139	0.140
61	0.178	0.181
62	0.142	0.142
63	0.161	0.160
64	0.160	0.159
65	0.172	0.175
66	0.170	0.171
67	0.158	0.157
68	0.159	0.161
69	0.165	0.164
70	0.150	0.149
71	0.156	0.157
72	0.184	0.186
73	0.230	0.232
74	0.201	0.202
75	0.159	0.157
76	0.150	0.150
77	0.139	0.138
78	0.146	0.146
79	0.153	0.152
80	0.142	0.142
81	0.135	0.136
82	0.148	0.146
83	0.177	0.177
84	0.186	0.186
85	0.179	0.178
86	0.148	0.150
87	0.138	0.138
88	0.150	0.151
89	0.135	0.136
90	0.149	0.150
91	0.128	0.130
92	0.164	0.164
93	0.184	0.185
94	0.162	0.165
95	0.148	0.150

Authors computation from online ads

Table 3.A.1: Root Mean Squared Errors

Chapter 4

Gender Discrimination

This paper is jointly written with Paul VERTIER

4.1 Introduction

Are women discriminated against in politics ? While decades of research have investigated the reasons behind the under-representation of women in politics, uncovering discriminatory behaviors of voters proved being a difficult task, because of the numerous selection effects which affect the observed and unobserved characteristics of women present in the political arena.

In this paper, we provide causal evidence of discrimination against women in politics. To do so, we use a unique feature of the French *Départementales* [1] elections of 2015, which allows us to unambiguously disentangle selection effects from preferences over female candidates in a real-world setting. For the first time in the history of French elections, candidates ran by pairs, which necessarily had to be gender-balanced. Therefore, each pair of candidates included a man and a woman (each with a substitute of the same gender). Upon casting their ballot, voters can only opt for one of the different pairs of candidates, so that for every pair, each male and female candidate receives exactly the same number of votes. If a pair is elected, both candidates are appointed to the same seat in the *Conseil Départemental* (the *Département* assembly where the elected candidates are seating), so that their fates are completely tied.

Crucially, within each pair, the order of appearance of the candidates on the ballot was determined by alphabetical order: this order determines only the place of the candidate's name on the ballot. As we argue, such a setting yields an as-good-as-random allocation of the order of gender on the ballot, and allows us to explore whether pairs where the woman appears first

1. The *Département* is a French territorial unit gathering numerous competences in terms of schooling, public infrastructures, culture, sports.

on the ballot have different electoral outcomes than pairs where the man appears first.

The rationale behind this test is that, although the order of appearance of the candidates on the ballot does not have any impact on the subsequent prerogatives attributed to the candidates, some voters may mistakenly have thought that the first candidate would be the "main" candidate. Indeed, since voters were typically used to voting for a single candidate and a substitute, the new rules are unlikely to have been fully understood by everyone. As the French statistical institute IFOP acknowledged some weeks before the election: "These elections were characterized by insufficient information", and "the introduction of pairs of candidates unsettled long-established landmarks" in the mind of voters. Therefore, any observed difference between pairs with a male or female candidate listed on the first position would mean that we observe two phenomena. First, limited attention from some voters, as defined by DellaVigna (2009). Indeed, because the fates of both candidates on a ballot are tied, if all voters knew perfectly the rules of the elections, we would not find any treatment effect. Secondly, a pure gender bias from these voters.

The identification of this bias comes from several particularly interesting features of our setting. First, the numbers of male and female candidates are exactly identical - in order to enforce strict parity in local councils. Secondly, while the characteristics of male and female candidates are on average different, candidates characteristics do not predict whether the male or the female candidate appears first on the ballot. The effect we measure is therefore unlikely to be affected by selection biases, since it consists in comparing whether identical pairs on average perform differently when the male or the female candidate is first on the ballot. Furthermore, our identification strategy is strengthened by the fact that parties did not seem to strategically match male and female candidates based on their surname in order, for example, to place the male candidate at the top of the ballot: indeed, the distribution of the first letter of male and female surnames are identical.

Comparing treated and untreated pairs of candidates of identical political affiliations across precincts, we show that right-wing pairs where the female candidate appears first lose about 1.5 percentage points in shares of vote during the first round, while on average this is not the case of pairs from other parties. These effects substantially affected the outcome of the election: indeed, the affected pairs were 4 points less likely to go to the second round or to win the election.

This setting not only allows to identify pure discrimination, but also to characterize the type of discrimination at stake. Discrimination is often viewed as being either taste-based or statistical. In the first case, voters dislike voting for female candidates whatever their characteristics or the information they have about them. In the second case, voters apply stereotypes on women candidates because of a lack of information about the characteristics of the candidates. We argue that, in our setting, our treatment effect reflects statistical rather than taste-based discrimination against female candidates. To identify it, we follow a methodology similar to the one developed by Altonji and Pierret (2001) and exploit a unique feature of the French electoral law, which states that the candidates can report additional information about themselves on the ballot - such as their political experience, age, occupation, or picture. Comparing treatment effects between ballots with reported information and ballots without any information, we show that, for the right-wing pairs, discrimination disappears when information about the candidates is displayed.

We show that these missing votes do not reflect differential abstention, and did not translate into blank and null votes; instead they translated into higher shares of votes for the competing candidates. However, the competing pairs with a female candidate listed first did not receive more votes than others. Such a result stacks the desk against our interpretation of the results as reflecting statistical rather than taste-based discrimination. Indeed, if our result was driven by taste-based discrimination, we should have observed that pairs of candidates with a male candidate listed first benefited more from the discrimination against right-wing women.

Finally, we explore two different types of heterogeneity. First, we show that discrimination does not depend directly on the observed characteristics of the candidates - namely previous political experience and age. Assuming that these characteristics are a proxy for candidates' quality, this alleviates the concern that the results are directly driven by differences of quality between male and female candidates. Secondly, we test whether discrimination depends on the characteristics of the precincts. We show that, while electoral discrimination does not vary with the age, unemployment rate and level of education of the population, it is greater in areas with high gender discrimination on the labor market, as measured by the unexplained component of a Oaxaca-Blinder decomposition of wage gaps at the local level.

These results bear important implications for the public debate around electoral discrimination. First of all, while our results show discrimination against right-wing female candidates, it does not imply that right-wing voters are more prejudiced against women than voters from other parties. Indeed, the presence of limited attention is necessary for the identification of discrimination. Not observing discrimination against the female candidates of other parties can simply indicate that they are less subject to the limited attention bias. Secondly, since the amount of information available about the candidates on the ballot seems to play an important role on the outcome of the election, it calls for a more general reflexion about a potential standardization of the ballots' layout. Finally, since electoral discrimination seems to be higher in places with a greater gender discrimination on the labor market, policies aiming at reducing gender biases in politics are likely to be more effective if coordinated with policies on other markets.

Our contribution to the literature is threefold. First, we contribute to the debate about the reasons why women are underrepresented in politics. Many studies analyzed the selection processes faced by women upon entering in politics. Women might select themselves less into politics because of a lack of self-confidence (Hayes and Lawless (2016)) or differential returns from politics (Júlio and Tavares (2017)). More generally, women face tradeoffs between family balance and competitive professional environments (Bertrand, Goldin, and Katz (2010)). Conditional on entering politics, parties might also fail at promoting women to high positions and at fielding them in winnable races (Sanbonmatsu (2010), Thomas and Bodet (2013), Esteve-Volart and Bagues (2012), Casas-Arce and Saiz (2015)), even though their entrance in politics often causes an increase in the quality of elected officials (Baltrunaite et al. (2014), T. J. Besley et al. (2017)). Yet, evidence on the last hurdle potentially faced by women in politics (namely, discrimination from voters) are mixed, and if anything, tend to argue that discrimination against women does not exist.[2]

Secondly, our study is among a small group of studies causally identifying statistical discrimination in politics in a real-world setting. Understanding the determinants of gender discrimination is of particular importance since women in office are likely to behave differently than men in office (Chattopadhyay and Duflo (2004), Ferreira and Gyourko (2014), Brollo and Troiano (2016)). The debate over whether discrimination involves discriminatory tastes (Becker (1957)) or imperfect information (Phelps (1972), Arrow et al. (1973)) is a long-standing one. Current evidence on gender-discrimination in politics vastly points towards the existence of statistical discrimination. Numerous survey studies show that different types of individuals have different preferences over female politicians: McDermott (1998) and Burrell (1995) find that women are more likely to prefer female candidates, while K. Dolan (1998) finds that minorities and elderly are more likely to vote for women. McDermott (1997) argues that liberal voters are more likely to prefer female candidates. Such preferences are likely to be driven by gender stereotypes (Koch (2002)). In particular, in a context of low information, the gender of the candidate can be interpreted by the voters as signals about the ideology of the candidates: McDermott (1998) shows that female candidates are typically perceived as more liberal and more dedicated to honest government. Evidence from lab experiments also tend

2. Analyses of aggregate votes generally found that male and female candidates have equal success rates in elections, thus arguing that voters do not have gender biases (Darcy and Schramm (1977), Seltzer, Newman, and Leighton (1997), McElroy and Marsh (2009)). Some studies even argue that women might have an electoral advantage compared to men (Black and Erickson (2003), Borisyuk, Rallings, and Thrasher (2007)), and that after their first election, they are at least as likely to be reelected as men (Shair-Rosenfield and Hinojosa (2014)). Milyo and Schosberg (2000) even argue that the barriers to entry faced by women makes female incumbent of higher quality than male incumbents, resulting in an advantage for female incumbents. On the other hand, several studies argue that voter biases are marginal compared to partisan preferences (K. A. Dolan (2004), K. Dolan (2014), Hayes and Lawless (2016)).

to point the existence of different mechanisms leading to statistical discrimination. Leeper (1991) showed that even when women candidates emit ”masculine” message, voters attribute them ”feminine” characteristics. Huddy and Terkildsen (1993) showed that gender-based expectations over policies were more related to gender-traits stereotypes than to gender-beliefs stereotypes. King and Matland (2003) show that biases against women are likely to depend on partisan preferences, while Mo (2015) shows that both explicit and implicit attitude against women shape the probability of voting for female candidates.

However, very few studies managed to propose causal identifications of discrimination in politics using natural experiments. Most of the studies on gender in politics rely primarily on aggregate data, surveys or laboratory experiments, which are problematic for several reasons. Raw comparisons of aggregate data are unlikely to fully control for the selection process leading to the observed political competition. This is especially true if male and female candidates are likely to differ in unobserved characteristics which might drive both their probabilities of running as a candidate and of winning the election. Respondents' answers in surveys might be affected by characteristics of the interviewer, such as her gender (Huddy et al. (1997), Flores-Macias and Lawson (2008), Pino et al. (2011), Benstead (2013)), religion Blaydes and Gillum (2013) or language Lee and Pérez (2014)). Finally, while laboratory experiments allow disentangling more accurately the mechanisms leading to potential gender-biases, they are hardly likely to represent real-world election settings.

By overcoming these issues, natural experiments are particularly appealing. Discrimination on the labor market has been plausibly identified through a vast range of field and natural experiments, involving audit and correspondence studies, and the precise mechanisms behind observed discrimination have been extensively discussed (see, among others, Bertrand and Mullainathan (2004), Bertrand, Chugh, and Mullainathan (2005), Charles and Guryan (2008), and Bertrand and Duflo (2017) for a survey). Recent developments of big data also have allowed to plausibly identify statistical discrimination on the housing market (Laouénan and Rathelot (2017)). However, field experiments are hardly applicable in the political arena - in particular since the secrecy of the vote prevents from fully understanding voters' motives - and natural experiments remain rare. However, recent studies managed to exploit natural experiments and to causally identified discrimination from voters - mostly in a statistical way. Bhavnani (2009), Beaman et al. (2009) and De Paola, Scoppa, and Lombardo (2010) suggest that reserved seats for women in office is an efficient way of reducing gender stereotypes and statistical discrimination, while Lippmann (2018) find evidence of a backlash or stereotype threat effect against women only in cities where the incumbent is a woman. Relatedly Pino et al. (2011) shows that women living in environments emphasizing traditional gender roles are less likely to vote for women[3].

3. To the best of our knowledge, only one study identified taste-based discrimination in an electoral setting

Finally, our analysis provides evidence of limited attention from voters. Since the seminal work of Simon (1955), various pieces of research - coming especially from laboratory experiments - suggested that attention is a scarce resource and that individuals make decisions using only part of the available information (see DellaVigna (2009) for a survey). Voters might themselves be myopic, punishing or rewarding incumbents for what happens shortly before the election (Achen and Bartels (2004)), and replacing information about a whole electoral term (which might be more difficult to access) by easy-to-grasp information about the last year in office (Healy and Lenz (2014)). However, to the best of our knowledge, no study provided evidence as regard to whether individuals actually know the rules of the election when they cast their ballot. By focusing on a type of discrimination which is possible only because of limited attention of the voters, we therefore show that a non-negligible part of them were subject to limited attention concerning the rules of the election [4]. We therefore also contribute to a recent stream of research showing how ballot layout can influence voters' decision. Recent evidence showed that minor candidates are likely to perform better when their name is located close to the name of a major candidate (Shue and Luttmer (2009)), or when it is listed at the top of the ballot (Ho and Imai (2006), Ho and Imai (2008) among others). Relatedly, the number of decisions to make on a ballot can induce "choice fatigue", which substantially affects abstention (Augenblick and Nicholson (2015)). Because our identification relies upon ballot order effects, it therefore reasserts that limited attention concerning the rules of an election can play a key role on aggregate outcomes. From this standpoint, this paper is to the best of our knowledge among the first to highlight the link between limited attention and discrimination in politics. [5]

The remainder of the paper is structured as follows. Section 2 describes the institutional setting and the data we use. We provide descriptive statistics and various balance-checks showing that selection into the treatment is unlikely. Section 3 describes our estimation strategy. Section 4 gathers our main empirical results. Section 5 studies potential channels for our results and Section 6 concludes.

(Broockman and Soltas (2017), on racial discrimination in Republican primary elections in the United States. Another field where gender-biases have been explored through the lens of natural experiments is the field of academic recruitment - see Bagues, Sylos-Labini, and Zinovyeva (2016) for example

4. Whether this limited attention is due to differential costs of acquiring electoral information regarding the electoral rules is left for further research

5. A recent contribution from Bartoš et al. (2016) shows that in contexts of complete information, discrimination can occur if processing all the available information is costly. In such a case, agents might focus only on a subset of information, thus triggering statistical discrimination. As we argue later, such a setting is unlikely to apply to our context, since the amount of information to process by default in our setting is minimal.

4.2 Institutional Framework and Data

4.2.1 Institutional Framework

This study relies on data from the 2015 French departmental elections, which took place on March 22nd and March 29th. Departmental councellors were elected in 2,054 *cantons* (subdivisions of the *départements*). In each of these precincts, lists ran by pairs which necessarily had to be gender-balanced. Each candidate of a pair had to have a substitute of the same sex as her. Overall, 9,097 pairs of candidates ran for office.

Within each list, the order of the candidates on the ballot was determined by alphabetical order. Such a requirement is imposed by the article L.191 of the French electoral legislation. The rules for printing electoral ballots are also stringent: it must be printed in only color on a blank sheet of format 105x148 mm, weigh between 60 and 80 grams per square meter and be in landscape format. For each candidate, the name of its substitute must be written right after its name, using a smaller font. According to the articles L.66, L.191, R.66-2, R.110 and R.111 of the electoral code, any ballot not respecting these requirement is considered as null. Figure 4.1 shows examples of compliant ballots, as communicated by the Ministry of Interior.

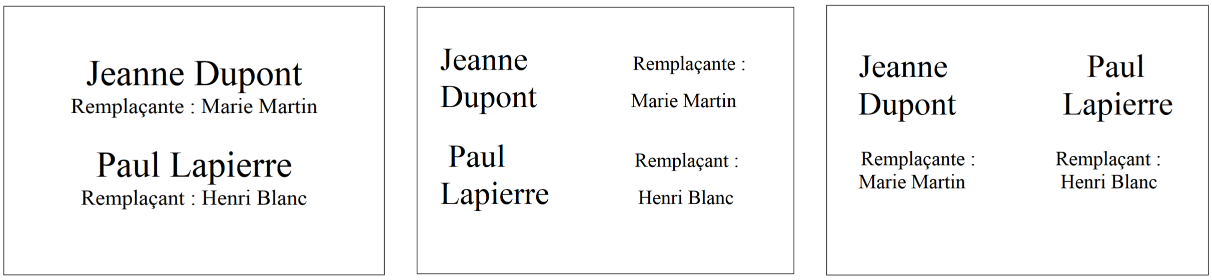


Figure 4.1: Examples of valid ballots

Importantly, the ballots on the day of the election are the only ones to be subject to these requirements, which do not affect campaign advertisement leaflets or electoral posters.

4.2.2 Data and Descriptive Statistics

For this analysis, we retrieved information about all the pairs of candidates from the Ministry of Interior. Our database includes information on age, gender, incumbency status, political affiliation and socioprofessional categories of each of these candidates. We matched these information with the *Répertoire National des Elus*, to know whether the candidates also had other political experience at the municipal, regional or parliamentary level. Finally, we also matched these information with sociodemographic information at the precinct-level, retrieved from the 2013 Census.

In order to carry on our analysis, we classified candidates into different partisan groups. We classified as extreme-left the lists labeled as *Communists, Extreme-Left, Front de Gauche* and *Parti de Gauche*. We classified as left-wing the lists labeled as *Parti Socialiste, Union de la Gauche, Radicaux de Gauche* and *Divers Gauche*. We classified as right-wing the lists labeled as *MoDem, Union du Centre, Union des Démocrates et des Indépendants, Debout La France, Divers-Droite, Union des Droites, UMP*. Finally we classified as extreme-right the lists labeled as *Front National* and *Extreme Droite*.

We first begin by documenting the differences between candidates of different partisan groups in Table 4.1. Overall, 28% of candidates were left-wing, a number which is comparable to the share of right-wing candidates. 14% of candidates were classified as extreme-left, while 22% were classified as extreme-right. Concerning political experience we categorized a candidate as having previous political experience if she was, at the time of election, either an incumbent, a municipal councellor in a municipality belonging to the precinct, a regional councellor, or a member of parliament.

For all parties, the share of male candidates with political experience is greater than the share of female candidates with political experience. Incumbents were slightly more numerous among right-wing candidates (69% of men and 53% of women) than among left-wing candidates (63% of men an 46% of women). Only 29% of men and 19% of women were previously elected among extreme-left candidates. These proportions shrink to respectively 15% and 9% among extreme right candidates. Except for extreme-right candidates, the candidates of all parties were on average between 52 and 54 years old, and the male candidates are older than the female candidates. Extreme-right candidates are younger (around 50 years old), and among them, female candidates are older than male candidates. Finally, a majority of male and female candidates came from the private sector or were retired. Civil servants and teachers were over-represented among left-wing and extreme-left candidates, while intermediary professions were over-represented among the right-wing candidates. Finally, we find that within each party, half of the pairs of candidates had the female candidate listed first.

Balance checks

In this section, we test the as-good-as-random nature of the order of appearance of female candidates on the ballot, namely we check whether the pairs where the female candidate is listed first differ on observable characteristics compared to pairs where the male candidate is listed first. For sake of brevity, we focus both on the full population of candidates, and on the subsamples that we will use later in our analysis.

As we argue in the next section, in order to identify causal effects of the treatment, our

	All		Extreme Left		Left		Right		Extreme Right	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Previous Political Exp. (W)	0.344	0.475	0.194	0.395	0.462	0.499	0.526	0.499	0.094	0.292
Previous Political Exp. (M)	0.470	0.499	0.293	0.455	0.631	0.483	0.685	0.465	0.153	0.361
Age (W)	51.410	12.061	53.273	11.714	51.651	10.789	51.528	10.878	50.739	14.750
Age (M)	52.533	12.927	53.718	12.774	54.022	11.602	53.226	12.128	49.741	15.260
Farmer (W)	0.019	0.136	0.015	0.122	0.012	0.107	0.032	0.177	0.009	0.096
Intermediary Profession (W)	0.057	0.233	0.016	0.126	0.028	0.164	0.085	0.279	0.086	0.281
Private Sector Employee (W)	0.279	0.449	0.226	0.418	0.253	0.435	0.286	0.452	0.347	0.476
Liberal Occupation (W)	0.068	0.252	0.038	0.192	0.073	0.260	0.091	0.288	0.035	0.183
Education Occupation (W)	0.115	0.319	0.147	0.354	0.154	0.361	0.095	0.294	0.052	0.222
Civil Servant(W)	0.117	0.321	0.162	0.368	0.163	0.370	0.106	0.308	0.047	0.212
Public Firm Worker (W)	0.039	0.194	0.063	0.243	0.045	0.207	0.035	0.183	0.021	0.143
Other Occupation(W)	0.099	0.299	0.050	0.219	0.077	0.266	0.108	0.311	0.152	0.359
Retired (W)	0.206	0.404	0.282	0.450	0.196	0.397	0.161	0.367	0.250	0.433
Farmer (M)	0.034	0.181	0.014	0.116	0.028	0.164	0.059	0.236	0.022	0.146
Intermediary Profession (M)	0.096	0.294	0.017	0.129	0.056	0.229	0.135	0.342	0.143	0.350
Private Sector Employee (M)	0.235	0.424	0.232	0.422	0.188	0.391	0.214	0.410	0.316	0.465
Liberal Occupation (M)	0.079	0.269	0.030	0.170	0.072	0.259	0.127	0.333	0.046	0.209
Education Occupation (M)	0.104	0.306	0.147	0.355	0.133	0.339	0.070	0.255	0.069	0.254
Civil Servant(M)	0.101	0.301	0.118	0.322	0.147	0.354	0.082	0.274	0.056	0.231
Public Firm Worker (M)	0.039	0.194	0.063	0.244	0.052	0.221	0.034	0.181	0.015	0.120
Other Occupation(M)	0.054	0.226	0.044	0.205	0.046	0.209	0.055	0.229	0.061	0.239
Retired (M)	0.259	0.438	0.335	0.472	0.280	0.449	0.224	0.417	0.271	0.445
Woman First	0.506	0.500	0.502	0.500	0.496	0.500	0.524	0.500	0.502	0.500
Observations	9097		1250		2507		2714		1929	

This table presents the mean and standard deviation of the characteristics of the candidates. Columns 1 and 2 report information for the full population of candidates, while the remaining columns reported the mean and standard deviation by party.

Table 4.1: Characteristics of male and female candidates by partisan affiliation

estimation needs to satisfy the *Stable Unit Treatment Value Assumption* (SUTVA), which states that the potential outcomes of a unit are not affected by the treatment status of another unit. This hypothesis is likely to be violated if we consider altogether several candidates from a same precinct. Indeed, let us assume that the treatment affects negatively a given pair of candidates. One can therefore imagine that the votes they lost positively affected another pair of candidates from the same precinct (especially if the voters reacting to the treatment are non-partisan).

In order to avoid such a scenario, we run an analysis on different samples of candidates having the same partisan affiliation, and being the sole candidate of their party in their precinct[6]. Such subsamples meet the *SUTVA* assumption: while it is possible that these candidates are affected by the treatment status of candidates of other parties, they cannot be affected by the treatment status of other units in the sample.

In Table 4.2, we systematically test for imbalances, both on the whole population of candidates and on the subsamples of interest. To do so, we regress the dummy variable indicating whether the female candidate is listed first on the whole set of individual characteristics, as well as on some precinct characteristics. On the whole population of candidates, women in intermediary professions, private sector and liberal occupations are slightly more likely to be listed first. No imbalances are found for extreme-left candidates. Among left-wing candidates, women are slightly more likely to be on the top of the ballot when they are paired with a man working in a intermediary professions, and more so when they are themselves retired or working in an intermediary profession. Among right-wing pairs, women are more likely to be listed first on the ballot if they work in liberal occupations. Finally, among extreme-right candidates, younger female candidate are more likely to be on the top of the ballot. So do female candidates who are retired, civil servants, or working in liberal and intermediary professions. However, overall, whether we consider the full population of candidates or the restricted subsamples, the characteristics of the candidates explain very few (if any) of the variance of the treatment variable, and they are not jointly significant. Overall, these results suggest that if any selection into the treatment based on the characteristics of the candidates or on the characteristics of the political opponents exists, it is of low magnitude.

4.2.3 Manipulation of the treatment

An important related question is whether parties selected male and female candidates in order to have male candidates at the top of the ballot. In this case, we should observe that

6. By an abuse of language, we hereafter call "parties" the broad categorizations of *extreme-left, left-wing, right-wing and extreme-right* candidates, described above

Woman First	All	Restricted Samples			
		Extreme Left	Left	Right	Extreme Right
Previous Political Exp. (W)	0.019	0.018	0.003	0.025	0.030
	(0.012)	(0.037)	(0.029)	(0.029)	(0.042)
Previous Political Exp. (M)	-0.004	0.031	0.011	-0.056	-0.048
	(0.013)	(0.033)	(0.032)	(0.035)	(0.034)
Age (W)	-0.000	-0.001	-0.001	0.001	-0.002
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)**
Age (M)	-0.000	0.002	0.000	-0.002	-0.000
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Intermediary Profession (W)	0.059	-0.031	0.152	0.091	0.087
	(0.025)**	(0.120)	(0.092)*	(0.056)	(0.048)*
Private Sector Employee (W)	0.031	0.020	0.059	0.036	0.055
	(0.016)*	(0.051)	(0.048)	(0.041)	(0.033)
Liberal Occupation (W)	0.086	0.022	0.087	0.090	0.173
	(0.025)***	(0.085)	(0.065)	(0.053)*	(0.069)**
Education Occupation (W)	0.019	0.004	0.069	-0.018	0.032
	(0.020)	(0.056)	(0.052)	(0.058)	(0.059)
Civil Servant (W)	0.019	-0.010	0.055	-0.011	0.104
	(0.020)	(0.055)	(0.052)	(0.053)	(0.060)*
Retired (W)	0.013	-0.080	0.095	-0.019	0.141
	(0.020)	(0.055)	(0.056)*	(0.052)	(0.042)***
Intermediary Profession (M)	0.008	0.118	0.148	0.027	-0.075
	(0.023)	(0.127)	(0.072)**	(0.053)	(0.048)
Private Sector Employee (M)	0.015	0.078	0.005	0.023	-0.051
	(0.019)	(0.052)	(0.051)	(0.045)	(0.043)
Liberal Occupation (M)	0.018	0.058	0.053	0.004	-0.000
	(0.024)	(0.095)	(0.066)	(0.050)	(0.066)
Education Occupation (M)	-0.005	0.039	0.078	-0.026	-0.085
	(0.023)	(0.058)	(0.054)	(0.062)	(0.060)
Civil Servant(M)	-0.016	-0.017	0.045	-0.036	-0.056
	(0.022)	(0.060)	(0.052)	(0.058)	(0.062)
Retired (M)	0.011	0.002	0.033	0.059	-0.043
	(0.021)	(0.055)	(0.052)	(0.048)	(0.048)
XLeft	0.023				
	(0.024)				
Left	0.009				
	(0.022)				
Right	0.029				
	(0.022)				
XRight	0.014				
	(0.022)				
Adj. R2	0.00	0.00	-0.00	0.00	0.00
F	1.45	1.15	0.70	1.04	1.28
N	9,081	1,187	1,341	1,389	1,883

OLS Regressions. Column 1 considers all candidates. In columns 2 to 5 each subsample considers only the candidates who are the only ones of the considered party in the precinct where they run. The outcome is a variable equal to one if the female candidate is first on the ballot and zero otherwise. Standard errors in parentheses are clustered at the precinct level in column 1, and robust in columns 2 to 5.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 4.2: Determinants of the treatment (Total population of candidates and restricted samples)

P-Value	All	Restricted samples Extreme-Left	Left	Right	Extreme-Right
KS	0.211	0.782	0.094*	0.855	0.377
Median	0.320	0.774	0.132	0.622	0.474
MWW	0.385	0.652	0.0546*	0.583	0.372

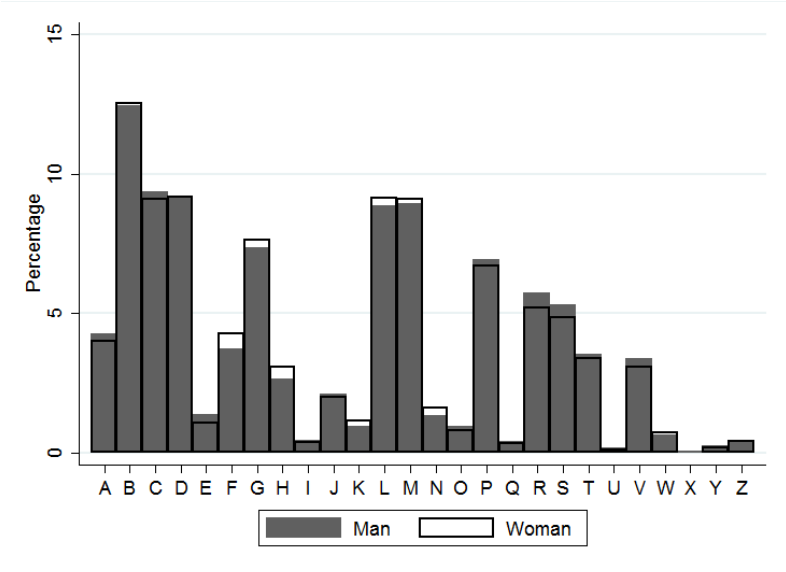
The table presents the P-values of three tests of equal distributions: Kolmogorov-Smirnov (KS), non-parametric test of equality of medians (Median), and Mann-Whitney-Wilcoxon rank-sum test (MWW). The null hypothesis is that the distributions of first letters in the surnames is the same across male and female candidates. Column 1 considers all candidates. In columns 2 to 5, each subsample considers only the candidates who are the only ones of the considered party in the precinct where they run.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 4.3: Tests of equal distributions of surnames initials

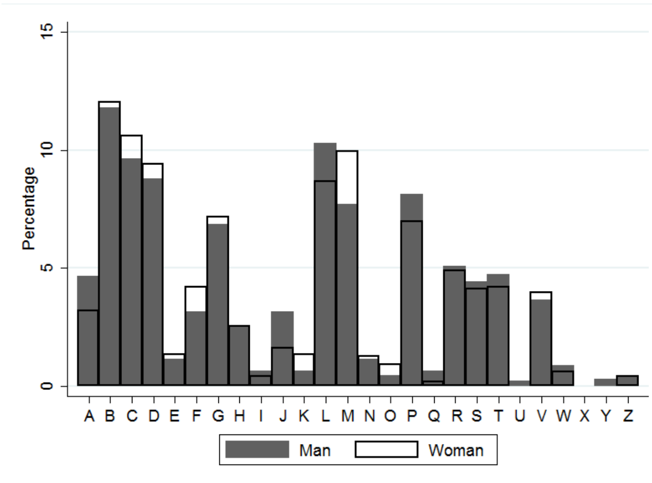
the distribution of first letters of surnames are different across gender. In Figure 4.2, we plot the frequency of each surname first letter for male and female candidates, both on the total population of candidates and on our subsamples of interest: in all cases, the distributions are strikingly similar. In Table 4.3, we formalize this graphical intuition by performing different tests of equal distributions. Namely, we perform the tests of Kolmogorov-Smirnov, of equality of medians, and of Mann-Whitney-Wilcoxon. Overall, for all the tests and all the samples of interest, we cannot reject the null hypothesis that the distributions are identical. The only exception is for the restricted subsamples of left-wing candidates, where the distributions seem slightly different : the Kolmogorov Test and the Mann-Whitney-Wilcoxon test reject the hypothesis of equal distributions at the 10% level. But as Figure 4.3c shows, this difference seems mainly driven by an over-representation of women with names beginning by the letter B, and is unlikely to represent a more general manipulation of the treatment. This suggests that parties did not strategically chose to match candidates based on their surnames. Finally, as additional checks for the absence of manipulation of the treatment, we report in Annex the share of votes received by candidates in the first round depending on the first letter of the candidates' surnames: we find that, for each first letter of the candidates' surnames, the share of votes is very close to the sample average.

4.2.4 Data on ballot layout

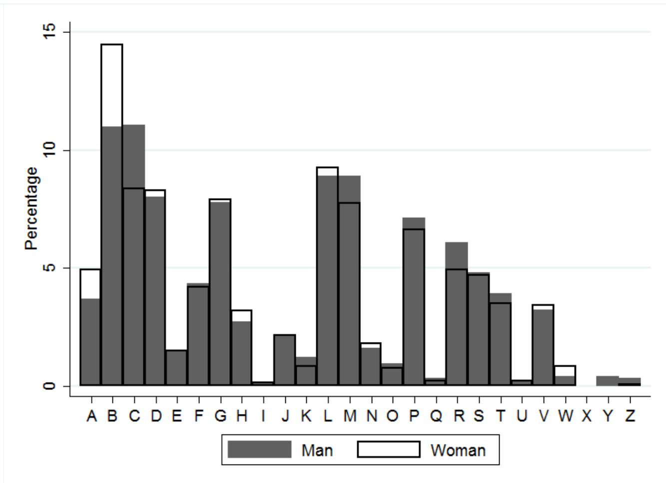
An important feature of the French electoral law is that it allows candidates to add additional information about themselves on the ballot, so long as it does not confuse the voter about their identity. In order to account for this specificity, we manually collected data on the electoral ballots that were used for these elections. While there does not exist a systematic recording of electoral ballots for the local elections in France, we could access a sample corresponding to about 12% of the electoral ballots of the considered elections. To do so, we used three types of data. First, the Centre for Political Research of SciencesPo (CEVIPOF) provided 780 ballots.



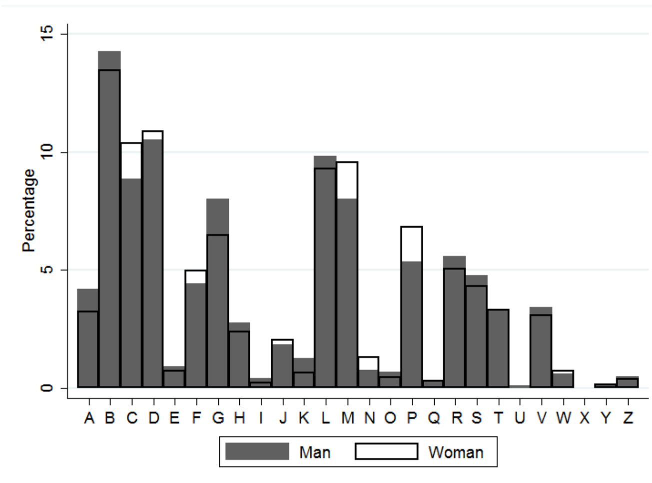
(a) Total population of candidates



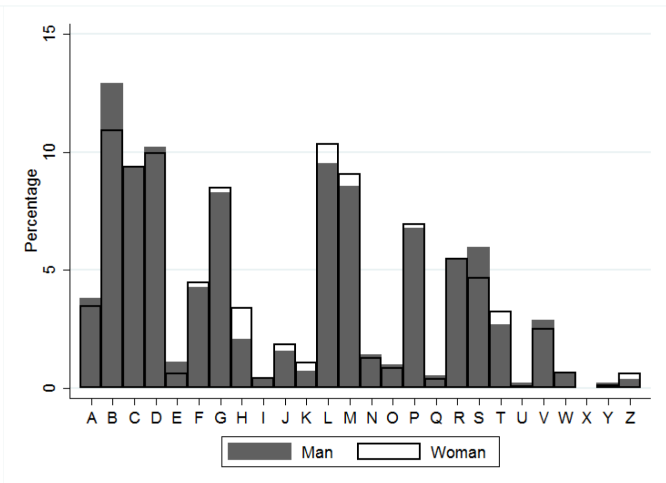
(b) Restricted Sample: Extreme Left



(c) Restricted Sample: Left



(d) Restricted Sample: Right



(e) Restricted Sample: Extreme Right

Figure 4.2: Distribution of surname initials across gender and parties

Secondly, exploiting the fact that some departments recorded a numeric version of the ballots (namely the departments of Allier, Aude, Ille-et-Villaine, Loire-Atlantique and Savoie), we systematically contacted the administrative centers in charge of the election. We managed to recover 168 ballots from the *Loire-Atlantique* department. Finally, we systematically looked up for pictures of ballots on the Internet, using Google, Twitter and Facebook keywords[7]. Using this methodology, we managed to recover 191 full ballots.

To the best of our knowledge, this represents the first effort to collect and analyze ballot layouts in a systematic way. Yet, because our dataset is not complete, it might be subject to biases. In particular, because the data collected by the Centre for Political Research of Sciences Po are based on voluntary contributions of voters, it tends to over represent precincts located in urban areas. Secondly, online data might over-represent famous candidates, who might be more likely to campaign online. On the other hand, it might also allow candidates without a strong visibility to get a wider audience. In Table 4.4, we regress the availability of the ballot on the main characteristics of the candidates for each of the subsamples of interest.

Overall, we find small differences in terms of age and socio professional categories: the ballots we analyze are those of slightly younger candidates, especially among left-wing candidates. We also find that the layout of right-wing candidates is less likely to be observed if the female candidate is working in the private sector or as a civil servant, or is retired. Conversely, among extreme left candidates, we are more likely to observe ballots including female candidates working in liberal occupations, and male candidates working in the private sector. Finally, among extreme-right candidates, ballots including men working in the education sector, as civil servants, in the private sector or intermediary professions are more likely to be observed. Nevertheless, three important comments need to be made. First and foremost, the position of the female candidate is not predictive of the availability of the ballot. Second, while some differences are significant (in fact, we can reject the null hypothesis of joint nullity of the estimates for the total population of candidates, and for the restricted samples of extreme-left and left-wing candidates) they explain a tiny share of ballot availability, as the adjusted R^2 is never above 2%. Finally, no party seems to be over represented in the sample.

In Table 4.5, we provide evidence that the treatment status is uncorrelated with the reporting decision and the kind of information reported. We categorized the type of information into three types: declared past or present political experience, age and occupation. Moreover, since it is possible to put the picture of the candidates on the ballot, we identified the pairs of candidates who did so. We observe, that out of 1,139 ballots available, 36% have some kind of information reported for at least one candidate : 35% of the ballots report information related

7. Using in particular requests such as "Bulletins de vote élections départementales 2015", or other versions of it

		Restricted Samples			
Ballot Availability	All	Extreme Left	Left	Right	Extreme Right
Woman First	-0.006 (0.007)	-0.005 (0.018)	-0.008 (0.018)	-0.018 (0.018)	-0.002 (0.015)
Previous Political Exp. (W)	-0.013 (0.008)	0.011 (0.024)	-0.011 (0.018)	-0.011 (0.019)	0.012 (0.029)
Previous Political Exp. (M)	-0.010 (0.008)	-0.010 (0.019)	-0.016 (0.021)	0.007 (0.022)	0.002 (0.022)
Age (W)	-0.000 (0.000)	-0.001 (0.001)	-0.002 (0.001)*	-0.000 (0.001)	0.000 (0.001)
Age (M)	-0.001 (0.000)***	-0.001 (0.001)	-0.004 (0.001)***	-0.001 (0.001)	0.000 (0.001)
Intermediary Profession (W)	-0.025 (0.016)	-0.078 (0.057)	-0.059 (0.046)	-0.018 (0.040)	-0.031 (0.029)
Private Sector Employee (W)	0.008 (0.011)	-0.028 (0.033)	-0.020 (0.029)	-0.056 (0.028)**	0.001 (0.022)
Liberal Occupation (W)	0.028 (0.017)	0.140 (0.070)**	-0.013 (0.041)	0.004 (0.039)	0.019 (0.048)
Education Occupation (W)	0.025 (0.014)*	-0.004 (0.037)	0.037 (0.035)	0.012 (0.043)	0.032 (0.042)
Civil Servant (W)	-0.005 (0.013)	-0.005 (0.036)	0.043 (0.034)	-0.061 (0.034)*	-0.025 (0.036)
Retired (W)	-0.005 (0.013)	-0.024 (0.035)	0.041 (0.034)	-0.068 (0.035)*	-0.019 (0.027)
Intermediary Profession (M)	0.027 (0.015)*	0.087 (0.095)	-0.058 (0.046)	0.012 (0.035)	0.074 (0.029)**
Private Sector Employee (M)	0.014 (0.012)	0.072 (0.034)**	-0.037 (0.037)	0.005 (0.030)	0.040 (0.023)*
Liberal Occupation (M)	0.004 (0.016)	0.082 (0.070)	-0.003 (0.047)	-0.002 (0.032)	0.050 (0.040)
Education Occupation (M)	0.005 (0.015)	-0.040 (0.032)	-0.027 (0.039)	-0.006 (0.039)	0.133 (0.041)***
Civil Servant(M)	0.008 (0.015)	-0.008 (0.035)	-0.038 (0.037)	0.031 (0.040)	0.106 (0.041)**
Retired (M)	-0.003 (0.013)	0.015 (0.035)	-0.021 (0.037)	-0.002 (0.029)	0.037 (0.027)
Left	0.010 (0.015)				
Right	-0.002 (0.015)				
XRight	-0.023 (0.015)				
XLeft	-0.015 (0.016)				
Adj. R2	0.01	0.02	0.02	-0.00	0.00
F	3.04	1.75	2.17	0.97	1.28
N	9,081	1,187	1,341	1,389	1,883

OLS Regressions. Column 1 considers all candidates. In columns 2 to 5 each subsample considers only the candidates who are the only ones of the considered party in the precinct where they run. The outcome is a variable equal to one if we could observe the ballot and zero otherwise. Standard errors in parentheses are clustered at the precinct level in column 1, and robust in columns 2 to 5.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 4.4: Determinants of ballot availability

	Man First	N	Woman First	N	Diff	T-Stat
At least one information	0.362	575	0.362	564	0.000	0.001
At least one information (M)	0.348	575	0.351	564	-0.003	-0.114
At least one information (W)	0.327	575	0.340	564	-0.013	-0.481
Information: Political Experience (M)	0.268	575	0.253	564	0.014	0.548
Information: Political Experience (W)	0.221	575	0.220	564	0.001	0.041
Information: Occupation (M)	0.050	575	0.060	564	-0.010	-0.726
Information: Occupation (W)	0.066	575	0.070	564	-0.005	-0.323
Information: Age (M)	0.009	575	0.005	564	0.003	0.682
Information: Age (W)	0.009	575	0.005	564	0.003	0.682
Photo	0.090	575	0.092	564	-0.002	-0.103

This table presents T-Tests of difference of information reporting across treatment status for the full sample of available ballots

Table 4.5: Balance check on reported information: all candidates

to the male candidate and 33.3% report information related to the female candidate. 26% of the ballots report information related to the political experience of the male candidate and 22% report information related to the political experience of the female candidate. 5.5% of male candidates report their occupations, while it is the case of 6.8% of female candidates. Less than 1% of male and female candidates report their age. Finally, about 9% of the candidates put their picture on the ballot. We also observe that the decision to report any information is very correlated between male and female candidates: out of 412 ballots with at least one information, 88% report information for both candidates. Importantly, none of these reporting decisions are correlated to the treatment.

4.3 Estimation strategy

Our main estimation strategy aims at analyzing whether candidates lose or gain from having the female candidate first on the ballot.

In an initial specification, we test whether, on average, the electoral performances of pairs where the female candidate is first on the ballot are different from those where the male candidate is first. Identification takes place within the potential outcomes framework from the Rubin Causal Model, where we assume two potential outcomes for each unit i - $Y_i(0)$ and $Y_i(1)$ - and the causal effect of the program on the unit i is defined as $\tau_i = Y_i(1) - Y_i(0)$. The actual observed outcome is defined as such:

$$Y_i^{obs} = \begin{cases} Y_i(0) & if \quad T_i = 0 \\ Y_i(1) & if \quad T_i = 1 \end{cases}$$

In this framework, the Average Treatment Effect is defined as $ATE = \mathbb{E}[Y_i(1) - Y_i(0)]$. A naive estimate of this quantity is given by $\overline{Y_1^{obs}} - \overline{Y_0^{obs}}$. In general, such a quantity is unbiased under the *Stable Unit Treatment Value Assumption* (SUTVA) and the *complete randomization assumption* .

As explained above, the *SUTVA* is likely to be violated if we do not restrict our analysis to a sample of observations which cannot interact with each other (meaning that the treatment status of one observation will not affect the outcome of any other unit). To do so, we therefore restrict our analysis to candidates who are the only ones to represent their party in the precinct.

The second assumption states that both the potential outcomes and the covariates are independent from the treatment. Formally, the condition writes as such:

$$T_i \perp (Y_i(0), Y_i(1), X_i)$$

In our setting, the treatment-assignment is based on a procedure which is supposedly as-good-as-random, since the order of the candidates (and hence the place of the female candidate) on the ballot is determined by alphabetical order. However, as have shown in the last section, while the treatment assignment is hardly affected by candidates' characteristics, the covariates are not systematically perfectly balanced across treatment status. In our setting, it therefore seems more plausible to assume the milder assumption of *unconfoundedness*, which states that the potential outcomes and the treatment are independent after controlling for covariates potentially affecting them. Formally, this assumption writes:

$$T_i \perp (Y_i(0), Y_i(1))|X_i$$

Our baseline OLS specification is therefore the following:

$$Y_i = \alpha + \beta T_i + \delta X_i + \epsilon_i \tag{4.1}$$

where Y_i is an outcome variable indicating the electoral performance of pair i, T_i is the treatment variable, which is equal to 1 if the female candidate in pair i is first on the ballot and 0 otherwise, X_i is a set of candidates characteristics, and ϵ_i is an error term. In such a setting, heterogeneous effects can be estimated by interacting a subset of the control variables X_i and $X_i^{'}$ with the treatment T_i.

While our main specification does not model how the electoral performance of a pair of candidates depends on the characteristics of the other candidates, in additional specifications we control for the average characteristics of the opponents of the considered pair, and compare the results of the different candidates pairwise.

4.4 Results

4.4.1 Main estimation

In this section, we present our main results, by estimating equation (1). In order to do so, we compare the scores received by candidates in the first round of the election in the control and in the treatment group. Note that in this setting, the number of candidates is not identical in each precinct, and the scores of pairs facing different are therefore not directly comparable. In order to make the electoral performances comparable across different number of candidates, we control in each regression for the number of candidates competing in the precinct.

Does the order of the candidates affect electoral the electoral performances of the pair ? Table 4.1 summarizes the estimates of such an average treatment effect across several specifications. Panel (A) reports results without any controls except the number of candidates in the precinct. Panel (B) reports results controlling for individual characteristics. Panel (C) involves the same control variables, but interacts the characteristics of male and female candidates. Panel (D) is similar to the third one, but also controls for precinct characteristics (including the average age of the population, the share of voters in rural areas, the share of voters with at least an undergraduate degree, and the unemployment rate, all as of 2013), and for the first letter of the female's surname.

Overall, the results suggest that the performances of extreme-left, left-wing and right-wing pairs are not affected by the order of appearance of the candidates. However, right-wing pairs lose a sizable share of votes if the female candidate is first. Estimates of the loss range between 1.4 and 1.9 points, representing between 4 and 5.4 percents of the average vote share. Importantly, the magnitude of the coefficient is very similar across the specifications, and especially stable in all the specifications including covariates, suggesting that the inclusion of covariates hardly affects the general pattern.

This discrimination had a substantial electoral impact. In Table 4.2, we show that gender discrimination prevented some right-wing pairs of candidates from winning the election. More specifically we regress a dummy variable indicating whether the considered pair reached the second round or won the election during the first round. Panel (A) includes no control except the number of competing candidates. Panel (B) includes the broadest set of controls - namely, interacted individual characteristics from the candidates, number of competing candidates, precinct characteristics and the first letter of the woman's surname. We find that right-wing candidates were between 3.9 and 4.9 percentage points less likely to reach the second round or win the election in the first round, corresponding to a lower probability ranging between 4.7 and 5.9 percents.

(A)	XLeft	Left	Right	XRight
Woman First	0.381	-0.291	-1.878	0.035
	(0.396)	(0.536)	(0.536)***	(0.348)
R^2	0.15	0.14	0.28	0.09
N	1,188	1,341	1,391	1,893
Indiv. Controls	N	N	N	N
Precinct characteristics	N	N	N	N
First letter of the woman's surname	N	N	N	N
Number of candidates	Y	Y	Y	Y
(B)	XLeft	Left	Right	XRight
Woman First	0.084	-0.206	-1.589	0.066
	(0.350)	(0.480)	(0.497)***	(0.327)
R^2	0.35	0.32	0.40	0.22
N	1,187	1,341	1,389	1,883
Indiv. Controls	Y	Y	Y	Y
Precinct characteristics	N	N	N	N
First letter of the woman's surname	N	N	N	N
Number of candidates	Y	Y	Y	Y
(C)	XLeft	Left	Right	XRight
Woman First	0.123	-0.149	-1.583	0.122
	(0.364)	(0.492)	(0.511)***	(0.335)
R^2	0.39	0.37	0.43	0.25
N	1,187	1,341	1,389	1,883
Indiv. Controls	Inter.	Inter.	Inter.	Inter.
Precinct characteristics	N	N	N	N
First letter of the woman's surname	N	N	N	N
Number of candidates	Y	Y	Y	Y
(D)	XLeft	Left	Right	XRight
Woman First	-0.085	-0.206	-1.397	0.429
	(0.420)	(0.586)	(0.581)**	(0.378)
R^2	0.43	0.41	0.49	0.38
N	1,187	1,334	1,389	1,882
Indiv. Controls	Inter.	Inter.	Inter.	Inter.
Precinct characteristics	Y	Y	Y	Y
First letter of the woman's surname	Y	Y	Y	Y
Number of candidates	Y	Y	Y	Y
Mean of Outcome Variable	10.66	28.44	34.91	25.79

OLS Regressions. Each subsample considers only the candidates who are the only ones of the considered party in the precinct where they run. The outcome variable is the share of votes received by each pair of candidates in the first round of the election. Panel (A) controls only for the number of candidates in the precinct. Panel (B) also controls for age, socioprofessional categories and political experience of male and female candidates. Panel (C) controls for the same variables but interacts the age of man and woman, the socioprofessional categories of man and woman, and the political experience of man and woman. Panel (D) adds to these controls the first letter of the woman's surname, as well as the unemployment rate, the average age of the population, the share of individuals with a graduate degree and the share of voters living in rural areas within the precincts. Robust standard errors between parentheses.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 4.1: Effect on share of votes in the first round

(A)	XLeft	Left	Right	XRight
Woman First	0.015	0.002	-0.049	-0.004
	(0.013)	(0.026)	(0.020)**	(0.023)
R^2	0.01	0.01	0.03	0.01
N	1,188	1,341	1,391	1,893
Indiv. Controls	N	N	N	N
Precinct characteristics	N	N	N	N
First letter of the woman's surname	N	N	N	N
Number of candidates	Y	Y	Y	Y
(B)	XLeft	Left	Right	XRight
Woman First	0.010	0.013	-0.039	0.002
	(0.015)	(0.030)	(0.022)*	(0.026)
R^2	0.26	0.26	0.25	0.22
N	1,187	1,334	1,389	1,882
Indiv. Controls	Inter.	Inter.	Inter.	Inter.
Precinct characteristics	Y	Y	Y	Y
First letter of the woman's surname	Y	Y	Y	Y
Number of candidates	Y	Y	Y	Y
Mean of the Outcome Variable	0.058	0.64	0.83	0.58

OLS Regressions. Each subsample considers only the candidates who are the only ones of the considered party in the precinct where they run. The outcome variable is a dummy variable indicating whether the pair of candidates went to the second round of the election or was elected in the first round. Panel (A) controls only for the number of candidates in the precinct. Panel (B) also controls for interacted age of man and woman, interacted socioprofessional categories of man and woman, interacted political experience of man and woman, the first letter of the woman's surname, as well as the unemployment rate, the average age of the population, the share of individuals with a graduate degree and the share of voters living in rural areas within the precincts. Robust standard errors between parentheses.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 4.2: Effect on probability of getting to the second round or of winning the election in the first round

(A)	XLeft	Left	Right	XRight
Woman First	0.006	-0.016	-0.045	-0.001
	(0.012)	(0.026)	(0.026)*	(0.006)
R^2	0.01	0.00	0.04	0.01
N	1,188	1,341	1,391	1,893
Indiv. Controls	N	N	N	N
Precinct characteristics	N	N	N	N
First letter of the woman's surname	N	N	N	N
Number of candidates	Y	Y	Y	Y
(B)	XLeft	Left	Right	XRight
Woman First	0.002	-0.016	-0.040	0.006
	(0.014)	(0.032)	(0.031)	(0.007)
R^2	0.22	0.19	0.24	0.14
N	1,187	1,334	1,389	1,882
Indiv. Controls	Inter.	Inter.	Inter.	Inter.
Precinct characteristics	Y	Y	Y	Y
First letter of the woman's surname	Y	Y	Y	Y
Number of candidates	Y	Y	Y	Y
Mean of the Outcome Variable	0.044	0.35	0.57	0.016

OLS Regressions. Each subsample considers only the candidates who are the only ones of the considered party in the precinct where they run. The outcome variable is a dummy variable indicating whether the pair of candidates eventually won the election. Panel (A) controls only for the number of candidates in the precinct. Panel (B) also controls for interacted age of man and woman, interacted socioprofessional categories of man and woman, interacted political experience of man and woman, the first letter of the woman's surname, as well as the unemployment rate, the average age of the population, the share of individuals with a graduate degree and the share of voters living in rural areas within the precincts. Robust standard errors between parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 4.3: Effect on probability of being elected

This gender bias seems to have affected the final result of the election. In Table 4.3, we regress a dummy indicating whether the considered pair won the election on the treatment status. Controls are defined in the same way as in Table 4.2. Overall, we find that, because of gender discrimination, right-wing pairs of candidates were between 4 and 4.5 points less likely to win the election. An important point is that the magnitude of the results is exactly the same as the magnitude observed when we considered the probability of going to the second round or winning the election in the first round. It suggests that the overall effect is channeled through the probability of reaching the second. In fact, we find no treatment effect during the second round[8]. This additional noise explains why our results are less significant: the simplest specification only yields significance at the 10% level, and the treatment effect is not significant anymore when we include covariates - even though the point estimates are very stable.

4.4.2 Alternative specifications

Full Sample

In Table 4.4, we run the same baseline model on the full population of candidates. While in such a setting we cannot exclude that the *SUTVA* is violated, it provides consistent evidence that our main estimates are not an artifact of our sample selection. Panel (A) reports average treatment effects on the vote shares during the first round on the population of candidates in each of the four specifications detailed in our main estimation - controlling in each of them for the party of the candidate. We find no evidence of treatment effects whatsoever.

However, when we interact the treatment with a dummy indicating that the pair of candidates is from the right-wing, we find a strongly negative interaction term, of the same magnitude than the one found in the main specification (i.e. between -1.4 and -1.5 percentage points).

Opponents' characteristics and dyadic estimation

In this section, we check that our estimates are not affected by the characteristics of the political opponents faced by a given pair of candidates. In Table 4.5, we run the most stringent regression of the main specification - including interacted individual characteristics, the first letter of the female's surname and the characteristics of the precinct - controlling for the average characteristics of the male and female opponents on the age, political experience and occupation dimensions, as well as for the share of opponents with a female candidate listed first. We still find a statistically significant effect on the restricted sample of right-wing candidates, even though the effect is smaller and drops down to 1 percentage point.

8. These results are available upon request.

(A)	(1)	(2)	(3)	(4)
Woman first	-0.117	-0.191	-0.172	-0.187
	(0.210)	(0.185)	(0.186)	(0.226)
R^2	0.40	0.54	0.54	0.55
N	9,097	9,081	9,081	9,018
Indiv. Controls	N	Y	Inter.	Inter.
Precinct characteristics	N	N	N	Y
First letter of the woman's surname	N	N	N	Y
Number of candidates	Y	Y	Y	Y

(B)	(1)	(2)	(3)	(4)
Woman First	0.445	0.489	0.443	0.432
	(0.492)	(0.493)	(0.502)	(0.506)
Extreme Left	-1.286	-1.070	-1.041	-0.910
	(0.447)***	(0.440)**	(0.444)**	(0.438)**
Left	12.081	8.007	7.988	7.972
	(0.465)***	(0.451)***	(0.456)***	(0.449)***
Right	15.981	11.044	11.064	11.076
	(0.508)***	(0.497)***	(0.499)***	(0.494)***
Extreme Right	12.703	14.880	14.845	14.989
	(0.459)***	(0.461)***	(0.466)***	(0.462)***
Woman First*Extreme Left	0.048	-0.383	-0.351	-0.338
	(0.628)	(0.609)	(0.617)	(0.607)
Woman First*Left	-0.143	-0.452	-0.388	-0.426
	(0.649)	(0.618)	(0.627)	(0.617)
Woman First*Right	-1.510	-1.464	-1.389	-1.418
	(0.695)**	(0.654)**	(0.659)**	(0.646)**
Woman First*Extreme Right	-0.378	-0.313	-0.214	-0.163
	(0.629)	(0.609)	(0.619)	(0.615)
R^2	0.40	0.54	0.54	0.55
N	9,097	9,081	9,081	9,018
Indiv. Controls	N	Y	Inter.	Inter.
Precinct characteristics	N	N	N	Y
First letter of the woman's surname	N	N	N	Y
Number of candidates	Y	Y	Y	Y

OLS Regressions. All columns consider the full population of candidates. The outcome variable is the share of votes received by each pair of candidates in the first round of the election. Panel (A) presents the treatment effect on the full population. Panel (B) interacts this treatment with the party of the candidates.ts the treatment with the party of the candidate. Column (1) controls only for the number of candidates in the precinct and the party of each candidate. Column (2) also controls for age, socioprofessional categories and political experience of male and female candidates. Column (3) controls for the same variables but interacts the age of man and woman, the socioprofessional categories of man and woman, and the political experience of man and woman. Column (4) adds to these controls the first letter of the woman's surname, as well as the unemployment rate, the average age of the population, the share of individuals with a graduate degree and the share of voters living in rural areas within the precincts. Clustered standard errors at the precinct level in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 4.4: OLS estimation on Full Sample

Share of votes in the first round	XLeft	Left	Right	XRight
Woman First	0.064	0.267	-1.065	0.427
	(0.401)	(0.537)	(0.512)**	(0.375)
R^2	0.48	0.52	0.59	0.40
N	1,187	1,333	1,387	1,882
Indiv. Controls	Inter.	Inter.	Inter.	Inter.
Precinct characteristics	Y	Y	Y	Y
First letter of the woman's surname	Y	Y	Y	Y
Number of candidates	Y	Y	Y	Y
Mean of opponents' characterics	Y	Y	Y	Y

OLS Regressions. Each subsample considers only the candidates who are the only ones of the considered party in the precinct where they run. The outcome variable is the share of votes received by each pair of candidates in the first round of the election. Each regression controls for the number of candidates in the precinct, the interacted age of man and woman, interacted socioprofessional categories of man and woman, interacted political experience of man and woman, the first letter of the woman's surname, and the average of each of these variables among the competing candidates in the precinct. It also controls for the unemployment rate, the average age of the population, the share of individuals with a graduate degree and the share of voters living in rural areas within the precincts. Robust standard errors between parentheses.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 4.5: Effect on votes in the first round, controlling for average characteristics of opponents

Finally, in order to take into account more thoroughly the structure of the political competition, we compute for each pair of candidates the difference between their score and the score of each of their opponents in the first round of the election. We then regress the relative score between the considered pair and its considered opponent on their respective characteristics and treatment statuses.

Formally, we therefore run the following estimation:

$$Y_{ij} = \alpha + \beta T_i + \gamma T_j^{'} + \delta X_i + \nu X_j^{'} + \epsilon_{ij} \tag{4.2}$$

where Y_{ij} is the difference between the score of the pair i and the score of the pair j, T_i is the treatment status of pair i, $T_j^{'}$ is the treatment status of pair j, $X_j^{'}$ is a set of characteristics of pair j, and ϵ_{ij} is an error term.

We run the specifications in the same fashion as in the main specification. Panel (A) controls only for the number of competing candidates. Panel (B) controls for the characteristics of each dyad of pairs. Panel (C) controls for the same characteristics, but interacting them within each pair of the dyad. Finally, panel (D) adds as controls the first letter of each woman in the dyad, and the sociodemographic characteristics of the precinct.

The results of this estimation are gathered in Table 4.6. The results look very similar to the main estimation: we do not find any treatment effect for extreme-left, left-wing and right-wing candidates, but we do a find a negative treatment effect for right-wing candidates, correspond-

(A)	XLeft	Left	Right	XRight
Woman First	0.595	-0.384	-2.058	-0.020
	(0.482)	(0.675)	(0.702)***	(0.463)
Woman First (Opponent)	0.193	0.105	-0.391	0.072
	(0.404)	(0.504)	(0.498)	(0.377)
R^2	0.09	0.03	0.01	0.07
N	4,450	4,413	4,333	6,603
Indiv. Controls	N	N	N	N
Indiv. Controls (Opponent)	N	N	N	N
Precinct characteristics	N	N	N	N
First letter of the woman's surname	N	N	N	N
Number of candidates	Y	Y	Y	Y
(B)	XLeft	Left	Right	XRight
Woman First	0.163	-0.002	-1.442	-0.060
	(0.432)	(0.537)	(0.567)**	(0.13)
Woman First (Opponent)	0.075	0.483	-0.160	0.312
	(0.325)	(0.381)	(0.374)	(1.03)
R^2	0.40	0.47	0.44	0.40
N	4,438	4,406	4,316	6,569
Indiv. Controls	Y	Y	Y	Y
Indiv. Controls (Opponent)	Y	Y	Y	Y
Precinct characteristics	N	N	N	N
First letter of the woman's surname	N	N	N	N
Number of candidates	Y	Y	Y	Y
(C)	XLeft	Left	Right	XRight
Woman First	0.110	0.042	-1.603	0.042
	(0.444)	(0.543)	(0.574)***	(0.466)
Woman First (Opponent)	0.017	0.470	-0.062	0.217
	(0.330)	(0.372)	(0.375)	(0.306)
R^2	0.43	0.50	0.47	0.42
N	4,438	4,406	4,316	6,569
Indiv. Controls	Inter.	Inter.	Inter.	Inter.
Indiv. Controls (Opponent)	Inter.	Inter.	Inter.	Inter.
Precinct characteristics	N	N	N	N
First letter of the woman's surname	N	N	N	N
Number of candidates	Y	Y	Y	Y
(D)	XLeft	Left	Right	XRight
Woman First	-0.049	0.315	-1.460	0.409
	(0.513)	(0.660)	(0.635)**	(0.504)
Woman First (Opponent)	0.067	0.530	0.087	0.189
	(0.326)	(0.371)	(0.363)	(0.288)
R^2	0.45	0.51	0.51	0.48
N	4,438	4,406	4,316	6,569
Indiv. Controls	Inter.	Inter.	Inter.	Inter.
Indiv. Controls (Opponent)	Inter.	Inter.	Inter.	Inter.
Precinct characteristics	Y	Y	Y	Y
First letter of the woman's surname	Y	Y	Y	Y
Number of candidates	Y	Y	Y	Y

OLS Regressions. Each subsample considers only the candidates who are the only ones of the considered party in the precinct where they run, and compares them to all of their political opponents. The outcome variable is the difference between the share of votes of the considered pair and the share of the considered competing pair. Panel (A) controls only for the number of candidates in the precinct. Panel (B) also controls for age, socioprofessional categories and political experience of man and woman, within the considered pair and the competing pair, as well as for the party of the competing pair. Panel (C) controls for the same variables but interacts the age of man and woman, the socioprofessional categories of man and woman, and the political experience of man and woman within the considered pair and the competing pair. Panel (D) adds to these controls the first letter of the woman's surname in the considered pair, as well as the unemployment rate, the average age of the population, the share of individuals with a graduate degree and the share of voters living in rural areas within the precincts. Standard errors clustered at the precinct level between parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 4.6: Results: Dyadic Specification

ing to between -1.4 and -2 percentage points. To the contrary, we do not find, in any of the specifications, that the treatment status of the considered opponent affects the score of the considered pair.

4.5 Channels

4.5.1 Taste-based or statistical discrimination ?

How can this observed gender discrimination be explained ? On the one hand, voters may be reluctant to vote for women, regardless of their characteristics or quality. We would then talk, in the spirit of Becker (1957), of taste-based discrimination. On the other hand, if the characteristics and quality of candidates are not perfectly observable by the voters, they might apply potentially negative group stereotypes on the female candidate. If that case, we would then talk, following the seminal contributions of Arrow et al. (1973) and Phelps (1972), of statistical discrimination. In this section, in the spirit of Altonji and Pierret (2001), we show evidence pointing towards the presence of statistical discrimination.

It is worth noticing that, in our particular setting, testing properly for the presence of statistical discrimination needs to cope with an additional element: the limited-attention bias from the voters. As we explained above, according to the electoral law, two elected candidates from a same ballot have exactly the same prerogatives once in office: there is no hierarchy between them. In this light, had voters perfectly known this framework, they should not be influenced by the relative position of the two candidates of the ballot.

Testing for statistical discrimination requires a shifter of information that affects the knowledge that the voters have of candidates, while keeping the level of information about the electoral rule constant. To do so, we exploit an additional feature of the electoral rule, that allows candidates to report additional information on the ballot. Importantly, this additional information is only about the candidate herself, and is not informative about the rule of the election[9]. Consequently, it is unlikely to affect the understanding that a voter has about the general rules of the election. Using this information we test whether, conditional on characteristics that we can observe thanks to administrative data but which might not be observed by the voters, discrimination is lower when these information are revealed on the ballot.

It is important to notice that, in the theory of statistical discrimination, individuals have imperfect information about the quality of the persons they face. Contrarily to some settings

9. In Annex, we report two examples of observed ballots, one without any information, and one with additional information about the two candidates

where quality is easily observable (such as transaction data on the housing market, for example Laouénan and Rathelot (2017)) getting a proper measure of the quality of a politician is difficult. Most of the literature on the topic proxied the quality of politicians with their education level (Ferraz and Finan (2009), Besley, Montalvo, and Reynal-Querol (2011), Daniele and Geys (2015) among others), or with the performance of their constituency (Alesina, Troiano, and Cassidy (2015), Daniele and Vertier (2016)). However, recent contributions found new ways of measuring political competence, notably through earnings and IQ score (T. Besley et al. (2017), Dal Bó et al. (2017)). In our study, we do not observe such characteristics, nor the actual performance of previously elected leaders in office: hence the extent to which we can control for the quality of politicians is limited. However, the information we have on candidates embeds part of it, since it includes previous political experience and occupation - which are arguably correlated with their level of education.

In Table 4.1, we show that reporting information matters for electoral results. For sake of brevity, we only present results on the whole sample of ballots that we could manually recover. Here again, we explain the share of votes received in the first round and present different specifications, with an increasing number of controls, and controlling in each of them for the number of candidates in the precinct and the party of the considered pair of candidates. The results presented in this table cannot be interpreted as causal, since the fact of reporting information might be correlated to unobservable characteristics which also matter for electoral success. Nevertheless, it is indicative of the role that information might play in the electoral process.

Overall, we find that, conditional on observed characteristics, the ballots which report at least one type of information for at least one candidate receive between 2.4 and 2.6 points more than their counterparts. This advantage seems to be coming from reported information about political experience: if at least one of the candidates mentions such experience on the ballot, the pair gains between 3 and 3.2 percentage points more. Conversely, if any of the candidates mentions her occupation or prints her picture, they do not seem to have an advantage[10].

In Table 4.2, we show how reported information affects discrimination against right-wing women in the first round of the election. Namely, we evaluate whether displaying information on the ballot affects the discrimination faced by right-wing female candidates. To do so, we interact the treatment variable with a dummy indicating whether any type of information is available on the ballot. In this case, we observe that, for right-wing candidates, discrimination disappears when information is displayed on the ballot: while, on ballots with no information, discrimination seems to be particularly high - with about 5 to 5.8 points less of received votes

10. Note that, because of bunching of information reporting, both by gender and by type of information, disentangling the impact of information by gender and by type is hardly feasible in our setting.

(A) - Full Sample of available ballots	(1)	(2)	(3)	(4)
At least one information	2.655 (0.686)***			
Photo		1.408 (1.000)		
Any information on political experience			3.279 (0.749)***	
Any information on occupation				-0.801 (1.123)
R^2	0.56	0.55	0.56	0.55
N	1,138	1,138	1,138	1,138
Indiv. Controls	Y	Y	Y	Y
Precinct characteristics	N	N	N	N
Number of candidates	Y	Y	Y	Y
(B) - Full Sample of available ballots	(1)	(2)	(3)	(4)
At least one information	2.438 (0.710)***			
Photo		1.297 (1.031)		
Any information on political experience			3.049 (0.789)***	
Any information on occupation				-0.949 (1.166)
R^2	0.58	0.57	0.58	0.57
N	1,138	1,138	1,138	1,138
Indiv. Controls	Inter.	Inter.	Inter.	Inter.
Precinct characteristics	N	N	N	N
Number of candidates	Y	Y	Y	Y
(C) - Full Sample of available ballots	(1)	(2)	(3)	(4)
At least one information	2.509 (0.712)***			
Photo		1.346 (1.059)		
Any information on political experience			3.151 (0.792)***	
Any information on occupation				-0.876 (1.157)
R^2	0.58	0.57	0.58	0.57
N	1,137	1,137	1,137	1,137
Indiv. Controls	Inter.	Inter.	Inter.	Inter.
Precinct characteristics	Y	Y	Y	Y
Number of candidates	Y	Y	Y	Y

OLS Regressions. Each column considers the full sample of candidates for which we could observe a ballot. The outcome variable is the share of votes received by the pair of candidates in the first round of the election. Panel (A) controls for the number of candidates in the precinct, as well as the age, socioprofessional categories and political experience of male and female candidates. Panel (B) controls for the same variables but interacts the age of man and woman, the socioprofessional categories of man and woman, and the political experience of man and woman. Panel (C) adds to these controls the unemployment rate, the average age of the population, the share of individuals with a graduate degree and the share of voters living in rural areas within the precincts. Clustered standard errors at the precinct level in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 4.1: Ballots with reported information gain more votes

Share of votes in the first round	(1)	(2)	(3)	(4)
Woman First	-4.962	-5.737	-5.813	-5.127
	(2.430)**	(1.975)***	(2.029)***	(1.811)***
Any Info. Ballot	-0.064	-2.435	-2.580	-2.846
	(2.068)	(1.782)	(1.899)	(1.733)
Woman First*Any Info. Ballot	5.292	7.521	7.584	6.710
	(2.931)*	(2.649)***	(2.704)***	(2.545)***
R^2	0.18	0.42	0.42	0.54
N	165	165	165	165
Indiv. Controls	N	Y	Inter.	Inter.
Precinct characteristics	N	N	N	Y
Number of candidates	Y	Y	Y	Y

OLS Regressions. Each column considers the restricted sample of right-wing pairs of candidates for which we could observe the ballot. The outcome variable is the share of votes received by the pair of candidates in the first round of the election. Column (1) controls only for the number of candidates in the precinct. Column (2) also controls for the age, socioprofessional categories and political experience of male and female candidates. Column (3) controls for the same variables but interacts the age of man and woman, the socioprofessional categories of man and woman, and the political experience of man and woman. Column (4) adds to these controls the unemployment rate, the average age of the population, the share of individuals with a graduate degree and the share of voters living in rural areas within the precincts. Robust standard errors in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 4.2: Information affects the level of discrimination among right-wing female candidates

when the female candidate is listed first - this effect is totally canceled out when at least one information about the candidates is revealed. This result holds for all the specifications even after controlling for individual and locals characteristics. Therefore, it suggests the presence of statistical discrimination.

Such a finding could be explained by the historically low representation of women among right-wing politicians - since, as the literature on the topic as shown (Beaman et al. (2009), De Paola, Scoppa, and Lombardo (2010)), exposure to women in office increases the probability of voting for them in the future. As a matter of fact, the main right-wing party has often preferred to field male candidates in various types of elections - notably during the parliamentary elections of the decade 2000 which were subject to gender quotas - while other parties were more compliant.

In the following paragraphs, we explore whether alternative explanations are likely to explain our results.

4.5.2 Are incumbents less likely to be discriminated ?

One might worry that the difference of vote shares that we observe when a female is listed first or second only reflect the differences of underlying characteristics existing between them. Let us assume that voters believe that the first candidate is the "main" candidate and that they do not have a preference over the gender of this candidate. If the quality of female candidates is lower than the quality of male candidates and the voters vote based the quality of the presumed "main" candidate, then the observed result might only reflect this underlying difference of quality between male and female candidates.

While we do not observe the quality of the candidates, we do observe a proxy of it: the incumbency status. In Table 4.3, we interact the treatment with the incumbency status of the candidates and show that discrimination is not responsive to it. Panels (A) and (B), we show that the treatment effect does not vary with respect to past political experience of either the female (Panel (A)) or the male candidate (Panel (B)), whatever the stringency of the set of included controls: in all cases, the interaction term is not statistically significant. Thus, unobserved difference of quality between male and female candidates is not likely to drive directly the effect we detect.

4.5.3 Where Did the Missing Votes Go ?

Right-wing pairs of candidates receive less votes when the female candidate is listed first on the ballot. A key question is therefore to understand where these lost votes go. A first hypothesis is that discriminatory voters did not show up on the day of election, leading to a differential abstention. This hypothesis cannot be ruled out, since every voters receive the ballots and electoral programs of all candidates at home. A second hypothesis is that voters who might have voted for the right-wing pair, were the male candidate first, end up casting no ballot at all or invalid ones: in this case, we would expect an increase in blank and invalid ballots. Finally, discriminatory voters might instead cast their ballot for another pair of candidates: in this case, we would expect an increase in the share of votes of the other candidates.

We test these hypotheses in Tables 4.4 and 4.5, focusing on constituencies where only one right-wing candidate ran, and on the treatment status of this candidate. Here again, we present results for different types of specification. The results in Table 4.4 suggest that there exists no differential abstention between the precincts where the female right-wing candidate was listed first and those where she was listed second. This result is somehow reassuring, since it confirms that the decisions leading to a lower share of votes for female-led right-wing candidates were unlikely to be made before the election day. Similarly, we do not find a higher share of blank or null votes in these constituencies. In both cases, this absence of effect holds whatever the specification.

In Table 4.5, we check whether the opponents of the right-wing candidate in these precincts receive a higher share of votes in the first round when the right-wing female candidate is listed first on the ballot. In Panel (A), we regress the score of each competing pair of candidates on

(A)	(1)	(2)	(3)	(4)
Woman First	-2.073	-1.528	-1.395	-1.161
	(0.858)**	(0.805)*	(0.804)*	(0.762)
Previously Elected (W)	5.334	4.175	4.107	3.716
	(0.752)***	(0.744)***	(0.748)***	(0.707)***
Woman First*Previously Elected (W)	0.243	-0.098	-0.309	-0.368
	(1.075)	(1.019)	(1.017)	(0.966)
R^2	0.33	0.40	0.43	0.48
N	1,391	1,389	1,389	1,389
Indiv. Controls	N	Y	Inter.	Inter.
Precinct characteristics	N	N	N	Y
Number of candidates	Y	Y	Y	Y
(B)	(1)	(2)	(3)	(4)
Woman First	-2.435	-2.083	-1.941	-1.835
	(1.135)**	(1.091)*	(1.138)*	(1.063)*
Previously Elected (M)	6.506	4.700	5.036	4.774
	(0.917)***	(0.905)***	(0.928)***	(0.877)***
Woman First*Previously Elected (M)	1.046	0.627	0.451	0.569
	(1.275)	(1.227)	(1.270)	(1.199)
R^2	0.34	0.40	0.43	0.48
N	1,391	1,389	1,389	1,389
Indiv. Controls	N	Y	Inter.	Inter.
Precinct characteristics	N	N	N	Y
Number of candidates	Y	Y	Y	Y

OLS Regressions. Each column considers the restricted sample of right-wing pairs. The outcome variable is the share of votes received by the pair of candidates in the first round of the election. Column (1) controls only for the number of candidates in the precinct. Column (2) also controls for the age, socioprofessional categories and political experience of male and female candidates. Column (3) controls for the same variables but interacts the age of man and woman, the socioprofessional categories of man and woman, and the political experience of man and woman. Column (4) adds to these controls the unemployment rate, the average age of the population, the share of individuals with a graduate degree and the share of voters living in rural areas within the precincts. Panel (A) interacts the treatment with the political experience of the female candidate. Panel (B) interacts the treatment with the political experience of the male candidate. Robust standard errors in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 4.3: Absence of treatment heterogeneity with respect to male and female characteristics on the right-wing ballots

(A) - Abstention Rate	(1)	(2)	(3)	(4)
Right-Wing Woman First	0.002	0.003	0.003	-0.001
	(0.003)	(0.003)	(0.003)	(0.002)
R^2	0.10	0.15	0.21	0.63
N	1,391	1,389	1,389	1,389
Indiv. Controls	N	Y	Inter.	Inter.
Precinct characteristics	N	N	N	Y
Number of candidates	Y	Y	Y	Y
(B) - Blank and Null Votes	(1)	(2)	(3)	(4)
Right-Wing Woman First	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.41	0.45	0.47	0.55
N	1,391	1,389	1,389	1,389
Indiv. Controls	N	Y	Inter.	Inter.
Precinct characteristics	N	N	N	Y
Number of candidates	Y	Y	Y	Y

OLS Regressions. Each column considers the restricted sample of precincts with only one right-wing candidate. In Panel (A), the outcome variable is the abstention rate in the precinct. In Panel (B), the outcome variable is the share of blank and null votes in the precinct. Column (1) controls only for the number of candidates in the precinct. Column (2) also controls for the age, socioprofessional categories and political experience of male and female candidates among the right-wing pair. Column (3) controls for the same variables but interacts the age of man and woman, the socioprofessional categories of man and woman, and the political experience of man and woman within the right-wing pair. Column (4) adds to these controls the unemployment rate, the average age of the population, the share of individuals with a graduate degree and the share of voters living in rural areas within the precincts. Robust standard errors in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 4.4: Abstention, Blank and Null votes do not depend on the treatment status of the right-wing candidate

(A)	(1)	(2)	(3)	(4)
Right-Wing Woman First	0.508	0.360	0.402	0.334
	(0.196)***	(0.187)*	(0.189)**	(0.186)*
R^2	0.44	0.57	0.58	0.58
N	4,333	4,321	4,321	4,321
Indiv. Controls	N	Y	Inter.	Inter.
Precinct characteristics	N	N	N	Y
Number of candidates	Y	Y	Y	Y
(B)	(1)	(2)	(3)	(4)
Right-Wing Woman First	0.383	0.264	0.305	0.221
	(0.327)	(0.293)	(0.294)	(0.292)
Woman First	0.147	0.091	0.080	0.049
	(0.362)	(0.313)	(0.314)	(0.313)
Right-Wing Woman First*Woman First	0.255	0.190	0.193	0.225
	(0.521)	(0.452)	(0.455)	(0.454)
R^2	0.44	0.57	0.58	0.58
N	4,333	4,321	4,321	4,321
Indiv. Controls	N	Y	Inter.	Inter.
Precinct characteristics	N	N	N	Y
Number of candidates	Y	Y	Y	Y

OLS Regressions. Each column considers the opponents of the right-wing pair within the restricted sample of precincts including only one right-wing pair. The outcome variable is the share of votes received by the considered competing pair in the first round of the election. Panel (A) reports the effect, for a political opponent of the right-wing pair, of having a female listed first on the right-wing ballot. Panel (B), interacts this effect with the treatment status of the considered political opponents. Column (1) controls only for the number of candidates in the precinct and the party of the considered competing pair. Column (2) also controls for the age, socioprofessional categories and political experience of male and female candidates within the considered pair. Column (3) controls for the same variables but interacts the age of man and woman, the socioprofessional categories of man and woman, and the political experience of man and woman. Column (4) adds to these controls the unemployment rate, the average age of the population, the share of individuals with a graduate degree and the share of voters living in rural areas within the precincts level in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 4.5: Votes for political opponents of the right-wing pairs

the treatment status of the right-wing pair. Overall, we find that when the right-wing female candidate is listed first on the ballot, the competing pairs receive on average between 0.33 and 0.51 points more. This effect is significant at least at the 10% level across all the specifications. In Panel (B), we propose an indirect test of absence of taste-based discrimination. Namely, for all competing pairs of candidate, we check whether the additional vote shares they receive when the right-wing woman is listed first differ with their own treatment status - i.e. with the position of the female candidate on their own ballot. Our results suggest that while opponents receive more votes when they face a right-wing pair with a female candidate listed first, this advantage does not depend on the position of the woman on their own ballot. This result therefore leads us to argue that the discrimination we identify is unlikely to be taste-based: had it been so, we would have expected opponents to receive less votes if their own female candidate was listed first. In other terms, we would have expected a negative and significant interaction term in the regressions of Panel (B).

Share of votes in the first round	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Woman First	-0.788	-0.690	-1.350	0.022	-0.636	-1.565	-0.902	-0.192
	(0.938)	(5.839)	(1.309)	(2.574)	(0.942)	(5.771)	(1.261)	(2.522)
Unemployment Rate	-38.170				-40.522			
	(4.618)***				(4.734)***			
Woman First*Unemployment Rate	-4.374				-5.134			
	(6.293)				(6.301)			
Mean Age		0.278				0.345		
		(0.084)***				(0.085)***		
Woman First*Mean Age		-0.013				0.008		
		(0.120)				(0.119)		
Share Graduate			3.769				2.082	
			(3.522)				(3.560)	
Woman First*Share Graduate			-0.019				-1.269	
			(4.888)				(4.753)	
Unexplained Wage Gap				-0.422				-0.393
				(0.185)**				(0.182)**
Woman First*Unexplained Wage Gap				0.153				0.109
				(0.271)				(0.267)
R^2	0.31	0.30	0.29	0.29	0.31	0.31	0.31	0.31
N	25,964	25,966	25,966	25,966	25,964	25,964	25,964	25,964
Indiv. Controls	Inter.	Inter.	Inter.	Inter.	Inter.	Inter.	Inter.	Inter.
Municipality characteristics	N	N	N	N	Y	Y	Y	Y
Number of candidates	Y	Y	Y	Y	Y	Y	Y	Y

OLS Regressions at the municipality level. Each column considers the restricted sample of right-wing pairs of candidates for which we could observe the ballot. The outcome variable is the share of votes received by the pair of candidates in the first round of the election. Columns (1) to (4) control for the number of candidates in the precinct, the interacted age of the man and woman, the interacted socioprofessional categories of the man and woman, and the interacted political experience of the man and woman. Columns (5) to (8) adds to these controls the unemployment rate, the average age of the population, the share of individuals with a graduate degree within the municipality and a dummy variable indicating whether this municipality is located in a rural area. Standard errors clustered at the precinct level in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 4.6: Heterogeneity with respect to local characteristics

4.5.4 Variation across precinct characteristics

In this section, we test whether discrimination with local characteristics of the precinct. Namely, we test whether the treatment effect that we find varies with respect to the level of education of the population (measured through the share of people above 15 holding a graduate degree), the unemployment rate among the population aged between 15 and 64, and the average age of the population. Finally, we relate our observed treatment effect to discrimination against women on the labor market. To do so, we build on data released by Chamkhi (2015), reporting unexplained wage gaps between men and women in 321 French employment zones in 2010. These unexplained wage gaps are computed from a Oaxaca-Blinder decomposition, controlling for a wide range of explanatory factors. We then interact this measure of discrimination with the treatment variable. In this section, we use municipality-level data for two reasons. First, the characteristics of local population and the vote shares are available at the municipality level. Secondly, because the precincts and the employment zones overlap, it is preferable to study the relationship between the electoral and job-market discrimination at the municipality level[11].

We present the results of these interactions in Tables 4.6, 4.7 and 4.8. In Table 4.6, we in-

11. Note that all the previous results also hold at the municipality level.

Share of votes in the first round	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Woman First	-1.244	-1.278	-1.371	-1.008	-1.155	-1.187	-1.163	-0.870
	(0.595)**	(0.576)**	(0.618)**	(0.624)	(0.595)*	(0.559)**	(0.599)*	(0.607)
Top Decile Unemployment	-3.329				-3.307			
	(0.588)***				(0.597)***			
Woman First*Top Decile Unemployment	-0.546				-0.651			
	(0.770)				(0.772)			
Top Decile Mean Age		2.476				2.734		
		(0.810)***				(0.805)***		
Woman First*Top Decile Unemployment		-0.606				-0.282		
		(1.145)				(1.141)		
Top Decile Share Graduate			1.288				1.086	
			(0.612)**				(0.614)*	
Woman First*Top Decile Share Graduate			0.135				-0.050	
			(0.890)				(0.875)	
Top Decile Unexplained Wage Gap				2.937				2.768
				(1.178)**				(1.162)**
Woman First*Top Decile Unexplained Wage Gap				-3.237				-2.736
				(1.521)**				(1.495)*
R^2	0.30	0.29	0.29	0.29	0.30	0.31	0.31	0.31
N	25,966	25,966	25,966	25,966	25,966	25,964	25,964	25,964
Indiv. Controls	Inter.	Inter.	Inter.	Inter.	Inter.	Inter.	Inter.	Inter.
Municipality characteristics	N	N	N	N	Y	Y	Y	Y
Number of candidates	Y	Y	Y	Y	Y	Y	Y	Y

OLS Regressions at the municipality level. Each column considers the restricted sample of right-wing pairs of candidates for which we could observe the ballot. The outcome variable is the share of votes received by the pair of candidates in the first round of the election. Columns (1) to (4) control for the number of candidates in the precinct, the interacted age of the man and woman, the interacted socioprofessional categories of the man and woman, and the interacted political experience of the man and woman. Columns (5) to (8) adds to these controls the unemployment rate, the average age of the population, the share of individuals with a graduate degree within the municipality and a dummy variable indicating whether this municipality is located in a rural area. Standard errors clustered at the precinct level in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 4.7: Heterogeneity with respect to local characteristics

Share of votes in the first round	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Woman First	-1.411	-1.321	-1.401	-1.477	-1.340	-1.185	-1.233	-1.305
	(0.569)**	(0.606)**	(0.581)**	(0.630)**	(0.571)**	(0.591)**	(0.566)**	(0.614)**
Bottom Decile Unemployment	3.670				3.349			
	(0.568)***				(0.557)***			
Woman First*Bottom Decile Unemployment	0.638				0.645			
	(0.860)				(0.867)			
Bottom Decile Mean Age		-0.567				-0.727		
		(0.581)				(0.573)		
Woman First*Bottom Decile Mean Age		-0.461				-0.634		
		(0.825)				(0.813)		
Bottom Decile Share Graduate			0.717				1.011	
			(0.744)				(0.717)	
Woman First*Bottom Decile Share Graduate			0.247				0.427	
			(0.969)				(0.926)	
Bottom Decile Unexplained Wage Gap				-0.876				-0.816
				(0.931)				(0.909)
Woman First*Bottom Decile Unexplained Wage Gap				0.853				1.098
				(1.595)				(1.551)
R^2	0.30	0.29	0.29	0.29	0.30	0.31	0.31	0.31
N	25,966	25,966	25,966	25,966	25,966	25,964	25,964	25,964
Indiv. Controls	Inter.	Inter.	Inter.	Inter.	Inter.	Inter.	Inter.	Inter.
Municipality characteristics	N	N	N	N	Y	Y	Y	Y
Number of candidates	Y	Y	Y	Y	Y	Y	Y	Y

OLS Regressions at the municipality level. Each column considers the restricted sample of right-wing pairs of candidates for which we could observe the ballot. The outcome variable is the share of votes received by the pair of candidates in the first round of the election. Columns (1) to (4) control for the number of candidates in the precinct, the interacted age of the man and woman, the interacted socioprofessional categories of the man and woman, and the interacted political experience of the man and woman. Columns (5) to (8) adds to these controls the unemployment rate, the average age of the population, the share of individuals with a graduate degree within the municipality and a dummy variable indicating whether this municipality is located in a rural area. Standard errors clustered at the precinct level in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 4.8: Heterogeneity with respect to local characteristics

teract the treatment variable directly with the different local characteristics of interest. For sake of brevity, we present only the results from the two most stringent specifications. For all the variables considered, we detect no interaction effect. However, one might worry that this absence of result comes from non-linear interactions. Therefore, in Tables 4.7 and 4.8, we present interactions with respect to the top and bottom deciles of each of the considered local characteristic variable.

Overall, we find no interaction effect with the top and bottom deciles of age, education and unemployment. However, we do find that discrimination is greater in areas belonging to the top decile of unexplained wage gap on the labor market. In particular, we find that in these areas, the discriminatory effect is greater by 2.7 to 3.2 percentage points, depending on the specification.

These results call for two comments. First the absence of interaction with the characteristics of the population in the precinct might reflect an aggregation effect, coming from the fact that different types of population might be subject to limited attention and discriminatory behaviors[12]. Secondly, the fact that gender discrimination in politics and on the labor market are linked suggests that policies aiming at reducing discrimination should tackle those different aspects simultaneously.

4.6 Conclusion

Among the numerous reasons which might explain why women are under-represented in politics, gender-bias of voters is frequently considered as a potential candidate. While several pieces of research argue that gender-biases are unlikely to play a role, isolating such effects using actual electoral data can prove complicated, due to the presence of selection effects.

In this paper, we isolate gender-biases from selection effects using a natural experiment in France. Using the fact that the candidates of the *Départementales* elections of 2015 had to run for the first time by gender-balanced pairs, and considering that the order of the candidates on the ballot is determined by alphabetical order, we show that the gender of the first candidate on the ballot is as good-as-random. This framework therefore allows us to disentangle cleanly selection effects and gender-biases, since we compare pairs of candidates which are on average similar, but which differ only in the order of male and female candidates on the ballot.

12. In fact, identifying the respective roles of these two effects among different categories of population cannot be done with aggregate administrative data, and calls for field or laboratory experiments which we reserve for future research.

We detect a sizable gender-bias affecting right-wing female candidates, due to voters who arguably were simultaneously subject to limited attention concerning the rules of the election and to discriminatory behaviors. Overall, the right-wing pairs where the female candidate was listed first on the ballot saw their relative score in the first round decrease by about 1.5 percentage points, and their probability of going to the second round or of winning the election in the first round decreasing by 4 percentage points. Furthermore, we provide evidence that this discrimination is rather statistical than taste-based.

Such results call for several important comments. First and foremost, while we find evidence of gender-biases against right-wing candidates, the absence of evidence concerning the candidates of other parties does not necessarily imply that they are not also affected by gender biases. Indeed, not detecting evidence of discrimination for other parties can be either explained by the fact that the voters are less subject to limited attention or that they discriminate less.

Secondly, since limited attention seems to be at the heart of our result, it is crucial to understand what are its determinants. Indeed, as acknowledged by DellaVigna (2009), understanding limited attention requires to know the cost of acquiring relevant information about the decision which is made - in our case, about the electoral rule. While setting prevents us from investigating this matter further, such findings raise important questions about how the electoral rules and the governmental action are perceived by the citizens.

Thirdly, since the information available on the ballot on the day of election seems to affect both the overall electoral performances of the candidates and the discrimination that women face, a broader consideration should be paid about to the design of electoral ballots.

Finally, since we find greater electoral discrimination in places where discrimination against women on the labor market is higher, gender discrimination among voters in politics is unlikely to be reduced without other coordinated policies.

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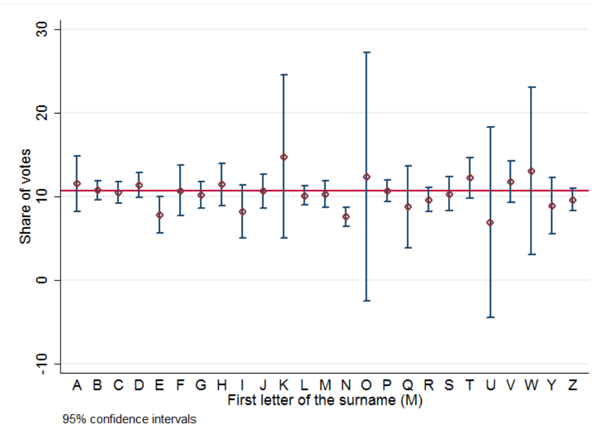
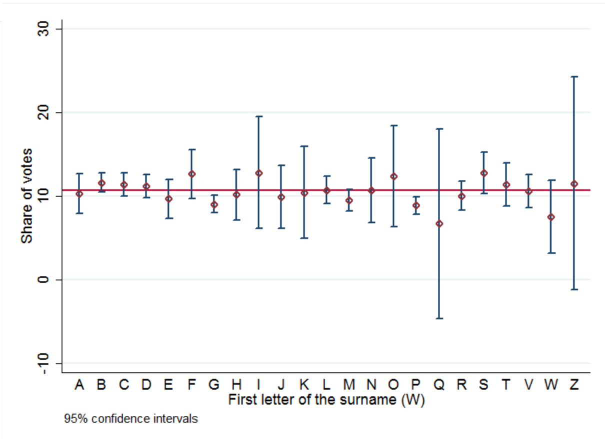
Appendix

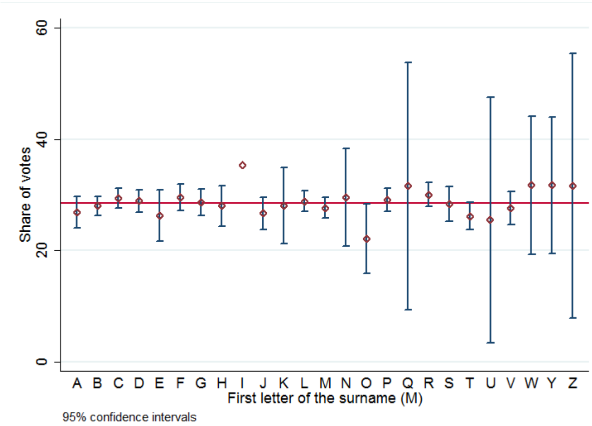
4.A Distribution of vote shares in each subsample, across first letter of surnames



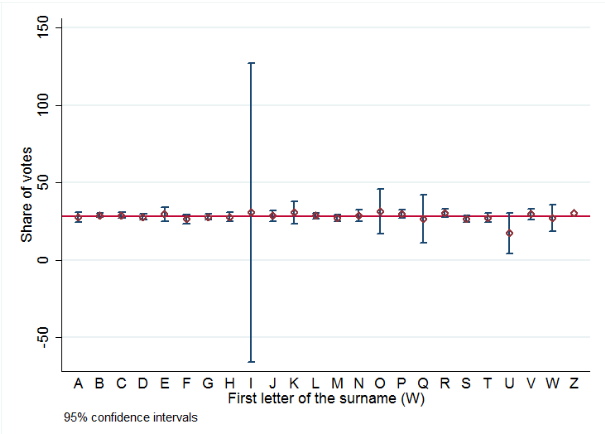
(a) Extreme Left, First letter of the man's surname



(b) Extreme Left, First letter of the woman's surname

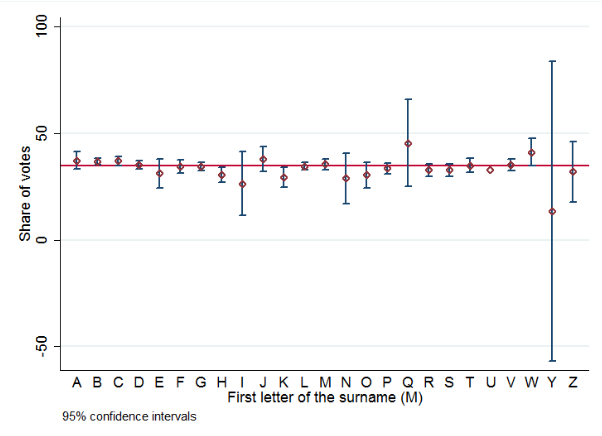


(c) Left, First letter of the man's surname

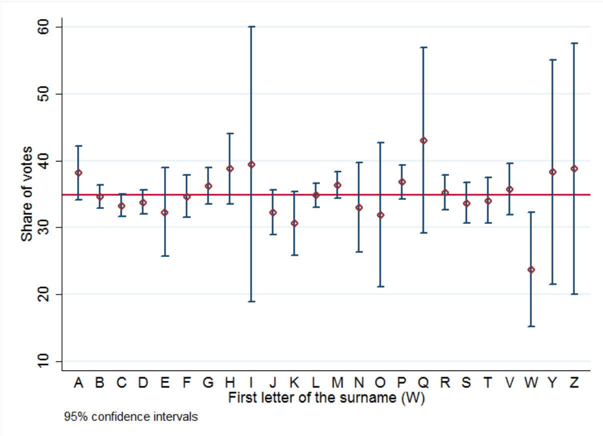


(d) Left, First letter of the man's surname

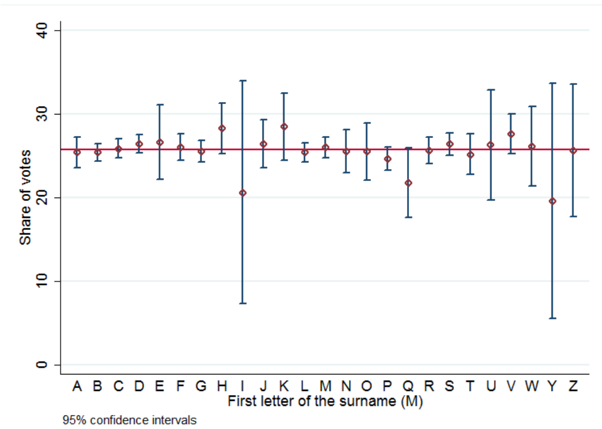
Figure 4.A.1: Distribution of vote shares in the first round across first letter of candidates' surname (Restricted samples, Extreme-Left and Left)



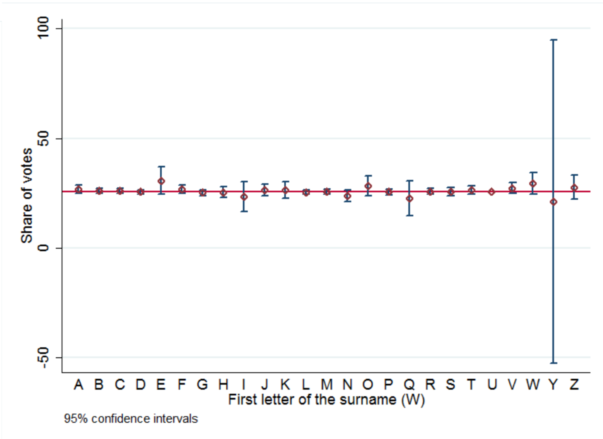
(a) Right, First letter of the man's surname



(b) Right, First letter of the woman's surname



(c) Extreme Right, First letter of the man's surname



(d) Extreme Right, First letter of the woman's surname

Figure 4.A.3: Distribution of vote shares in the first round across first letter of candidates' surname (Restricted samples, Right and Extreme-Right)

Chapter 5

Conclusion and research agenda

This dissertation had two objectives: improving the understanding of the French housing market and bringing new innovative methods to study economic issues. It focused on two subfields, namely urban economics and economic of discrimination, where getting data is particularly challenging. Having access to reliable data is a necessary prior step before investigating the role of the State, evaluating public policy or recommending policies. All the chapters focused on a precise empirical question, while it brings some answers, it raises numerous questions.

The first chapter investigated the determinants of local housing supply elasticities. It distinguishes between short run elasticities which reflect the reaction of the construction sectors from long run elasticities which describe the balances between agglomeration forces. Local geography turns out to be the main driver of short run elasticities while local regulation plays a crucial role in the long run. Studying the determinants of local housing regulations defines an interesting agenda particularly in France where mayors directly issue housing permits.

The second chapter investigated the extent to which Internet data can be used to describe the French rental market. Studying a database built on millions of online housing posts available on the two largest French rental websites, it shows that rental posts provide a right measure of local rental market. This rental data available at very small scale offers a lot of research opportunities. Among them, the issue of the spatial mismatch between jobs and housing units which needs to be tackle from the rental market point of view or the question of the efficiency of the rent control which was in place between 2014 and 2017 in the Parisian area.

The last chapter used a natural experiment to study gender discrimination in politics. It uses the 2015 departmental elections where, for the first time, candidates had to run by gender-balanced pairs. Exploiting the fact that the order of appearance of the names of the candidates on the electoral ballot was determined by alphabetical order – thus making the gender position on the ballot a random variable – it shows that right-wing candidates' ballots whose first candidate was a female received less votes than their counterparts where the male was in first position. The level of discrimination tends to decrease when candidates display information on their ballot making the discrimination rather statistical than tasted-based. This leaves room for public policies and the 2021 departmental elections will be interesting to study to compare the evolution of local gender discrimination.

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