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Abstract

This study gathered original data on French metropolitan statistical areas to estimate and decompose their inverse housing supply elasticity, describing how housing prices react to demand shocks. Our findings confirm that French cities are highly inelastic, with an estimated average supply elasticity of 0.5. Furthermore, leveraging a nationwide regulation protecting historical monuments as an instrument, we found that land-use regulations controlled by local authorities appear to be mainly responsible for this low supply elasticity.

JEL Codes – R31, R52, R21
Keywords – housing supply, land use regulation, real estate, urban growth

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1 Introduction

Understanding local housing supply elasticity is crucial for assessing the effectiveness of housing policies. Housing supply elasticity refers to the speed of adjustment of a housing stock when facing an increase in housing prices. If the housing supply is inelastic, demand shocks will be absorbed through an increase in prices instead of an adjustment of stocks. Alternatively, inverse housing supply elasticity is frequently defined as the elasticity of housing prices with respect to an increase in housing construction or population. In France, several studies have documented a systematic increase in housing prices following expansionary public policies, such as rent subsidies (Fack 2006), subsidized loans (Labonne and Welter-Nicol 2015) or tax credits to enhance construction (Bono and Trannoy 2019). Consequently, these national policies, which focus on relieving the affordability crisis for low-income households, might instead make it worse. Therefore, determining the drivers of local housing supply elasticity is key to understanding the effectiveness of housing policies.

Two drivers were identified in the seminal contribution of Saiz (2010). First, he highlighted the predominance of geographical constraints (materialized by steep slopes and flooded areas) as the main factor in supply inelasticity in the United States (US). Second, he stressed that land-use regulations have a significant yet marginal impact on housing supply elasticity in the US. The relative importance of these two drivers remains debated in the literature. Meanwhile, Hilber and Vermeulen (2016) and Büchler et al. (2021) drew attention to the significant influence of regulations on housing supply constraints in the United Kingdom (UK) and Switzerland. Following this literature, we empirically studied the relative importance of regulatory and geographical constraints for housing supply elasticity in France.

First, we built an original dataset describing the evolution of the real estate market in French metropolitan statistical areas (MSAs) from 2000 to 2018. We show the strong heterogeneity of local French land-use regulations proxied by the refusal rate of building permits, which ranges from 6% to 46%, with an average of 15%. This heterogeneity reflects the French regulatory context, where decisions on housing construction are decentralized and made at the municipal level, leaving strong discretionary power to mayors (Lévêque 2020). We complemented this evaluation of regulations with nationwide rules, such as the Historical Monuments Law (*Loi sur les Monuments Historiques*). In addition, following Saiz (2010), we developed geographical land constraint measures for French MSAs using geographic information system methods. We provide evidence that French MSAs are poorly geographically constrained, since 50% of urban areas have a share of undevelopable land below 5% (4% for the hundred largest). By comparison, the equivalent figure is 20% for the 95 largest MSAs in the US.

Second, we used two approaches to identify the functions of local housing supply elasticity. On one hand, urban growth could be endogenous to housing prices because of a simultaneity bias generated by the co-movements of the housing supply and demand curves, as underlined by Gorback and Keys (2020). To circumvent this issue, we relied on two exogenous demand shocks based on natural amenities (hours of sunlight) and labor market shocks. Labor market shocks were modeled as a shift-share instrument following the seminal contribution of Bartik (1992) and its recent developments (Goldsmith-Pinkham et al. 2020). In this approach, city growth is predicted using local sectoral labor specialization combined with national trends. The rationale for these two instruments is their strong correlation with housing demand (good weather and high local potential employment both attract inhabitants) and lack of direct impact on the production of dwellings.

On the other hand, there could be a reverse causality bias. As emphasized by Fischel (2001) and Hilber and Robert-Nicoud (2013), local homeowners have strong incentives to protect the value of their housing wealth, especially where housing prices are initially high, by pressuring local authorities to implement stringent land-use regulations. To overcome this issue, we provide a novel identification strategy by instrumenting the building permit refusal rate with a nationwide regulation. The *Loi sur les Monuments Historiques* requires additional administrative approval for building permits within a radius of 500 meters around historical monuments. We provide compelling evidence that this law, viewed at the national level, influences the local refusal rate of building permits while remaining orthogonal to the specific dynamics of cities, such as housing prices and population growth. In addition, as a robustness check we use another instrument in the largest urban areas, the *Loi Solidarité et Renouvellement Urbain* (SRU) which imposes mandatory social housing quotas. While relying on different samples and sources of variation, both instruments yield similar results.

In a nutshell, our key finding is that France and its urban areas are much more inelastic than their US counterparts and that this inelasticity is caused by stringent land-use regulations defined at the local authority level. French urban areas have, on average, a population-weighted housing supply elasticity of around 0.5, meaning that when prices increase by 1%, population or housing builds increase only by 0.5%. Saiz (2010) found that the average elasticity of US MSAs is more than three times larger (around 1.75). The average French inelasticity hides a large heterogeneity of local housing supply elasticities: among the 30 largest urban areas, Nice has an elasticity of 0.3, combining both regulatory and geographical constraints, while Nantes has an elasticity of 0.8. Our results demonstrate that land-use regulation is the key factor in the contemporary urban development of France. Upon decomposing the variance in supply elasticity between urban areas, we found that 60% of the variance is explained by regulatory constraints, while only 30% stems from geographical constraints.

Since French land-use regulations are mostly established at the municipal level, our results call for further research to understand mayors' heterogeneous decisions. As an illustration, Lévêque (2020) observed that mayors exhibit a tendency to prioritize their relatives during periods of low political competition, while Schmutz and Verdugo (2023) demonstrated that left-leaning mayors are more likely to support the construction of social housing. Additionally, our work raises an essential political and economic question: how should nationwide housing policies be coordinated and their efficiencies improved when land-use regulations are determined at the local authority level ?

The remainder of the paper is organized as follows. Section 2 presents the background and the current state of our knowledge on housing supply elasticity, including the role of land-use regulations. Section 3 presents a simplified version of the theoretical framework proposed by Saiz (2010) and our own econometric framework. Section 4 introduces the data utilized in this paper. Section 5 presents the main results, while Section 6 concludes the paper.

2 Background and literature review

2.1 Housing supply elasticity heterogeneity

Over the past few decades, several studies have documented broad heterogeneity in the magnitude of housing supply elasticity between countries. For example, Malpezzi and Maclennan (2001) compared housing supply elasticity in the United Kingdom and the United States, finding that the housing supply is fairly elastic in the US (between 1 and 4) but inelastic in the UK (between 0 and 1). More recent works, such as Caldera and Johansson (2013) and Cavalleri et al. (2019), extended this approach to most countries belonging to the Organisation for the Economic Cooperation and Development (OECD) and confirmed the large heterogeneity in housing supply elasticity.

This heterogeneity also appears when comparing cities within the same country, as documented in Green et al. (2005); Saiz (2010); Ihlanfeldt and Mayock (2014); Wheaton et al. (2014); Gorback and Keys (2020); Aastveit et al. (2020), who estimated the housing supply elasticity for several MSAs in the United States. More recently, Baum-Snow and Han (2019) for the US and Büchler et al. (2021) for Switzerland documented a large heterogeneity between neighborhoods or municipalities. As demonstrated by Bétin and Ziemann (2019), there is a clear connection between these different levels of aggregation, nationwide estimates of housing supply elasticity are correlated with the average supply elasticity of the largest MSAs. By providing estimates of housing supply elasticity for French urban areas, we contribute to documenting their large heterogeneity. Furthermore, we contribute to bridging macroeconomic and urban literature by showing that the order of magnitude of the differences between long-term macroeconomic supply elasticities is similar to those based on MSA-level estimates.

2.2 Drivers of housing supply elasticity

While there is a substantial literature on the large heterogeneity in the housing supply, the sources of this heterogeneity remain a dynamic subject of investigation. In a seminal contribution, Saiz (2010) argued that geographical and topological constraints, such as the presence of flooded areas and steep slopes, might generate large barriers that are responsible for a large part of the variation in housing supply elasticity in US cities. This finding was confirmed by Cosman et al. (2018), who showed that these constraints are even more important when located on the fringes of cities.

Another strand of the literature stresses that when the share of already artificialized land is high, the housing supply might be more inelastic. Indeed, already developed land is a hindrance to urban sprawl. Saiz (2010) and Liu (2018) highlighted the importance of urban sprawl at the MSA level. This important mechanism is not accounted for when measuring at lower levels of aggregation, such as zip codes (Baum-Snow and Han 2019; Gorback and Keys 2020), since at these levels, the land available for development is limited. Hence, Baum-Snow and Han (2019) found that the share of land already developed plays a significant role.
Finally, the regulation of the real estate market and land use might also be key drivers of this heterogeneity. For example, Green et al. (2005) showed that less elastic cities are often denser and more regulated than others. More recently, studies have provided more causal estimates of the impact of land-use regulation on supply elasticity. While Saiz (2010) attributed a limited role to land-use regulation in the US, Hilber and Vermeulen (2016) showed that regulation is likely mostly responsible for the inelastic supply in the United Kingdom. However, Hilber and Vermeulen (2016) did not look at housing supply elasticity per se but at house price-earnings elasticity, and their methods are not comparable to those of Saiz (2010). Equivalently, Büchler et al. (2021) also document the key role of both constraints for Swiss municipalities.

We contribute to this literature by leveraging the specificity of land-use regulation in France. Using a method and data similar to that of Saiz (2010) and considering the French case, we provide estimates of housing supply elasticity and document the effect of regulation on the French housing market. Overall, our findings support the conclusion of Hilber and Vermeulen (2016), and confirm the intuition in Cavalleri et al. (2019) and Bétin and Ziemann (2019) that land-use regulation explains why several European countries are more inelastic than the US. We found that geographical constraints play a significant but more limited role in France. This could be explained by the fact that most large French cities are located away from the shore in relatively plain areas. In line with Hilber and Vermeulen (2016), city size, density and the share of land developed also play a significant role in our explanation of the supply elasticity of large French cities.

2.3 Land-use regulation and real estate market dynamics

Land-use regulation in France is known for its strict framework, which comprises European (such as Nature 2000 areas), national (such as protections of historical monuments, SRU and littoral law) and local rules. These rules are usually summarized in a zoning plan, which is defined for each (or most) of the 36,000 French municipalities. In the absence of a zoning plan (i.e., a *Plan d'Occupation des Sols*), municipalities are subject to the *Règlement National d'Urbanisme* (RNU), which limits new development projects to already urbanized areas. Since 1983, municipalities have had the power to approve or reject all new construction projects that require formal approval, even under the RNU, and it has been shown that mayors and the municipal majority have significant discretionary power in this process, especially when political competition is low (Lévêque 2020).

This study contributes to the growing literature on the impact of land-use regulation in the specific context of France. The impact of land-use regulation on real estate market dynamics has been extensively studied (Glaeser et al. 2005; Ihlanfeldt 2007; Glaeser and Ward 2009; Saiz 2010; Ihlanfeldt and Mayock 2014; Turner et al. 2014; Hilber and Vermeulen 2016; Brueckner et al. 2017; Severen and Plantinga 2018; Gyourko and Krimmel 2021). The key challenge in identifying the impact of land-use regulation is to deal with the reverse causality bias, as property owners may implement land-use regulations to protect the value of their dwellings, as underlined by Fischel (2001) and Hilber and Vermeulen (2016). With our instrumental variable approach, we document the impact of land-use regulation on housing supply elasticity and contribute to the understanding of the role of local authorities in construction dynamics (Solé-Ollé and Viladecans-Marsal 2012 2013; Lévêque 2020; Tricaud 2021).

3 Theoretical and Empirical framework

3.1 The inverse supply elasticity of housing

To define the housing supply elasticity, we rely on a simplified version[1] of the framework exposed in Saiz (2010) and summarized in Liu (2018). In this setting, we consider a city k with a population Pop_k.

Households: In this city, neglecting the index k, homogeneous households consume an amenity A and a private good C and have the following utility where $\rho \in (0, 1)$:

$$u(c, A) = (C + A)^{\rho} \tag{1}$$

Households earn a wage w that is fully spent in the private good, housing and transport.

$$w = C + \lambda \times r' + t \times d \tag{2}$$

For the sake of simplicity, the model assumes that all households consume the same amount of housing λ, while r' is the unit rent of housing which will be given by the urban equilibrium. The model is a standard monocentric model where all jobs are located in the City Business District (CBD). Homogenous households are differentiated by the distance travelled to the CBD and thus face a linear transport cost $t \times d$ (where t is the monetary cost per distance commuted and d the distance

[1] The main difference is that we consider a linear city instead of a circular city as in Saiz (2010).

of the consumer's residence to the CBD). In the urban equilibrium, all households have the same utility [2] $\bar{u}$ that is normalized to zero. We get:

$$A - \lambda \times r' + w - t \times d = 0 \tag{3}$$

From this equilibrium condition, we can derive the bid rent function depicting the relationship between the rent and the distance to the CBD :

$$r(d) = \lambda \times r' = A + w - t \times d = r_0 - t \times d \tag{4}$$

where $r_0 = A + w$

Developers: Developers are price takers, and buy an amount of land L at price p_L which depends on the distance to CBD d. They build L^β dwellings at a unit cost cc, and sell housing space at a unit price P. They thus maximize the following profit function:

$$\Pi = P(d) \times L^\beta - cc \times L^\beta - p_L(d) \times L \tag{5}$$

The developer's first order condition is:

$$\frac{\partial \Pi}{\partial L} = \beta(P(d) - cc)L^{(\beta-1)} - p_L(d) = 0 \tag{6}$$

$$p_L(d) = \frac{\beta(P(d) - cc)L^\beta}{L} \tag{7}$$

Using the market clearing condition between housing supply and demand on the real estate market, the equilibrium quantity of housing Q, is given by:

$$Q = L^\beta = \lambda Pop \tag{8}$$

We can express the price of dwellings as a function of construction costs and land price:

$$P(d) = cc + \frac{p_L(d) \times L}{\beta \times Q} \tag{9}$$

Considering that the price of a dwelling is the actualized value of rent in the asset market steady state equilibrium if there is no uncertainty, we can rewrite this function as:

$$P(d) = \frac{r(d)}{i} = cc + \frac{p_L(d) \times L}{\beta \times Q} = \frac{r_0 - t \times d}{i} \tag{10}$$

Definition of the inverse supply elasticity: As in Saiz (2010), we assume that households consume a fixed amount of land $\lambda = 1$. We suppose that households live on a straight line, the line starts in the CBD ($d = 0$) and ends when $d = Pop = Q$[3]. At the fringe, the land price is assumed to be equal to the agricultural land price

[2] Following the conventional Alonso-Muth-Mills models as in Brueckner (1990), all inhabitants reach the same level of utility through competition in the land markets.

[3] We posit that each individual lives in a separate house which leads to the number of housing units being equal to the population $Pop = Q$.

p_A that we normalize to 0 (i.e. when $d = Pop$, $p_L(Pop) = 0$). Using Equation (10) with $d = Pop$, the rent in the city center can be expressed as follows:

$$r_0 = i \times cc + t \times Pop = i \times cc + t \times Q \tag{11}$$

and the price in the center is simply:

$$P(0) = cc + \frac{t \times Q}{i} \tag{12}$$

The average price in the city is equivalent to the price at the average distance from the city border i.e. when $d = \frac{Q}{2}$. From Equations (10) and (11) with $d = \frac{Q}{2}$, we can express the average price of dwellings $\tilde{P^S}$, in other words, the housing supply equation, as a function of the city size (expressed as population Pop or housing stock Q):

$$\tilde{P^S} = cc + \frac{t \times Q}{2i} \tag{13}$$

The inverse supply elasticity, β^S describes how the average price reacts to an exogenous growth of population or housing stock driven by a demand shock and is defined as follows[4]:

$$\beta^S = \frac{\partial \tilde{P^S}}{\partial Q} \times \frac{Q}{\tilde{P^S}} = \frac{t \times Q}{2i \times \tilde{P^S}} \tag{14}$$

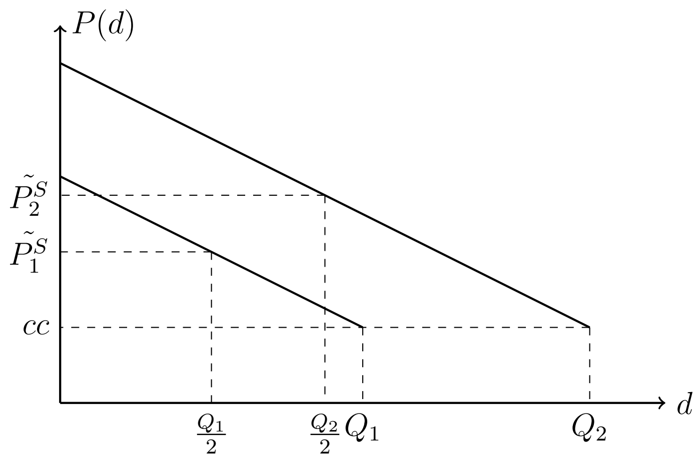


Figure 1: City growth in the monocentric model

The inverse housing supply elasticity describes how a monocentric city reacts to a growth in its population (or housing stock) i.e. when the city fringe is moving from Q_1 to Q_2. In Figure 1, we represent the negative relationship between

[4] We start from Equation (13), take the log on both sides and differentiate w.r.t $ln(Q)$, which leads to:

$$\beta^S = \frac{\partial \tilde{P^S}}{\partial Q} \times \frac{Q}{\tilde{P^S}} = \frac{\partial ln(\tilde{P^S})}{\partial ln(Q)} = \frac{\partial ln(cc + \frac{t \times e^{ln(Q)}}{2i})}{\partial ln(Q)} = \frac{\frac{t \times e^{ln(Q)}}{2i}}{cc + \frac{t \times e^{ln(Q)}}{2i}} = \frac{t \times Q}{2i \times \tilde{P^S}}$$

housing price and distance from the CBD (cf. Equation (10)). As the total population grows (from Q_1 to Q_2), the average price in the city increases (from $\tilde{P_1^S}$ to $\tilde{P_2^S}$). The magnitude of this increase depends on the curve's slope in Figure 1, i.e. of β^S.

Several comments arise from Equation (14). First, one key parameter of the housing supply elasticity is the transport cost. A growth in the transport cost will turn the housing supply less elastic (respectively the inverse housing supply more elastic) as $\frac{\partial \beta^S}{\partial t} > 0$. Second, large cities (high Q or Pop) are more inelastic since $\frac{\partial \beta^S}{\partial Q} > 0$. In addition, as Combes et al. (2019) underlined, larger cities face higher congestion costs such as traffic jams (i.e. Pop is positively correlated with t) which reinforce their housing supply inelasticities.

This framework was extended in two ways. First, Saiz (2010) assumed that the city is circular and highlighted the role of the land available around the CBD: a coastal city which have less land available would be more inelastic. This would change the position of the average price level, and land availability would increase as one goes further from the CBD. In a circular city, the definition of the inverse housing supply elasticity would become:

$$\beta^S = \frac{\frac{1}{2} \times t \times \left(\frac{1}{\pi}\right)^{\frac{1}{2}} \times \Gamma^{-\frac{1}{2}} \times Q^{\frac{1}{2}}}{3i\tilde{P}} \tag{15}$$

where Γ is the share of land available around the CBD. This share is key for US cities, Saiz (2010) demonstrated that US cities supply elasticities are positively correlated with land availability.

Second, Liu (2018) relaxed the assumption of a homogeneous consumption of housing by allowing floor space to enter into the utility function. The author showed that, when the production of dwellings is measured with floor space instead of the number of dwellings, the resulting elasticity (resp. inverse) will be higher (resp. lower).

3.2 Econometric Framework

We followed Saiz (2010) and began with Equation (13) to estimate the supply elasticity. Taking logs and totally differentiating, we got the following:

$$dln(\tilde{P}_k) = \sigma dln(cc_k) + \beta^S dln(Q_k) \tag{16}$$

where σ is the share of housing construction costs, while β^s is the inverse housing supply elasticity. From this definition, we can derive two empirical counterparts to be estimated from the data. First, the average housing supply elasticity for all cities can be estimated using the following equation:

$$\Delta ln(\tilde{P}_k) = \alpha + \beta^s \times \Delta ln(Q_k) + \sigma \Delta ln(cc_k) + \epsilon_k \tag{17}$$

where α is a constant and ϵ_k an error term[5]. Some factors, such as the share of land available as well as transport costs and land-use regulations, can influence the magnitude of housing supply elasticity. To document this, the following model can be estimated:

$$\Delta ln(\tilde{P}_k) = \alpha + [\beta^{Land} \times (1 - \Gamma_k) + \beta^{Reg} \times LUR_k] \times \Delta ln(Q_k) + \sigma \Delta ln(cc_k) + \epsilon_k \quad (18)$$

where Γ_k measures the share of land available around the CBD and LUR_k is the degree of land-use regulation.

3.3 Identification Issues

The empirical calculations of Equations (17) and (18) raise two main econometric challenges.

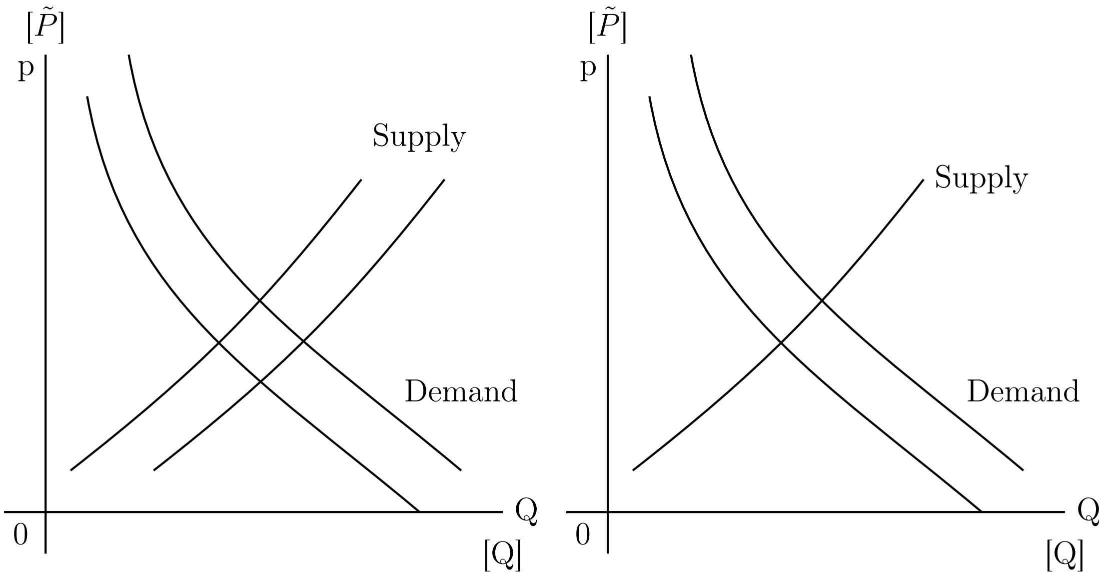
1. The simultaneity bias: To identify supply elasticity, it is necessary to address the issue of simultaneity bias. In other words, the raw variations in price and quantity could arise from the simultaneous movement of the supply and demand curves caused by a wide variety of shocks (Gorback and Keys 2020; Garcia-López et al. 2015). As a result, a simple regression of housing quantity variation on price variation will be biased toward zero because the displacement of the supply and demand curves may eliminate the correlation between price and quantity. This situation is illustrated in Panel a of Figure 2.

To address this issue, we used exogenous demand shocks generated by instrumental variables. Various types of shocks can be used for this purpose. Saiz (2010) used demand shocks originating from the labor market, building shift-share instruments in accordance with Bartik (1992). The idea is to use early employment levels and national growth rates in each industry to forecast city growth due to composition effects. We constructed a Bartik-type instrument to create labor market shocks based on the 1990 employment structure. As emphasized by Goldsmith-Pinkham et al. (2020), the Bartik instrument must satisfy the exclusion restriction, meaning that it only affects the housing supply through its effect on housing demand and not through any other direct or indirect channels. However, if the construction sector played a significant role in our instrument, the exclusion restriction would be violated. Therefore, we provide a standard Rotemberg decomposition in Table E.1 to show that the largest sectors contributing to the first stage are counseling activities, wholesale of non-food products and telecommunications, finance and restaurant activities. These sectors are likely to influence the demand for labor, and there is no particular reason why these shares should be correlated with the supply of housing.

Finally, to avoid relying solely on the Bartik-type instrument, we followed Saiz (2010) and exploited another source of variation based on natural amenities: hours

[5] As in Saiz (2010), Liu (2018) and Büchler et al. (2021), we do the regression in first-difference. In other words, we consider the changes in values and quantities, initial scale differences (urban areas fixed effects) are differenced out. In addition, we assume that changes in local construction costs are exogenous to local changes in housing demand as in Gyourko and Saiz (2006).

of sunlight. As documented by Glaeser et al. (2001), sunny cities attract more inhabitants than low-amenity cities. This second instrument allowed us to conduct additional meaningful over-identification tests because the sources of variation behind the two instruments were different.



(a) The simultaneity bias

(b) Identified supply curve

Figure 2: Identification of supply elasticity

2. The endogeneity of regulation: Identifying the role of land-use regulations might be challenging. As stressed by Fischel (2001), reverse causality might arise, as rising land values might prompt local authorities to increase regulations to protect these values. Additionally, unobserved variables could bias estimates of the impact of local land-use regulations. For example, changes in transport infrastructure or in the political majority might be associated with changes in both land-use regulation and housing market dynamics. Finally, the refusal rate might be subject to a measurement bias as households and developers might anticipate refusal preventing them to submit some projects.

Our approach tackles this issue in several ways. First, although land-use regulations are typically set at the municipality level, we worked at the urban area level and computed an aggregate refusal rate, which reflects the decentralized decisions of several mayors. Thus, the heterogeneity in land values within urban areas could mitigate the reverse causality bias, as the urban area refusal rate might reflect more localized concerns than citywide dynamics. To support this argument, we present the results in Table 1, where we regressed the refusal rate of building permits in urban areas on housing prices, income and housing growth. We observe that the refusal rate is not correlated with price or income growth, but there is a significant negative relationship with city growth (measured through housing stock growth). This could indicate a potential endogeneity problem, as the refusal rate might be associated with specific characteristics of cities. In particular, cities with more growth might refuse fewer building permits to avoid exacerbating the affordability crisis.

To deal with this issue, we developed an instrumental variable approach. In the last column of Table 1, we show that the national rule of protecting areas around historical monuments is correlated with the refusal rate which makes it a relevant instrument. The variation in the refusal rate generated by these additional requirements should be independent from city-specific dynamics, as a national commission of architects provides the required authorization for the projects in these delimited areas, and is less likely to be influenced by local pressures. Hence, it would be an exogeneous instrument. To satisfy the exclusion restriction, the Historical Monuments Law should not influence housing price dynamics other than through land-use regulation and the refusal rate. If the presence of historical monuments reflects the level of amenities that households might increasingly value, this assumption might be violated. To test for this eventuality, we examine the correlation between these regulations and housing price variations in Table A.1. The fact that the share of area covered by historical monument law is not correlated with price, income and city growth partially relieves our concerns.

As a robustness check, we use another nationwide regulation: the Article 55 of the SRU law (see Chapelle et al. (2022) for more details on this law). The SRU law imposes social housing quotas in municipalities with a population above 3,500 inhabitants in large agglomerations. For large enough urban areas, the area covered by the law is arguably exogenous, as it depends on past social housing construction and distribution as well as the size of municipalities composing the urban area. Therefore, we use the share of land covered by the law as an alternate instrument. This robustness check could confirm our findings by exploiting a different source of exogenous variation for a subsample composed of the 50 largest urban areas.

Table 1: Correlates of the refusal rate of building permits with city dynamics

	Refusal rate of building permit				
	(1)	(2)	(3)	(4)	(5)
Share of land unavailable (25km radius)	0.003 (0.019)	0.014 (0.021)	0.016 (0.021)	0.019 (0.021)	0.019 (0.021)
$\Delta ln(\tilde{P})$, 2000-2010		-0.037 (0.029)	-0.036 (0.029)	-0.028 (0.029)	-0.031 (0.029)
$\Delta ln(Income)$, 2000-2010			-0.040 (0.106)	0.022 (0.108)	0.016 (0.107)
$\Delta ln(Q)$, 2000-2010				-0.164** (0.066)	-0.176*** (0.066)
Share of land under historical monuments					0.277** (0.122)
R^2	0.000	0.005	0.006	0.025	0.041
Observations	319	319	319	319	319

Note: The dependent variable is the refusal rate of building permits taken from Sit@del2. $\Delta ln(\tilde{P})$, $\Delta ln(Income)$ and $\Delta ln(Q)$ correspond to the log variation in housing price, average household fiscal income and number of dwellings respectively. The regression constant is not reported. For details about data sources and constructions of variables, see Section 4.
Estimates of the equation: $Refusal_i = \alpha_0 + \alpha_1 \times \Delta ln(\tilde{P}) + \alpha_2 \times \Delta ln(Income) + \alpha_3 \times \Delta ln(Q) + \epsilon_i$
** $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.* Standard errors in parenthesis.

4 Data

We built a dataset using the 1999 definition of urban areas made by the *Institut National de la Statistique et des Etudes Economiques* (INSEE) (for more details see Aliaga et al. (2015)). Throughout the rest of the paper, we use long differences (between 2000 and 2010, as well as 2000 and 2018 for robustness checks). Therefore, we focus on long-run housing dynamics.

Our selection of these urban areas was based on several factors. First, they align with our conceptual framework, as they are defined as grouping municipalities combining commuting flows and the contiguity of building. As a result, most of the urban sprawl occurred within these areas, allowing us to capture the dynamics of these cities. Additionally, defining these areas relies on a method similar to that used to define MSAs in the US, where comparable studies have been conducted. Lastly, these areas correspond with those utilized in prior research exploring the cost of agglomeration in France such as Combes et al. (2019).

To construct the final dataset, we collected data on the supply of housing and population figures to measure $\Delta ln(Pop)$, as well as on housing prices, construction costs, land availability, and housing regulations, for the 319 urban areas on the mainland of France (excluding Alsace-Moselle due to housing price data restrictions). This section provides a description of the dataset construction.

4.1 Measuring housing prices

Measuring supply elasticity requires following how average housing prices, $\tilde{P}$, change over time. To this end, we relied on transaction data compiled by French notaries, as in Combes et al. (2019), which are available for every odd year from 2000 to 2012. We complemented this dataset with the exhaustive transaction dataset *Demande de Valeurs Foncières* (DV3F) compiled by the *Centre d'études et d'Expertise sur les Risques, l'Environnement, la Mobilité et l'Aménagement* (CEREMA) starting in 2010. These databases contain information on second-hand dwelling prices, location, transaction date and characteristics, such as the number of bathrooms, cellars, balconies, parkings and land surfaces for houses. The construction of the average price index at the urban area level took place in two steps.

Construction of Municipal indices: Following Rosen (1974), we used the transaction data to build municipal hedonic indices in the 6,500 municipalities belonging to the 319 urban areas. These municipalities are quite small, as their average radius is three kilometers. To construct these indices, we estimated the following hedonic model for each transaction i occurring in year $t(i)$ in municipality $m(i)$:

$$ln(p_{i,m(i),t(i)}) = \beta \times X_i + \delta_{m(i)} + \mu_{t(i)} + \epsilon_i \tag{19}$$

where $ln(p_{i,m(i),t(i)})$ is the log of the price regressed on a set of hedonic characteristics (X_i), a municipality fixed effect $(\delta_{m(i)})$ to control for local unobserved variables and a year fixed effect $(\mu_{t(i)})$. The constant quality average housing price $P_{m,t}$, for a municipality m in year t, is given by:

$$P_{m,t} = e^{\delta_m + \mu_t + \frac{1}{n_{m,t}} \sum_{i=1}^{n_{m,t}} \beta X_i + \frac{1}{2}\sigma^2} \tag{20}$$

where $n_{m,t}$ is the number of housing transactions in municipality m in year t, and σ is the root mean square error.

Aggregation: The estimates of hedonic prices were performed at the city level and thus required the computation of an average price for each urban area k: $\tilde{P_{k,t}}$. We aggregated the constant quality average price for each municipality $P_{m,t}$ weighted by the number of dwellings in 1999.

$$\tilde{P_{k,t}} = \sum_{m \in k} \frac{H_{m,1999} \times P_{m,t}}{H_{k,1999}} \tag{21}$$

where $H_{m,1999}$ is the number of dwellings of municipality m in 1999.

4.2 Measuring the quantity of housing

Our simplified theoretical framework assumed an equivalence between the total housing supply and population. Therefore, we gathered data on the number of households, total population and stock of dwellings.

Stock of dwellings and quantity of floor space: The stock of dwellings $Q_{k,t}$ can be determined using the *FIchier des LOgements dans les COMmunes* (FILOCOM). This dataset is an exhaustive repertory of all dwellings localized at the municipality level, that is compiled every two years from 1995 to 2017. This repertory allowed us to count the total number of dwellings in the urban area as well as the total floor space, as suggested in Liu (2018).

Population: The urban population can be estimated using the census. The last exhaustive censuses took place in 1990 and 1999. Since 2005, a continuous census has provided yearly estimates that can be used every five years to estimate city growth (i.e. the 2005 population count should only be compared with the 2010 population count to measure urban growth). Alternatively, FILOCOM also provides estimates of the number of fiscal households and the population every two years.

Table 2: Descriptive statistics

	Mean	Std.Dev.	Min	Max
Panel a) Real estate dynamics				
Price per sqm, 2000	875	276	421	2893
Price per sqm, 2010	1769	768	979	9292
Price per sqm, 2018	1778	852	835	8792
$\Delta ln(\tilde{P})$, 2000-2010	0.63	0.13	0.27	1.16
$\Delta ln(\tilde{P})$, 2000-2018	0.57	0.19	0.02	1.18
Population, 1999	134 166	648 320	8154	11 174 743
Population, 2010	143 377	698 502	7385	12 030 140
Population, 2018	148 348	723 058	6912	12 429 316
$\Delta ln(Pop)$, 2000-2010	0.05	0.07	-0.10	0.24
$\Delta ln(Pop)$, 2000-2018	0.07	0.11	-0.26	0.53
Dwellings, 2000	65 302	312 012	3534	5 377 560
Dwellings, 2010	72 211	331 225	3807	5 682 247
Dwellings, 2018	78 413	354 154	4595	6 052 054
$\Delta ln(Q)$, 2000-2010	0.13	0.05	0.00	0.34
$\Delta ln(Q)$, 2000-2018	0.19	0.08	-0.02	0.59
Floor area, 2000	4 832 376	20 582 100	291 428	3.51e+08
Floor area, 2010	5 566 284	22 703 613	324 343	3.85e+08
Floor area, 2018	6 138 532	24 545 329	400 431	4.15e+08
$\Delta FloorArea$, 2000-2010	0.16	0.05	0.04	0.31
Panel b) Other characteristics				
Area (sqkm)	526	981	14	14585
Share of land unavailable (25km radius)	0.14	0.18	0.00	0.83
Refusal Rate	0.15	0.06	0.03	0.46
Share of land under historical monuments	0.04	0.03	0.00	0.18
Share of land under the littoral law	0.00	0.01	0.00	0.13
Average temperature in January	4.05	2.04	-5.89	8.98
Average Sun Hours	52 711	9231	42 106	77 970

Note: $\Delta ln(P)$, $\Delta ln(income)$, $\Delta ln(Q)$ and $\Delta ln(Pop)$ correspond to the log variation in housing price, average fiscal income, population and number of dwellings respectively.
Sample: 319 French MSAs, MSAs from Alsace-Moselle were excluded as data on housing prices were not available from 2012 to 2018.

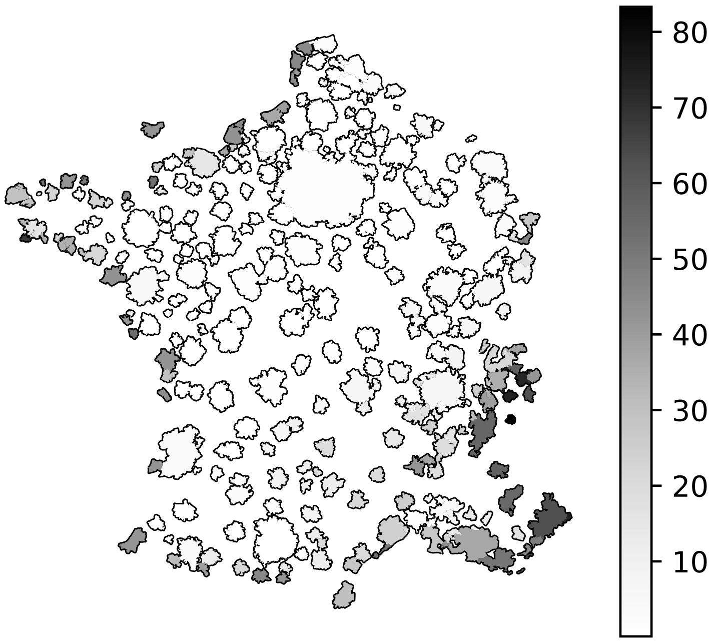
4.3 Measuring land availability and land-use regulations

Land availability: We closely followed the method described in Saiz (2010) to measure the share of land available in a radius around the CBD. First, we defined the CBD of urban areas, following the method of Combes et al. (2019) for France. We took the average of the barycenters of the municipalities of the urban area weighted by the number of jobs in each municipality. We then created a shapefile with the land constraint following the definition of Saiz. Land was defined as unavailable when 1) the slope computed from the raster file of the BD TOPO[6] was above 15% and 2) the area was flooded, i.e., covered by an ocean, rivers or lakes, as defined in

[6] BD TOPO and BD TOPAGE are geographic datasets produced by the French National Institute of Geographic and Forest Information (IGN). They provide a comprehensive and accurate representation of the French territory in terms of its topography, hydrography, and other geographical features.

BD TOPAGE for the latter two. We then intersected a buffer with a radius of 25 km from the CBD with the polygons of unavailable areas to measure the share of land unavailable around the CBD. Results are reported in Figure 3. Constrained areas are mostly concentrated on the shore or in the Alps, close to the frontier with Switzerland. Table 2 and Figure 3 emphasize the strong heterogeneity and low stringency of geographical constraints in French urban areas. Share of land unavailable varies from 0 to 83% with a standard deviation of 18 percentage points and a median of 5%.

Figure 3: Share of land unavailable due to geographical constraints, 25 km radius

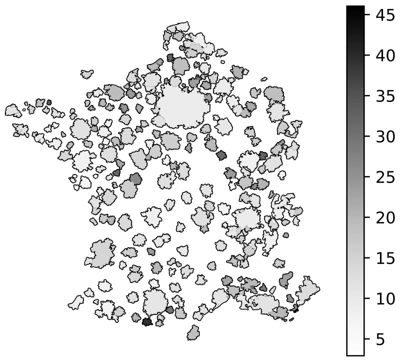


Note: Share of land flooded by water or with a slope above 15% in a 25 km radius around the barycenter of French urban areas. Author's computation from the BD TOPO (IGN), the BD Topage (IGN) and the French Census (INSEE).
Sample: 319 French MSAs, MSAs from Alsace-Moselle were excluded as data on housing prices were not available from 2012 to 2018.

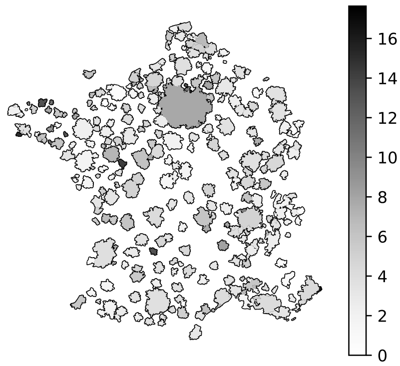
Land Use Regulation: One important challenge is to gather data on land-use regulations, as no index equivalent to the Wharton land-use Regulation Index exists for France. To this end, we followed Hilber and Vermeulen (2016) and relied on the refusals of building permits. We took advantage of the centralized information system for building permits Sit@del2, provided by INSEE, to measure the rate of refusals of building permits over the period under study. We complemented this local measure of land-use regulation with an instrument built from nationwide rules. We proposed to use the area covered by the rule protecting historical monuments, which states that any project in a radius of 500 meters around these monuments is subject to additional administrative approval from the French building association. To build this instrument, we webscraped the list of monuments and their coordinates, and created a buffer around these monuments. These buffers were then merged to avoid double counting and intersected with the municipalities of the urban areas to measure the surface area covered by this rule. Figure 4 reports the average refusal rate and the share of land under historical monument law. Table 2 and Figure 4 underline the stringency of land-use regulations in French urban areas: the average building permits refusal rate is 15% and ranges from 3% to 46%. Finally, we note that our measurement of land-use regulation is not correlated with topological constraints, such as the share of land that is covered by water or too steep for development (cf. Table 1), which differs from the findings of Saiz (2010).

Figure 4: Land use regulation

(a) Refusal rate of building permits, in percentage



(b) Share of land under the historical monuments law, in percentage



4.4 Other variables

Labor market shocks: To account for labor market shocks, we combined the exhaustive data from the French 1990 census, which provided the decomposition of the labor force in 99 sectors for each urban area. We then computed the growth rate of each sector using the yearly data published by the French statistical agency [7] for 88 sectors. We performed some minor adjustments to map the 99 census sectors to the 88 growth sectors and could thus build a standard shift-share instrument, as detailed in Saiz (2010) and Goldsmith-Pinkham et al. (2020). National growth rates are computed using the leave-one-out method to avoid using own-observation information.

Income: Income variables are built from the income tax files provided by the finance ministry. The dataset, *Impôt sur le Revenu par COllectivité territoriale* (IRCOM) reports the total income and number of fiscal households in every municipality. These statistics can be aggregated to build a measure of average income in all urban areas.

[7] https://www.insee.fr/fr/statistiques/4981497?sommaire=4981513

Meteorological conditions: We relied on the SYNOP dataset [8] published by Meteo France which provides precise in situ observation for several stations. We built a balanced panel of stations and matched each urban area to its closest station. We then recorded the average temperature and degree of sunlight over 20 years for each urban area.

Construction costs: The dataset used to build the official construction cost index calculated by INSEE is, unfortunately, only available from 2017[9]. Therefore, we used an alternate source to compute the variation in construction costs. The dataset used is the *Enquête sur les Prix des Terrains à Bâtir* (EPTB), provided by the Ministry of Housing, which contains information on construction costs from 2006 onward. We could thus compute the variation in construction costs from 2006 to 2010 and 2018.

5 Estimates and decomposition of MSA-level inverse housing supply elasticity

5.1 The homogeneous inverse housing supply elasticity

Baseline estimates: We estimated the average inverse housing supply elasticity in French urban areas using Equation (17) based on the price and population growth between 2000 and 2010. The results are reported in Table 3. In panel a, the results of measuring city growth using population are presented. The first column reports the Ordinary Least Squares (OLS) estimate, which displays an average inverse housing supply elasticity of 0.65. In other words, if population grow by 1%, housing prices would increase by 0.65%. However, one major caveat of this approach comes from the simultaneity discussed in Section 3.3 linked to the co-movements of the supply and demand curves, which might bias our point estimate toward 0. Therefore, we turned to the instrumental variable (IV) approach described in Section 3.3 to identify exogenous demand shocks. The second column reports the estimates using the Bartik shift-share instrument alone. The first stage appears reasonably strong, with an F statistic of 29, compared to the critical 5% value in Stock and Yogo (2002) of 13.91, thus the instrument is relevant. As expected, the point estimate of elasticity increases to reach 1.9. Column 3 presents the results of using yearly hours of sunlight instead of the shift-share instrument. The point estimate increases to 2.7, but this estimate is not statistically different from the previous IV estimate. Finally, the last column shows the results of jointly using the two instruments, allowing us to perform over-identification test. The p-value of 0.311 allowed us to reject the endogeneity of the instrument, strengthening our confidence in the exclusion restriction. In Panel b, the results are reported for the same exercise performed using the number of dwellings instead of the population. The point estimates of the

[8] https://donneespubliques.meteofrance.fr/?fond=produit&id_produit=90&id_rubrique=32

[9] This index is calculated from the survey *Indice du Coût de la Construction et le Prix de Revient des Logements Neufs* (ICC-PRLN).

IV estimates are higher, but also less precisely estimated, probably because the first stage is also weaker.

Overall, there are several takeaways from this first exercise. First, the housing supply appears relatively inelastic in France. Indeed, the point estimates suggest an inverse supply around two when measured with population, four when measured with dwellings. This would imply a supply elasticity between 0.25 and 0.5, meaning that when prices increase by 1%, population or dwellings increase only by a range of 0.25% to 0.5%. Second, French cities appear much more inelastic than their US counterparts. In comparison, Saiz (2010) reported an average housing supply elasticity of 1.75 when measured by population over a 30-year horizon, while Liu (2018) estimated an elasticity of 0.8 when measured by dwellings reported on Zillow.[10]

Alternate independent variables and time horizon: We perform different robustness checks, as shown in Table B.1 in the Appendix. First, to understand the discrepancy between estimates using dwellings and population, we estimated the model using households (i.e., main residences). The magnitude of the results is relatively close to the results for dwellings. Indeed, housing is consumed by households rather than by individuals on their own, which allowed us to reconcile panels a and b and supports the assumption that, when measured at the household level, $Pop = Q$. Second, in panel b of Table B.1, we followed Liu (2018) and measured the elasticity using the quantity of dwelling spaces instead of units. When using the surface, the first stage appears much weaker, and the point estimates are less precise. If they appear to be larger than when dwellings were used, the lack of precision prevents any conclusions. Third, following Hilber and Vermeulen (2016), we substituted income for dwellings and population growth. The results appear to be of the same order of magnitude, as income is also a proxy for housing demand. If the first stage appears to be weak using sunlight hours as an IV, and results in a rejection of the over-identification test, this problem tends to vanish when using a longer time horizon (see panel c in Table B.2). Finally, in panels a and b in Table B.2 , the robustness of our results is depicted in the longer run, extending to 2018 as the final year. In panel a, point estimates for the population remain approximately the same, while the estimates in panel b, which use dwellings, are more precisely estimated and get closer to those based on population and households.

Rotemberg weights: We follow Goldsmith-Pinkham et al. (2020) to compute Rotemberg weights in Table E.1. The largest sectors contributing to the first stage are counseling activities, wholesale of non-food products and telecommunications, finance and restaurant activities. These sectors are likely to influence the demand for labor, and there is no particular reason why these shares should be correlated with

[10] Estimates based on the American Housing Survey (AHS) display a lower supply elasticity (0.4) but housing price data are less comparable to our house price index and AHS is not exhaustive. Liu (2018) emphasizes the use of surface, our results for France using surface are systematically lower than the estimates based on surface for the US.

the supply of housing. To check for this eventuality, we follow Büchler et al. (2021) and regress the shares and the Bartik instrument on the vacancy and homeownership rates as well as their variations. As seen in Table E.2, the R^2 remains very low.

Summary: The order of magnitude of our estimates, like the estimates of Liu (2018) and Saiz (2010), is in line with that of macroeconomic estimates comparing France and the US, as in Caldera and Johansson (2013) and Cavalleri et al. (2019). More recent studies, such as Baum-Snow and Han (2019) and Gorback and Keys (2020), point to a more inelastic supply in the US. The discrepancy between Saiz (2010) and those authors might be explained by the use of zip code-level data, as spillover effects of a demand shock on neighborhoods might not be accounted for, leading to an underestimation of supply elasticity. In the next section, we explore the decomposition of housing supply average elasticity to understand what could be constraining developers' reactions.

Table 3: Estimation of inverse housing supply elasticity (2000-2010)

	$\Delta ln(P)$: 2000 − 2010			
	(1)	(2)	(3)	(4)
Panel a) Using Population				
$\Delta ln(Pop)$	0.65***	1.92***	2.67***	2.41***
	(0.13)	(0.51)	(0.46)	(0.43)
R^2	0.11	.	.	.
Obs	319	319	319	319
F-stat		27.15	43.10	27.46
P-value				0.14
Panel b) Using dwellings				
$\Delta ln(Q)$	0.49***	3.47***	4.32***	4.10***
	(0.13)	(1.26)	(0.91)	(0.88)
R^2	0.04	.	.	.
Obs	319	319	319	319
F-stat		11.47	22.48	13.10
P-value				0.51
Bartik	N	Y	N	Y
Hours of sun	N	N	Y	Y

Note: The table shows the coefficient of an OLS (Column 1) and 2SLS estimations (Columns 2 to 4) of an urban area housing supply equation. On the left-hand side, we try to explain changes in housing prices ($\Delta ln(\tilde{P})$) by urban area between 2000 and 2010. On the right-hand side, the main explanatory endogenous variable is the change in housing demand (measured through population $\Delta ln(Pop)$ or number of dwellings $\Delta ln(Pop)$ between 2000 and 2010. The instruments used for demand shocks are a Bartik shift-share of the 1990 urban area industrial composition and the log of January average hours of sun. The identifying assumptions are that the covariance between the residuals of the supply equations and the instruments are zero. The p-value corresponds to the Sargan-Hansen test, if it is above 0.1, we failed to reject the null hypothesis that the instruments are exogenous. The F-test assesses the instruments relevance, it is a joint test of of correlation of instruments with the endogenous regressors after controlling for the exogenous regressors.
Estimates of the equation: $\Delta ln(\tilde{P}_k) = \beta^s \times \Delta ln(Q_k) + \sigma \Delta ln(cc_k) + \alpha + \epsilon_k$, controls include variation in construction costs.
* *p < 0.1,* ** *p < 0.05,* *** *p < 0.01.* Standard errors in parenthesis.

5.2 Heterogeneity of inverse supply elasticity

5.2.1 Estimation of the determinants of inverse supply elasticity

Table 4 shows the estimates from Equation (18), where we decompose the inverse supply elasticity between regulatory and geographical constraints. In Column 2, we introduce the share of unavailable land because of topological constraints (flooding or a steep slope). As in Saiz (2010), it enters significantly into the elasticity of the housing supply. A one standard deviation increase of the share of unavailable land leads to an increase of the inverse housing supply elasticity of 1.9. In Column 3, we introduce land-use regulation measured through the building permit refusal rate, the coefficient is significant and reduces housing supply elasticity. A one standard deviation increase of the refusal rate increases the inverse supply elasticity by 3.6. It appears that the elasticity of housing supply depends critically on both regulations and physical constraints.

Following Equation (15), larger metro areas should be more inelastic. The most parsimonious way to capture this effect is to interact the variation of the quantity of dwellings and the population in the regression. Therefore, Column 4 introduces city size, the coefficient although small is strongly significant, which confirms the intuition that larger cities are more inelastic. The coefficient on the refusal rate increases because the variables are not standardized and the introduction of population decreases the coefficient of $\Delta ln(Q)$, which turns negative and insignificant. Finally, land-use regulation might be endogenous as underlined in Section 3.3, particularly with respect to city dynamics, therefore we instrumented the refusal rate with the historical monuments law. City size is obviously correlated with city dynamics, we instrumented it with the population in 1900. The identifying assumption being that past population is strongly correlated with current population through births and deaths, and not directly impacting current housing prices. Since our endogenous variable appears in interacted form, we include in the IV list the interactions between their instruments. The point estimates remained unchanged in Column 5.

Table 4: Decomposition of inverse housing supply elasticity

	$\Delta ln(P)$: 2000 − 2010				
	(1)	(2)	(3)	(4)	(5)
$\Delta ln(Q)$	3.91***	2.55***	1.87***	-2.51	-1.67
	(0.78)	(0.62)	(0.52)	(1.66)	(1.58)
$\Delta ln(Q) \times$ $share\, unavailable$		1.917***	1.90***	2.25***	2.16***
		(0.54)	(0.51)	(0.45)	(0.45)
$\Delta ln(Q) \times$ $Refusal\, Rate$			3.63**	8.58*	8.62*
			(1.44)	(4.86)	(5.05)
$\Delta ln(Q) \times ln(Pop)$				0.25***	0.18**
				(0.08)	(0.07)
Obs	319	319	319	319	319
Bartik	Y	Y	Y	Y	Y
Hours of sun	Y	Y	Y	Y	Y
Past Population	N	N	N	N	Y
National regulation	N	N	N	N	Y

Note: The table shows the coefficient of 2SLS estimations of an urban area housing supply equation. The specification and instruments used for demand shocks are as in Table 3. Demand shocks are interacted with the unavailable land share (due to geography, $1-\Gamma$ in Equation (18)) , the building permit refusal rate (which corresponds to the ratio between the number of refusals and the number of dwellings authorized) and the log of the MSA population in 1999 ($ln(pop)$). Population and the refusal rate are treated as endogenous using the population in 1900 and the historical monument law (national regulation) as instruments. Because we are instrumenting for $ln(Q) \times refusal\ rate$ and $ln(Q) \times ln(pop)$, we also include the interaction between the national regulation, past population and the demand instruments in the IV list in Column 5.
Estimates of the equation: $\Delta ln(\tilde{P_k}) = [\beta^{Land} \times (1-\Gamma_k) + \beta^{Reg} \times LUR_k + \beta^{Pop} \times ln(pop)] \times [\Delta ln(Q_k)] + \sigma \Delta ln(cc_k) + \alpha + \epsilon_k$, controls include variation in construction costs.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parenthesis.

5.2.2 Robustness Checks

We performed several robustness checks.

Alternate time horizon: We extended the time horizon of our study. Table C.3 in the Appendix reports the same exercise using variations from 2000 to 2018. The results remain unchanged although the impact of the refusal rate is more significant and precisely estimated. The resulting elasticities are closely correlated.

Additional interaction terms: We investigated the role of density and the share of already developed land. Bétin and Ziemann (2019) found that, for large metropolitan areas in OECD countries, a large part of the heterogeneity in land-use regulation comes from pre-existing density. In the same vein, Hilber and Vermeulen (2016) and Baum-Snow and Han (2019) showed that the share of land already developed might play a significant role in explaining the heterogeneity in housing supply elasticity. In Tables C.1 and C.2, we introduce the share of developed land, or density, as an additional interaction variable. In the last column, we also instrument them with past population density. Both variables appear to enter significantly into our regression although the coefficients related to density are close to zero. To assess the importance of these variables, we look into the correlation between predicted elasticities between specifications in Tables 4, C.1 and C.2. As shown in Table C.7, predicted elasticities with the share of already developed land or density have a coefficient of correlation between 0.90 and 0.95 with those generated by the simplest model. The lower importance of the share of land already developed differs from the recent findings in Baum-Snow and Han (2019), but this result can be easily explained by the fact that these variables are correlated with city size. Moreover, when measuring the MSA-level housing supply, urban sprawl is more important than when measuring the zip code level housing supply, and thus reduces the importance of past density.

Removing the smallest urban areas: The sizes of the cities in our sample are extremely heterogeneous, the standard deviation between urban areas populations is around 700 000 inhabitants (see Table 2). To limit the influence of the smallest MSAs, we removed the cities with fewer than 20,000 inhabitants, which corresponds to the bottom quartile of our sample. The results, reported in Table C.4, remain unchanged. In the last column, we also provide the results of estimating our models by weighting the observations with the cities' 2000 populations. The results remain qualitatively unchanged. Overall, our different predictions for MSA-level housing supply elasticities are highly correlated, as reported in Table C.7.

Alternate measures of city growth: We also reproduced this decomposition with alternate measures for the quantitative variables (population, households and income). The results are very similar, as shown in Table C.5.

Alternative instrumental variable: There might remain concerns that the historical monument regulation might not be fully orthogonal to the attractiveness of the MSAs. To relieve this last concern, we perform a last robustness check using another nationwide regulation: the Article 55 of the SRU Act. This law forces municipalities with a population above 3,500 inhabitants in large urban areas (or 1,500 inhabitants in Paris urban area) to have at least 20% of social housing. The thresholds of population and social dwellings create large variations in terms of territory covered by the law in each urban area. In those territories, some projects might be rejected more often to favour social dwellings. In Table C.6, we report our estimates for the 50 largest urban areas. Results are similar to those reported in Table C.4 when weighting observations with population.

5.3 Heterogeneity between inverse supply elasticities of MSAs

Using coefficients of Column 5 in Table 4, we compute and report in Figure 5 the predicted inverse housing supply elasticities and their decompositions for the 8 largest MSAs (and 2 average MSAs). Paris urban area does not appear much more inelastic than other cities. If it has the reputation of being an expensive city, the urban area of Paris does not cover only the city center but is very extended and comprises more than 1,200 local authorities that might have a more flexible housing supply. On the other hand, the coastal cities of Nice and Marseille appear much more inelastic, as they combine a high level of geographical constraint with a high level of land-use regulation. We report the estimated elasticities for the 30 largest urban areas in Table D.1.

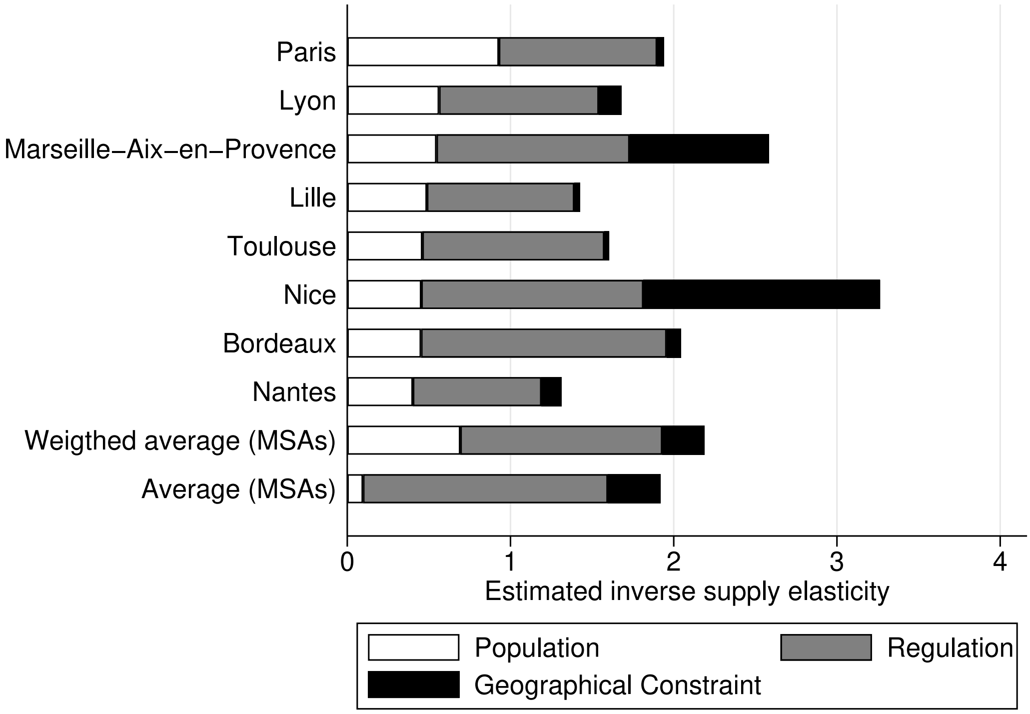
Two interesting facts arise from these elasticities. First, the major share of MSAs housing supply inelasticities comes from land-use regulations. For example, in the Paris urban area, removing land-use regulations would dramatically reduce the inverse supply elasticity, which would drop from 1.942 to 0.972. The resulting housing supply elasticity would thus rise from 0.45 to almost 1. On the other hand, removing geographical constraints would have a very small impact (a drop from 1.942 to 1.898) on inverse elasticity, as Paris urban area is poorly constrained by geography. While land-use regulation is a key driver for all large urban areas, geography only appears to be key for a limited number of coastal MSAs (Aix-Marseille, Nice, Toulon and Brest) and Grenoble, which is located in the Alps. In a city with the average (or weighted average) characteristics of French MSAs, the housing supply elasticity is mainly driven by land-use regulation, while the role of geography remains marginal. Overall, our results show that land-use regulation explains the largest share of the housing supply elasticity of French urban areas. Like Bétin and Ziemann (2019), we demonstrated that nationwide estimates of housing supply elasticity are correlated with the average supply elasticity of the largest MSAs.

A simple way to assess the relative importance between regulatory and geographical constraints in explaining housing supply elasticity is to do a Shorrocks-Shapley decomposition of the R-squared[11]. As presented in Table A.2, the Shorrocks–Shapley decomposition of the R-squared shows that the refusal rate explains 65% of the variance in predicted elasticity while geographical constraints account for only 30%. A major result of our paper is that land-use regulations are mostly responsible for the low supply elasticity of French MSAs.

When a similar decomposition was performed on the US data provided in Saiz (2010), a much higher share of the variance was explained by the geographical constraint (76%) and a much lower share by the Wharton land-use regulation index (12%) as highlighted in Table F.1. In general, large French cities are located away from the shore in relatively plain areas, which reduces the role of natural constraints in the country. Our results suggest that the wide gap observed between elastic countries such as the US, where Saiz (2010) and Liu (2018) demonstrated the predominance of natural constraints, and inelastic ones such as France, arises from the difference in the level of land-use regulation in the two countries' MSAs.

[11]The Shorrocks-Shapley decomposition of the R-squared is a method of decomposing the total R-squared into contributions from individual independent variables in the model. The basic idea behind this decomposition is to compute the change in the R-squared when each independent variable is added to the model individually.

Figure 5: Decomposition of housing supply elasticities

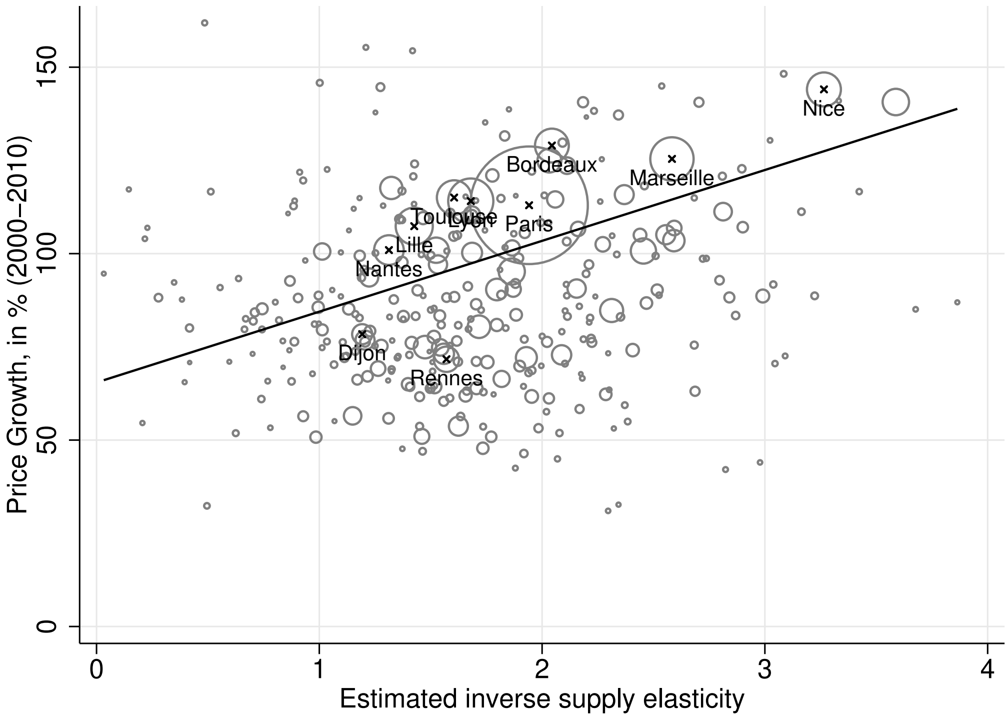


Note: The inverse supply elasticity is obtained from the coefficients of Column 5 in Table 4. Population is the sum of the $-1.665 + 0.184 \times ln(pop)$. We assign, -1.665, the coefficient on $\Delta ln(Q)$ to population because the log of population is truncated and its inclusion drives this coefficient to negative values. Alternate specifications using $ln(Pop) - ln(min(Pop)$ instead of $ln(pop)$ yield a coefficient close to 0 and thus a similar decomposition. Regulation is given by $8.619 \times Refusal\,Rate$, geographical constraint by $2.161 \times share\,unavailable$.

As expected, housing supply elasticity is correlated with cities' real estate dynamics and with price growth in particular, as illustrated in Figure 6. This correlation also holds when investigating the growth in housing prices from 2000 to 2018 (see Figure C.1 in appendix). In Table A.3, we compare the characteristics and dynamics of MSAs above and below the median housing supply elasticity. Inelastic cities tend to be larger and more expensive. By construction, they are more regulated and geographically constrained. They also experienced a larger price growth from 2000 to 2010 and a smaller drop from 2010 to 2018. There is no significant difference in the growth of housing stock, which tends to be smaller in inelastic cities.

Overall, these results are in line with what has been shown in the US by Glaeser et al. (2008) and Ihlanfeldt and Mayock (2014). In a nutshell, Figure 6 shows that a simple linear combination of geographical and regulatory constraints remains correlated with the evolution of prices, even without taking into account the heterogeneous demand shocks that urban areas faced.

Figure 6: Estimated housing supply elasticity and price growth



Note: The inverse supply elasticity corresponds to the prediction from estimates reported in column 5 in Table 4. Price growth is computed from local price index. The radius corresponds to the relative population of urban areas in 2000.

6 Concluding remarks

In this paper, we estimated the housing supply elasticities of French urban areas. Our results can be summarized as follows. First, French urban areas appear much less elastic than their US counterparts. Specifically, French urban areas have, on average, a population-weighted housing supply elasticity of around 0.5, meaning that when prices increase by 1%, population or housing builds increase only by 0.5%. By comparison, Saiz (2010) found that the average elasticity of US MSAs is more than three times larger (around 1.75). This finding, at the MSA level, is consistent with the macroeconomic estimates of housing supply elasticity made by Caldera and Johansson (2013) and Bétin and Ziemann (2019) for both countries. Therefore, in the medium term, housing prices in French urban areas tend to grow rapidly following an exogenous demand shock.

We documented the heterogeneity of the elasticity between urban areas to identify its main drivers, and highlight the crucial importance of land-use regulations determined by local authorities. We identified the latter by relying on instrumental variations generated by a nationwide rule concerning historical monuments. Upon decomposing the variance in supply elasticity between urban areas, we found that 60% of the variance is explained by regulatory constraints, while only 30% stems from geographical constraints. Land-use regulation was shown to be the main factor responsible for the inelastic housing supply in France, confirming previous findings on the key importance of land-use regulation in real estate market dynamics (Gyourko and Molloy 2015).

Our results have implications for the effectiveness of housing policies, as this inelastic supply tends to convert housing subsidies into higher housing prices and rents, which has been shown by Fack (2006). As housing supply elasticity is closely connected with local authorities' decisions, our results support the view that nationwide policies stimulating production oor demand for dwellings should be coordinated with local policies, and adapted to the local regulatory environment. Further work could investigate the differentiated impact of public interventions on local real estate markets based on their respective supply elasticities. Moreover, low housing supply elasticities resulting from land-use regulations might have other adverse consequences for the national economy, such as the misallocation of workers and activities, as discussed by Hsieh and Moretti (2019).

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A Additional Tables

Table A.1: Correlates of the share of land covered by the historical monuments regulation with cities dynamics

	Share of land under historical monument law			
	(1)	(2)	(3)	(4)
Share of land unavailable (25km radius)	0.006 (0.009)	0.001 (0.010)	-0.000 (0.010)	-0.001 (0.010)
$\Delta ln(\tilde{P})$		0.015 (0.013)	0.014 (0.013)	0.009 (0.014)
$\Delta ln(Income)$			0.038 (0.049)	0.027 (0.049)
$\Delta ln(Q)$				0.033 (0.026)
R^2	0.001	0.006	0.008	0.013
Obs	319	319	319	319

Note: The dependent variable is the share of land under historical monuments law. $\Delta ln(\tilde{P})$, $\Delta ln(income)$ and $\Delta ln(Q)$ correspond to the log variation in housing price, average fiscal income and number of dwellings respectively. Estimates of the equation: $Share_i = \alpha_1 \times \Delta ln(P) + \alpha_2 \times \Delta ln(income) + \alpha_3 \times \Delta ln(Q) + \epsilon_i$
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parenthesis.

Table A.2: Shorrocks-Shapley decomposition of inverse housing supply elasticity

	Inverse Elasticity			
	Baseline	2000-2018	Including share of developed land	Weighted by population
Geographical Constraints	0.30	0.28	0.24	0.09
Refusal Rate	0.65	0.66	0.65	0.78
$ln(pop)$	0.04	0.05	0.03	0.13
Share of land developed	.	.	0.09	.
Total	1	1	1	1

Note: Shorrocks-Shapley decomposition of the R-squared as defined in Wendelspiess Chávez Juárez (2015). $ln(pop)$ corresponds to the log of the MSA population in 1999. By design, the total R-squared is 1.
Lecture note: The refusal rate explains 65% of the variance of the baseline elasticity.

Table A.3: Comparison of elastic and inelastic cities

	Elastic (above median)			Inelastic (below median)			Difference		
	Average	Sd	N	Average	Sd	N	Diff	Tstat	pvalue
Population	75632	131493	160	193068	906421	159	-117436	-1.62	0.11
Income	13791	1190	160	14116	1631	159	-325.2**	-2.04	0.04
Average Price	808.8	176.2	160	941.9	335.5	159	-133.1***	-4.44	0.00
Refusal Rate	10.99	3.31	160	18.05	6.31	159	-7.06***	-12.52	0.00
Share unavailable	6.78	10.08	160	21.38	21.17	159	-14.61***	-7.88	0.00
Dynamics (2000-2010)									
Population growth	5.73	7.53	160	5.39	6.56	159	0.34	0.43	0.67
Housing stock growth	12.65	6.95	160	12.32	5.10	159	0.33	0.48	0.63
Housing price growth	85.70	22.47	160	92.16	28.14	159	-6.46**	-2.27	0.02
Income growth	54.07	5.99	160	54.77	4.77	159	-0.70	-1.16	0.25
Dynamics (2010-2018)									
Population growth	2.32	6.49	160	0.87	4.96	159	1.45**	2.24	0.03
Housing stock growth	7.83	5.38	160	7.41	4.05	159	0.41	0.78	0.44
Housing price growth	-5.26	8.52	160	-4.49	10.79	159	-0.77	-0.71	0.48
Income growth	13.72	3.69	160	14.40	4.53	159	-0.69	-1.48	0.14
Dynamics (2000-2018)									
Population growth	8.40	12.58	160	6.53	10.97	159	1.87	1.41	0.16
Housing stock growth	21.64	11.74	160	20.78	9.13	159	0.86	0.73	0.47
Housing price growth	76.29	29.35	160	84.55	39.47	159	-8.26**	-2.12	0.04
Income growth	75.27	10.27	160	77.12	10.18	159	-1.85	-1.61	0.11

Lecture note: Elastic cities had a population growth rate of 5.7% , while inelastic cities had a population growth rate of 5.4% between 2000 and 2010. This difference was not statistically significant ($p - value > 0.1$).
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B Robustness checks: average housing supply elasticity

Table B.1 reproduces the specification of Table 3 using different outcomes. Panel a uses the number of households measured by the census instead of population on the same time span (2000-2010). Results are between those using households and dwellings.

Panel b uses the surface instead of the number of dwellings as suggested in Liu (2018), the direction of the bias does not appear to be the same as in the US. However, the instruments are weak and the point estimates thus quite imprecise. Point estimates based on dwellings and surface are statistically indistinguishable.

Panel c computes an elasticity between income and price in the spirit of Hilber and Vermeulen (2016), results suggest that income is a relatively close proxy to demand compared to population or dwellings.

Table B.1: Estimate of average housing supply elasticity: alternative dependent variables

	$\Delta ln(P) : 2000 - 2010$			
	(1)	(2)	(3)	(4)
Panel a) Using households				
$\Delta ln(households)$	0.58***	2.59***	3.61***	3.26***
	(0.16)	(0.83)	(0.79)	(0.72)
R^2	0.07	.	.	.
Obs	319	319	319	319
F-stat		16.82	25.99	16.40
P-value				0.22
Panel b) Using surface				
$\Delta ln(surface)$	0.41***	4.16**	5.93***	5.29***
	(0.15)	(1.64)	(1.48)	(1.32)
R^2	0.03	.	.	.
Obs	319	319	319	319
F-stat		9.34	13.71	8.69
P-value				0.35
Panel c) Using income				
$\Delta ln(income)$	0.95***	3.62***	6.94***	4.99***
	(0.31)	(1.11)	(1.39)	(1.06)
R^2	0.06	.	.	.
Obs	319	319	319	319
F-stat		28.54	22.40	19.50
P-value				0.02
Bartik	N	Y	N	Y
Hours of sun	N	N	Y	Y

Note: The specifications are the same as in Table 3 except that we use either the variation of the number of households ($\Delta ln(households)$), or the dwelling surface (in square meters, $\Delta ln(surface)$), or the fiscal income ($\Delta ln(income)$).
* *p < 0.1*, ** *p < 0.05*, *** *p < 0.01*. Standard errors in parenthesis.

Table B.2 reproduces the specification of Table 3 and Table B.1 using a longer time difference ranging from 2000 to 2018.

Table B.2: Estimate of average housing supply elasticity: 2000-2018

	$\Delta ln(P) : 2000 - 2018$			
	(1)	(2)	(3)	(4)
Panel a) Using population				
$\Delta ln(Pop)$	0.43***	2.36***	2.32***	2.33***
	(0.08)	(0.58)	(0.38)	(0.38)
R^2	0.12	.	.	.
Obs	319	319	319	319
F-stat		18.17	37.62	21.88
P-value				0.94
Panel b) Using dwellings				
$\Delta ln(Q)$	0.49***	3.16***	3.61***	3.45***
	(0.09)	(0.81)	(0.62)	(0.59)
R^2	0.10	.	.	.
Obs	319	319	319	319
F-stat		16.08	23.88	15.25
P-value				0.59
Panel c) Using income				
$\Delta ln(income)$	0.71***	5.20***	5.51***	5.42***
	(0.18)	(1.54)	(0.98)	(1.00)
R^2	0.09	.	.	.
Obs	319	319	319	319
F-stat		13.25	23.02	13.91
P-value				0.83
Bartik	N	Y	N	Y
Hours of sun	N	N	Y	Y

Note: The specifications are the same as in Table 3, except they are estimated from 2000 to 2018, and income is use as an explanatory variable in Panel c.
* *p < 0.1, ** p < 0.05, *** p < 0.01.* Standard errors in parenthesis.

C Robustness checks and complementary tables: decomposition

Table C.1 reproduces the same specification as Table 4 introducing the share of land developed as in Hilber and Vermeulen (2016) and Baum-Snow and Han (2019). Overall, results look the same, if the share of land developed enters significantly in the equation, the resulting predicted elasticity is strongly correlated (0.95) with the more parsimonious model.

Table C.1: Decomposition of inverse housing supply elasticity, with the share of land developed

	$\Delta ln(P) : 2000 - 2010$				
	(1)	(2)	(3)	(4)	(5)
$\Delta ln(Q)$	4.10***	2.54***	1.85***	-1.72**	-3.04***
	(0.88)	(0.67)	(0.56)	(0.78)	(1.15)
$\Delta ln(Q) \times$ $share\,unavailable$		2.12***	2.07***	1.78***	1.92***
		(0.57)	(0.54)	(0.44)	(0.45)
$\Delta ln(Q) \times$ $Refusal\,Rate$			3.74**	5.12***	11.11***
			(1.46)	(1.25)	(3.87)
$\Delta ln(Q) \times ln(H)$				0.21***	0.17***
				(0.06)	(0.06)
$\Delta ln(Q) \times$ $sharedeveloped$				4.77***	3.23**
				(1.34)	(1.42)
Obs	319	319	319	319	319
Bartik	Y	Y	Y	Y	Y
Hours of sun	Y	Y	Y	Y	Y
Past Population	N	N	N	N	Y
National regulation	N	N	N	N	Y

Note: The specifications are the same as in Table 4, except we add the share of already developed land (measured as the ratio as the surface built on the total surface) as an explanatory variable.
* *p < 0.1,* ** *p < 0.05,* *** *p < 0.01.* Standard errors in parenthesis.

Table C.3 reproduces Table 4 on a longer time span. Result are consistent with those of Table 4.

Table C.2: Decomposition of inverse housing supply elasticity, with density

	$\Delta ln(P) : 2000 - 2010$				
	(1)	(2)	(3)	(4)	(5)
$\Delta ln(Q)$	4.10***	2.54***	1.85***	-0.99	-1.68**
	(0.88)	(0.67)	(0.56)	(0.79)	(0.86)
$\Delta ln(Q) \times$ $share\, unavailable$		2.12***	2.07***	1.93***	2.05***
		(0.57)	(0.54)	(0.43)	(0.40)
$\Delta ln(Q) \times$ $Refusal\, Rate$			3.74**	5.40***	7.91**
			(1.46)	(1.30)	(3.22)
$\Delta ln(Q) \times ln(Pop)$				0.14**	0.11**
				(0.07)	(0.05)
$\Delta ln(Q) \times density$				0.003***	0.002**
				(0.001)	(0.001)
Obs	319	319	319	319	319
Bartik	Y	Y	Y	Y	Y
Hours of sun	Y	Y	Y	Y	Y
Past Population	N	N	N	N	Y
National regulation	N	N	N	N	Y

Note: The specifications are the same as in Table 4, except we add the population density (measured as the ratio between population and the urban area surface) as an explanatory variable.
** p < 0.1, ** p < 0.05, *** p < 0.01.* Standard errors in parenthesis.

Table C.3: Decomposition of inverse housing supply elasticity (2000-2018)

	$\Delta ln(P) : 2000 - 2018$				
	(1)	(2)	(3)	(4)	(5)
$\Delta ln(Q)$	3.44***	2.56***	1.94***	-1.59	-1.32
	(0.59)	(0.50)	(0.37)	(1.20)	(1.10)
$\Delta ln(Q) \times$ $share\, unavailable$		1.32***	1.40***	1.82***	1.83***
		(0.42)	(0.39)	(0.40)	(0.39)
$\Delta ln(Q) \times$ $Refusal\, Rate$			3.36*	7.99***	8.50***
			(1.75)	(2.95)	(3.06)
$\Delta ln(Q) \times ln(Pop)$				0.20***	0.17***
				(0.06)	(0.06)
Obs	319	319	319	319	319
Bartik	Y	Y	Y	Y	Y
Hours of sun	Y	Y	Y	Y	Y
Past Population	N	N	N	N	Y
National regulation	N	N	N	N	Y

Note: The specifications are the same as in Table 4, except they are estimated from 2000 to 2018.
** p < 0.1, ** p < 0.05, *** p < 0.01.* Standard errors in parenthesis.

Table C.4 reproduces Table 4 removing urban areas below 20,000 inhabitants (5 first columns) or weighting by population (Column 6). Results are consistent with those of Table 4.

Table C.4: Decomposition of inverse housing supply elasticity, removing urban areas below 20,000 inhabitants or population-weighted

	$\Delta ln(P) : 2000-2010$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta ln(Q)$	3.27***	2.10***	1.80***	-1.34	-2.49	-10.93***
	(0.76)	(0.60)	(0.55)	(1.01)	(1.98)	(2.12)
$\Delta ln(Q) \times$ $share\,unavailable$		2.15***	2.18***	2.35***	2.48***	2.71***
		(0.59)	(0.60)	(0.53)	(0.58)	(0.48)
$\Delta ln(Q) \times$ $Refusal\,Rate$			2.20	3.12**	11.13*	24.30**
			(1.63)	(1.52)	(6.19)	(9.52)
$\Delta ln(Q) \times ln(Pop)$				0.23***	0.23**	0.65***
				(0.08)	(0.11)	(0.08)
Obs	238	238	238	238	238	319
Bartik	Y	Y	Y	Y	Y	Y
Hours of sun	Y	Y	Y	Y	Y	Y
Past Population	N	N	N	N	Y	Y
National regulation	N	N	N	N	Y	Y

Note: The specifications are the same as in Table 4, except we remove urban areas below 20 000 inhabitants in Columns 1 to 5, and weighted by population in Column 6.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parenthesis.

Table C.5 investigates the robustness of the specification with alternate measures of Q.

Table C.5: Decomposition of inverse housing supply elasticity, alternative measurements of the housing stock

	$\Delta ln(P)$: 2000 − 2010			
	(1)	(2)	(3)	(4)
$\Delta ln(Q)$ measured with:	Dwellings	Population	Households	Income
$\Delta ln(Q)$	-3.19***	-3.64**	-2.63***	1.67
	(1.12)	(1.63)	(0.98)	(1.56)
$\Delta ln(Q)\times$share unavailable	2.18***	6.08***	2.95***	0.46**
	(0.52)	(2.17)	(0.80)	(0.21)
$\Delta ln(Q)\times$ Refusal Rate	16.07***	23.75***	16.46***	4.18**
	(4.48)	(6.84)	(4.44)	(1.65)
$\Delta ln(Q) \times ln(Pop)$	0.17**	0.05	0.11	0.03
	(0.07)	(0.15)	(0.07)	(0.02)
Obs	319	319	319	319
Bartik	Y	Y	Y	Y
Hours of sun	Y	Y	Y	Y
Past Population	Y	Y	Y	Y
National regulation	Y	Y	Y	Y

Note: The specifications are the same as in Table 4, except $\Delta ln(Q)$ correspond to the log variation in the number of dwellings (Column 1), the population (Column 2), the number of households (Column 3), the average fiscal income (Column 4).
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parenthesis.

Table C.6: Decomposition of inverse housing supply elasticity, using the Article 55 of the SRU Act as an instrument

	$\Delta ln(P) : 2000 - 2010$				
	(1)	(2)	(3)	(4)	(5)
$\Delta ln(Q)$	5.57**	3.68**	2.65*	-10.75***	-12.26***
	(2.74)	(1.60)	(1.41)	(1.68)	(1.55)
$\Delta ln(Q) \times$ $share\,unavailable$		2.21	2.24*	2.91***	2.96***
		(1.37)	(1.22)	(0.56)	(0.47)
$\Delta ln(Q) \times$ $Refusal\,Rate$			4.37	6.29**	15.43*
			(4.58)	(2.75)	(9.34)
$\Delta ln(Q) \times ln(Pop)$				0.88***	0.85***
				(0.15)	(0.20)
Obs	50	50	50	50	50
Bartik	Y	Y	Y	Y	Y
Hours of sun	Y	Y	Y	Y	Y
Past Population	N	N	N	N	Y
Area Covered by Art. 55	N	N	N	N	Y

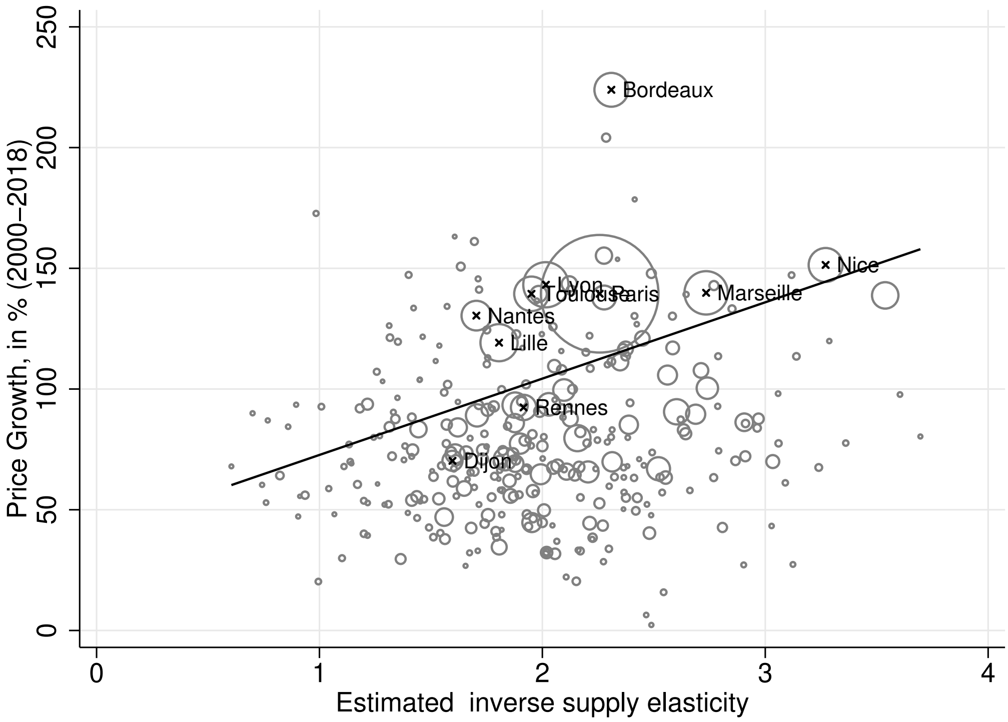
Note: The specifications are the same as in Table 4, except the sample is restricted to the 50 largest urban areas and the refusal rate is instrumented with the share of the urban area covered by the SRU act.
* *p < 0.1, ** p < 0.05, *** p < 0.01.* Standard errors in parenthesis.

Table C.7: Correlation matrix between predicted inverse housing supply elasticities

	Inverse Elasticity (baseline)	Inverse Elasticity (2000-2018)	Inverse Elasticity (weighted)	Inverse Elasticity (with density)	Inverse Elasticity (with land developed)
Inv Elasticity (baseline)	1				
Inv Elasticity (2000-2018)	1.00***	1			
Inv Elasticity (weighted)	0.95***	0.96***	1		
Inv Elasticity (with density)	0.91***	0.91***	0.83***	1	
Inv Elasticity (with land developed)	0.95***	0.95***	0.90***	0.96***	1

*Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Figure C.1: Estimated housing supply elasticities and price growths, 2000-2018



Note: The inverse supply elasticity corresponds to the prediction from estimates reported in column 5 in Table 4. Price growth is computed from local price index. The radius corresponds to the relative population of urban areas in 2000.

D Estimated elasticities for the 30 largest urban areas

Table D.1: Estimates of inverse elasticities for the 30 largest urban areas

AU1999	Urban Area	Elasticity (baseline)	Elasticity (w.o land use regulation)	Elasticity (w.o geograph. constraint)	Elasticity (2000-2018)
1	Paris	1.942	0.972	1.898	2.257
2	Lyon	1.680	0.702	1.541	2.016
3	Marseille-Aix-en-Provence	2.583	1.400	1.730	2.735
4	Lille	1.426	0.523	1.391	1.806
5	Toulouse	1.605	0.491	1.575	1.951
6	Nice	3.265	1.905	1.814	3.271
7	Bordeaux	2.044	0.540	1.956	2.309
8	Nantes	1.313	0.524	1.190	1.704
10	Toulon	3.588	1.538	2.408	3.538
11	Douai-Lens	1.864	0.369	1.849	2.157
12	Rennes	1.571	0.357	1.557	1.916
13	Rouen	1.524	0.347	1.519	1.878
14	Grenoble	2.455	1.633	1.162	2.602
15	Montpellier	2.033	0.879	1.473	2.277
16	Metz	2.312	0.372	2.245	2.521
17	Nancy	1.475	0.348	1.423	1.833
18	Clermont-Ferrand	1.717	0.429	1.584	2.029
19	Valenciennes	1.323	0.369	1.246	1.707
20	Tours	1.797	0.315	1.762	2.097
21	Caen	2.592	0.621	2.247	2.740
22	Orleans	1.929	0.306	1.893	2.205
23	Angers	1.559	0.304	1.512	1.900
24	Dijon	1.192	0.341	1.105	1.597
25	Saint-Etienne	1.686	0.649	1.287	1.993
26	Brest	2.088	0.916	1.410	2.313
27	Havre	2.555	1.223	1.567	2.688
28	Mans	1.624	0.243	1.613	1.953
29	Reims	1.205	0.239	1.197	1.609
30	Avignon	2.369	0.337	2.263	2.562

Note: AU1999 corresponds to the Insee code of the 1999 definition of urban areas.
Lecture note: in the Paris urban area, removing land-use regulations would reduce the inverse supply elasticity from 1.942 to 0.972, while removing geographical constraints would only reduce it to 1.898.

E Diagnosis of the Bartik instrument

This section presents standard diagnosis of the Bartik instrument from Goldsmith-Pinkham et al. (2020).

Table E.1: Summary of Rotemberg weights

Panel A: Negative and positive weights

	Sum	Mean	Share
Negative	-2.168	-0.041	0.406
Positive	3.168	0.069	0.594

Panel B: Correlations of industry aggregates

	α_k	g_k	β_k	F_k	Var(z_k)
α_k	1				
g_k	0.199	1			
β_k	0.002	0.176	1		
F_k	-0.021	0.256	0.045	1	
Var(z_k)	0.011	-0.050	-0.040	-0.098	1

Panel C: Top 5 Rotemberg weight industries

	$\hat{\alpha}_k$	g_k	$\hat{\beta}_k$	95 % CI
Activité d'études, conseil et assistance (821)	0.652	1.549	4.072	(3.030,7.775)
Commerce de gros non alimentaire (631)	0.194	2.340	3.626	(1.995,7.470)
Télécommunications et postes (801)	0.155	1.109	0.494	(-0.500,1.755)
Organismes financiers (941)	0.173	1.423	2.910	(0.885,10.000)
Hôtels, cafés, restaurants (721)	0.157	1.116	4.865	(2.400,10.000)

Note: Authors' computations using the programs from Goldsmith-Pinkham et al. (2020). This table reports statistics about the Rotemberg weights. Panel A reports the share and sum of negative weights. Panel B reports correlations between the weights ($\hat{\alpha_k}$) , the national component of growth, the just-identified coefficient estimates of β^s, the first-stage F-statistic of the sector share ($\hat{F_k}$), and the variation in the sector shares across locations ($var(z_k)$). Panel C reports the top five industries according to the Rotemberg weights. The g_k is the national industry growth rate, β_k is the coefficient from the just-identified regression, the 95 percent confidence interval is the weak instrument robust confidence interval using the method from Chernozhukov and Hansen (2008) over a range from -10 to 10.

Table E.2: Relationship between industry shares and characteristics

	(1) Sector 631	(2) Sector 721	(3) Sector 801	(4) Sector 821	(5) Sector 941	(6) Bartik
Homeownership rate	-0.01	0.06	-0.01	-0.06	-0.00	-0.14
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.08)
Vacancy rate	0.01	-0.18	0.03	-0.09	0.04	0.09
	(0.02)	(0.13)	(0.03)	(0.04)	(0.03)	(0.36)
ΔHomeownership rate	-0.03	-0.52	0.04	-0.25	-0.01	-0.74
	(0.02)	(0.13)	(0.04)	(0.05)	(0.02)	(0.31)
ΔVacancy rate	-0.01	0.20	-0.10	-0.03	0.02	-0.65
	(0.02)	(0.07)	(0.03)	(0.03)	(0.04)	(0.29)
R^2	0.02	0.15	0.03	0.21	0.01	0.05
Observations	319	319	319	319	319	319

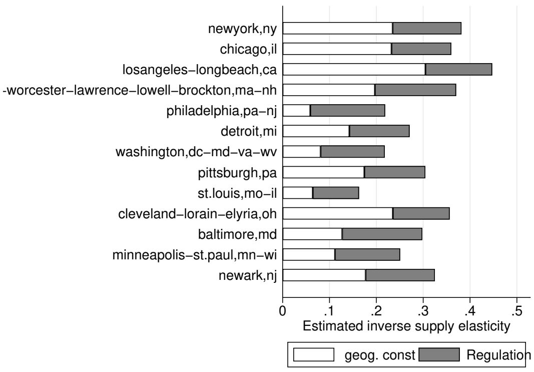
Note: Each column reports results of a single regression of a sector (Columns 1 to 5) or the Bartik instrument (Column 6) on the homeownership and vacancy rates in 2000, and their variation between 2000 and 2010. Sectors are defined in Panel C from Table E.1.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parenthesis.

F Decomposition of supply elasticity in the US

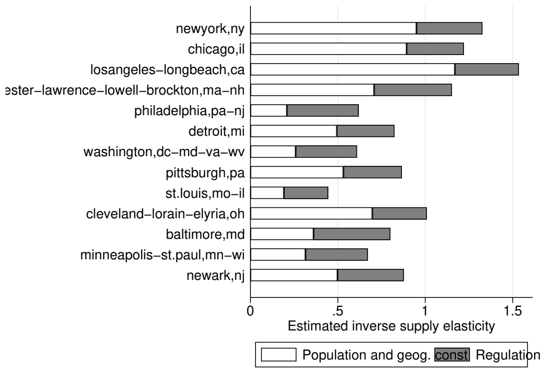
We report some decompositions of inverse housing supply elasticities estimated by Saiz (2010) in the United States.

Figure F.1: Decomposition of inverse supply elasticities in the US for the largest MSAs

(a) Decomposition of housing supply elasticity, without population



(b) Decomposition of housing supply elasticity, main specification



Note: Author's computation from Saiz (2010). Panel a) comes from point estimates reported in Table V, column 1 from Saiz (2010). Panel b) comes from point estimates in Table V from Saiz (2010). Geographical constraint and land use regulation comes from Saiz (2010) while population data comes from the US census.

Table F.1: Shorrocks-Shapley of inverse housing supply elasticity, US

	Inverse Elasticity	
	W.o population	With population
Land use regulation	0.11	0.12
Geographical Constraint	0.89	0.76
$Ln(pop)$	.	0.08
Total	1	1

Notes: Author's computation from Saiz (2010). Column 1 comes from point estimates reported in Table V, column 1's dependent variable comes from Saiz (2010). Column 2's dependent variable comes from point estimates in Table V from Saiz (2010). Geographical constraint and land use regulation comes from Saiz (2010) while population data comes from the US census.