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Modelling the Aggregate Effects of Housing Supply Policies

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Modelling the Aggregate Effects of Housing Supply Policies

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Abstract

What are the aggregate effects of housing supply-side policies, such as zoning reforms? In structural models, the answer involves characterising the equilibrium housing price function. I show that a housing price function should separately characterise how policies affect: 1) the response of house prices to *new* demand ("Elasticity Effect"); 2) the cost of satisfying existing housing demand ("Baseline Effect"). While the former can be calibrated to match estimates of price-demand elasticities such as Saiz (2010), the latter requires a separate calibration. However, popular models in Urban Economics and Economic Geography do not separately characterise and calibrate the Baseline and Elasticity Effects, introducing potential biases in the estimation of long-run policy effects. I propose a characterisation that makes such biases explicit, nests most popular characterisations, and allows to separately characterise and estimate the two effects. Calibrating the Baseline Effect to conservative empirical estimates from the literature, I find housing supply policy effects up to one order of magnitude larger than other characterisations applied to the same model.

Keywords: housing supply, structural models, zoning, bias

JEL Classification: R1, R23, R31

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1 Introduction

What are the aggregate consequences of Not-In-My-Backyard (NIMBY) policies in high-productivity cities? What are the General Equilibrium effects of restrictive zoning policies? These are central questions in both the political debate of several countries, and the economic literature (Ganong and Shoag, 2017; Herkenhoff, Ohanian and Prescott, 2018; Hsieh and Moretti, 2019; Bryan and Morten, 2019; Duranton and Puga, 2023; Parkhomenko, 2023; Fajgelbaum and Gaubert, 2025; Greaney, 2025). In practice, addressing these questions involves characterising the market-clearing house price function of a location choice model and performing a counterfactual exercise. However, the price functions commonly used in Urban Economics and Economic Geography models are rarely designed with the explicit goal of performing such counterfactuals.[1]

I show that a model's house price function should account for two effects of housing supply policies. First, how policies affect the reaction of house prices to *additional* demand. I refer to this effect as the "Elasticity Effect". Second, how they change the cost of satisfying *existing* ("baseline") demand in a given location. I refer to this effect as the "Baseline Effect".

To understand the difference between the two effects, consider a policy increasing permitted building heights above their constrained level. Since it is now possible to build tall, additional demand puts lower pressure on long-run prices, as land costs can be spread out over more units. That is, the price-demand elasticity is reduced. This is the *"Elasticity Effect"*. Moreover, if housebuilding becomes sufficiently cheaper, looser zoning regulations can create competition among developers to accommodate the *existing* population. To prevent the creation of excess supply, even when demand is constant, prices must fall until building new housing becomes unprofitable for developers.[2] This is the *"Baseline Effect"* of housing supply policies.

[1] An exception is Duranton and Puga (2023), who endogenise the price effects of regulations with an ad-hoc structure.

[2] Notice how the concept of "unprofitability" would include factors such as permitting risk, approval processes, or mere changes in the optimal profit point in case of oligopolistic competition.

I then use the Baseline/Elasticity Effect framework to uncover the implicit biases of popular housing sector characterisations in Economics models. The biases arise from the common practice of calibrating the Elasticity Effect to match empirical estimates of the price/demand elasticities such as Saiz (2010). Problematically, when the price function does not allow to separately characterise and calibrate the Elasticity and Baseline Effects, implicit assumptions are made on the latter. As a consequence, this approach introduces biases, pricing puzzles or even lack of identification of the aggregate housing policy effects.

Finally, I introduce a well-characterised housing price function that separately characterises the Baseline Effect of regulations while preserving tractability. Other common characterisations are nested as particular cases. I show that, for reasonable but somewhat conservative calibrations of the price function and its Baseline Effect, other well-identified functions can underestimate the aggregate GDP gains of reducing regulations that hold back housing supply by more than one order of magnitude due to underestimating the Baseline Effect.

1.1 Related Literature

Several contributions in Urban Economics and Economic Geography have studied how house-building regulations limit construction output and how, in turn, this affects house prices, individual location choices and, ultimately, aggregate GDP (Ganong and Shoag, 2017; Herkenhoff, Ohanian and Prescott, 2018; Hsieh and Moretti, 2019; Bryan and Morten, 2019; Parkhomenko, 2023; Fajgelbaum and Gaubert, 2025; Greaney, 2025). However, performing counterfactual policy exercises requires a model and - thus - specific structural assumptions that affect estimated policy effects. This paper contributes to the literature in two ways. First, I introduce a framework to understand the economic intuition and possible biases behind the characterisation of housing in popular models of spatial misallocation. Second, using a simple location choice model, I show that several popular characterisations of the housing sector may severely underestimate aggregate gains from housing supply, or even lack identification.

In this sense, this study is close to Greaney (2025), which shows how the seminal paper by Hsieh and Moretti (2019) suffers from scale effects. The issue arises *only* when performing the very specific housing regulation counterfactual on price-demand elasticities. I generalise this argument in two directions. First, to a larger set of popular housing characterisations and counterfactuals. Second, to more general set of implicit assumptions that may bias the estimation of the effects housing policy. To do so, I introduce a clear and formal separation between the Elasticity and Baseline Effect, which allows me to pin-point the exact implicit assumptions of any characterisations.

This analysis is also motivated by studies such as D'Amico et al. (2024), Babalievsky et al. (2023), and Parkhomenko (2023), which show how regulations can affect housing TFP or developers' "production multiplier".[3] D'Amico et al. (2024) provides causal evidence that regulations reduce the size of construction firms, reducing economies of scale. In Parkhomenko (2023), regulations simultaneously affect both TFP and the capital-land mix. I highlight the theoretical and quantitative importance of accounting for "Baseline Price" effects of regulations (which nest TFP effects) and introduce a family of housing price functions that allows to flexibly characterise and calibrate such effects.

This paper indirectly relates to the literature studying the endogenous determination of housing supply restrictions and their aggregate effects (Bunten, 2017; Parkhomenko, 2023; Duranton and Puga, 2023). While this paper does not specifically examine the endogeneity of regulations, it provides useful tools to assess what counterfactuals can be studied in a given model, even when regulations are endogenous. For example, Parkhomenko (2023) uses a price function susceptible to scale effects. Instead, Duranton and Puga (2023) avoids problematic assumptions by explicitly introducing "permitting costs" as a separate house price component and counterfactual experiment.

[3]See the literature review by Baum-Snow and Duranton (2025) for a more complete discussion of productivity trends and determinants in housing supply.

1.2 Organisation

Section 2 formally introduces the difference between Baseline and Elasticity Effects of housing supply policies. In Section 3 I uncover the hidden assumptions that popular model characterisations make on the Baseline Effects and introduce a well-characterised house price function. In Section 4 I quantify the differences in estimated policies effects between different characterisations and discuss how to calibrate the well-characterised house price function. Section 5 extends the discussion to further characterisations and counterfactuals. Section 6 takes stock of the findings.

2 Baseline and Elasticity Policy Effects

Consider a simple location choice model in which each individual demands one unit of housing. Locations differ in their house price P_j. Individuals live in the location which maximises their utility, potentially including idiosyncratic preferences. Let l_j denote the share of individuals who reside in j in equilibrium. Assume that P_j, the market-clearing house price of a location, is a function of local population shares and a vector of supply and demand parameters $\mathbf{b}_j$: $P_j = P(l_j, \mathbf{b}_j)$, twice differentiable in all parameters. $\mathbf{b}_j$ may capture total population, permit regulations, and any other relevant characteristic of demand, supply, and market structure.[4] Then, the market-clearing price can be approximated as:

$$P_j(l_j, \mathbf{b}_j) \approx \underbrace{P(\bar{l}_j, \mathbf{b}_j)}_{\substack{\overline{P}_j \\ \text{Baseline Price}}} + \underbrace{\frac{\partial P(\bar{l}_j, \mathbf{b}_j)}{\partial l_j}}_{\substack{\text{Price-demand} \\ \text{Elasticity}}}(l_j - \bar{l}_j),$$

Here, $\bar{l}_j$ denotes the reference demand level at location j, which may vary across locations.[5] Hence, $\overline{P}_j$ is the "reference" price level of j, achieved when demand is at its reference point $\bar{l}_j$. The second term on the right-hand side represents the price-demand "elasticity" which,

[4]While not necessary for discussion, one can assume that such price function originates from the profit-maximising behaviour of developers, as in Baum-Snow and Duranton (2025).

[5]For example, it could be the population shares of each location in a given, arbitrary year.

in practice, is estimated by matching empirical estimates such as Saiz (2010). This linear relationship is exact for a class of log-additive price functions.

Consider now the partial equilibrium effect of changing a housing supply parameter $\gamma_j \in \mathbf{b}_j$ (e.g., zoning regulations) to a new value γ_j'. For a small change in γ_j, the partial equilibrium change in price can be approximated as:[6]

$$\underbrace{\frac{\partial P_j(l_j, \mathbf{b}_j')}{\partial \gamma_j}}_{\text{Policy Effect}} \approx \underbrace{\frac{\partial P(\bar{l}_j, \mathbf{b}_j)}{\partial \gamma_j}}_{\text{Baseline Effect}} + \underbrace{\frac{\partial^2 P(\bar{l}_j, \mathbf{b}_j)}{\partial l_j \partial \gamma_j}(l_j - \bar{l}_j)}_{\text{Elasticity Effect}}. \tag{1}$$

The first term on the right-hand side represents the "Baseline Effect" of changing the housing supply technology. It captures how the market-clearing price changes under the new policy, assuming demand was at the reference level $\bar{l}_j$. The second term, named the "Elasticity Effect", captures how the supply technology changes the price/demand elasticity $\partial P(l_j, \mathbf{b}_j)/\partial l_j$ and, thus, how much the demand in excess of the reference level, $l_j - \bar{l}_j$, affects the price.

In simpler words, changes to the supply technology γ_j can affect both the cost of supplying housing in addition to the reference demand $\bar{l}_j$ (Elasticity Effect), and the cost of satisfying reference demand $\bar{l}_j$ itself (Baseline Effect). For example, increasing building height limits not only reduces the cost of supplying *additional* housing (Elasticity Effect) but, as marginal costs fall and expected profits rise, baseline prices must also fall to avoid excess supply. Other sources of Baseline Effects may include how regulations negatively affect construction TFP (D'Amico et al., 2024) or developers' incentives (Babalievsky et al., 2023) and, thus, output.

3 Baseline and Elasticity Effects in Economic Models

The distinction between Baseline and Elasticity Effects is crucial to understand two separate consequences of housing supply policies: the effect on baseline prices, and the effect arising

[6]The General Equilibrium effect includes the additional term $\frac{\partial P()}{\partial l_j} \nabla_\gamma (l_j - \bar{l}_j)$, capturing how equilibrium population shares change as a consequence of the policy vector $\gamma = [\gamma_1, \ldots, \gamma_J]$.

from changing the price-demand elasticity.

In practice, most Urban Economics and Economic Geography models choose the policy parameter γ to be the price-demand elasticity itself, calibrated following approaches such as Saiz (2010), Baum-Snow and Han (2024), Albouy and Ehrlich (2018) and Hilber and Vermeulen (2015), which map indices of regulatory restrictions (Gyourko, Saiz and Summers, 2008) into local elasticities. Baum-Snow and Duranton (2025) suggests these elasticities should be estimated during periods of price and *demand* growth to avoid biases from slack market periods.

Problematically, while these approaches are useful to estimate the Elasticity Effect, they are often used to inform and estimate the Baseline Effect as well. The reason is that the most common housing price functions do not allow for a separate characterisation and parametrisation of Elasticity and Baseline Effects. By calibrating the policy parameters to match the first, implicit assumptions are made on the second, introducing potential biases.

In Table 1, I make these assumptions explicit for a number of price functions commonly employed in the literature (functions I to IV). I then introduce a new supply-demand characterisation (function V) which solves the Baseline Effect characterisation issues while preserving tractability.[7] The first column shows the price function or, when microfounded, the demand-supply system. The second column derive the Baseline Price $\overline{P}_j$. The third column shows the Baseline Effect: the derivative of the (log) Baseline Price with respect to the policy parameter γ_j, representing the change in prices that would be realised if demand was kept exogenously fixed. The fourth column provides a brief description of the implicit assumptions or issues of the price function.

The notation follows that of Section 2, with the following additional terms. L is the total size of population in the economy, so that the population (level) of each location is $L_j = l_j L$. g is

[7] In Appendix C I provide an alternative characterisation with additional flexibility.

the ratio between current population L and reference population $\overline{L}$, representing the aggregate increase in housing demand from the reference point. A_j is a location's housing productivity parameter, to be intended as either TFP or TFP plus land factor productivity. As a reminder, $\overline{l}_j$ and l_j represent reference and current population shares, respectively.

Table 1: Baseline Effects of Different Supply Functions

Function	Baseline Price $\overline{P}_j$	Baseline Effect $\partial \ln(\overline{P}_j)/\partial \gamma_j$	Issues/Bias
Implicit Price Functions			
$(I)\ P_j = \tilde{P}_j(L_j)^{\gamma_j}$	$\tilde{P}_j(\overline{l}_j\overline{L})^{\gamma_j}$	$\ln(\overline{L}) + \ln(\overline{l}_j)$	Scale dependency on pop. $\overline{L}$
$(II)\ P_j = \tilde{P}_j\left(\frac{l_j g}{\overline{l}_j}\right)^{\gamma_j}$	$\tilde{P}_j$	0	Baseline Effect is 0
Supply/Demand Systems			
$(III)\ \begin{cases} H_j^s = A_j^{\frac{\gamma_j}{1+\gamma_j}} K^{\frac{1}{1+\gamma_j}} \\ H_j^d = \left(\frac{l_j g}{\overline{l}_j}\right) \end{cases}$	$(1+\gamma_j)\frac{r}{A_j^{\gamma_j}}$	$\frac{1}{1+\gamma_j} - \ln(A_j)$	Scale dependency on A_j
$(IV)\ \begin{cases} H_j^s = (A_j K)^{\frac{1}{1+\gamma_j}} \\ H_j^d = \left(\frac{l_j g}{\overline{l}_j}\right) \end{cases}$	$(1+\gamma_j)\frac{r}{A_j}$	$\frac{1}{1+\gamma_j}$	$\frac{\partial \ln(\overline{P}_j)}{\partial \gamma_j}$ only depends on γ_j
$(V)\ \begin{cases} H_j^s = (1+\gamma_j)^{-\alpha_j} \times (A_j K)^{\frac{1}{1+\gamma_j}} \\ H_j^d = \left(\frac{l_j g}{\overline{l}_j}\right) \end{cases}$	$(1+\gamma_j)^{1+\alpha_j(1+\gamma_j)} \times \frac{r}{A_j}$	$\alpha_j(1+\ln(1+\gamma_j)) + \frac{1}{1+\gamma_j}$	NA

Notes: L_j is the population of location j, l_j is the population share, and $\overline{l}_j$ is the reference share. A_j is housing TFP. K is capital input, with price r. L is total population growth, and g is the ratio between current and reference population, so that $\overline{L} = L/g$. γ_j is the parameter directly affected by the policy. $\tilde{P}_j$ (function 2) is a constant reference price for location j, so that $P_j = \tilde{P}_j$ whenever $l_j = \overline{l}_j$ and $g = 1$.

Price function (I) has been adopted in several structural models in the Economic Geography literature (Glaeser, Gyourko and Saks, 2005; Diamond, 2017; Ganong and Shoag, 2017; Hsieh and Moretti, 2019; Bryan and Morten, 2019). However, it suffers from a crucial issue: the price effect of changing γ_j depends on the population size $\overline{L}$.[8] Hence, as noted by Greaney (2025), the effects of this specific policy counterfactual are not identified.[9]

Price function (II) (Diamond and Gaubert, 2022; Greaney, 2025; Greaney, Parkhomenko and

[8]See Greaney (2025) for a proof. Ganong and Shoag (2017) recognises the issue. Duranton and Puga (2023) also uses this equilibrium price function, but does not consider the γ parameter a policy parameter. Instead, regulations are captured via a separate component of housing costs.

[9]In particular, neither the Elasticity Effect nor the Baseline Effect is identified.

Van Nieuwerburgh, 2025)[10] solves the scale-dependency of function (I). However, this price function implicitly assumes that the Baseline Effect of γ_j is zero: the market-clearing price at the baseline demand level $\bar{l}_j$ is a constant. Problematically, this feature creates two pricing puzzles when conduction counterfactuals on γ_j. First, that prices can fall below the Baseline Price $\tilde{P}_j$ only if demand falls ($l_jg < \bar{l}_j$).[11] Second, and as a consequence, improving supply elasticities everywhere may not reduce house prices in any location if the General Equilibrium spatial distribution of population is unchanged. I provide a proof of the paradox in Appendix A. This is a problematic assumption if, for example, changes in regulations affect both housing productivity and the price-demand elasticity at the same time.

Supply-demand system (III) features a Cobb-Douglas supply function, as in Gaubert and Robert-Nicoud (2025), Herkenhoff, Ohanian and Prescott (2018) and Parkhomenko (2023).[12] Combes, Duranton and Gobillon (2021) argue that a Cobb-Douglas functional form provides a good approximation of construction costs for single-family homes in France. However, the Baseline Effect depends on the *level* of A_j (representing TFP or a land factor). Since the normalisation of the average A_j is arbitrary, the Baseline Effect is not identified. Also puzzlingly, for $A = 1$, sufficiently above-average productivity locations with tight regulations ($A_j > \exp[1/(1+\gamma_j)] > 1$) experience *negative* Baseline Effects from additional regulations.

The supply-demand system (IV) presents a production function with capital-augmenting tech-

[10] Diamond and Gaubert (2022) use the notation $P_j = \left(H_j^s/\overline{H}_j^s\right)^{\gamma_j}$, where $\overline{H}_j$ is baseline housing supply at $P_j = 1$. In equilibrium, H_j^s is function of population shares l_j, and $\overline{H}_j^s$ of baseline shares $\bar{l}_j$. Hence, it is of the same family as (II). Greaney, Parkhomenko and Van Nieuwerburgh (2025) uses this functional form for equilibrium rents, rather than (ownership) prices.

[11] In fact, to avoid this issue, Greaney, Parkhomenko and Van Nieuwerburgh (2025) perform a counterfactual by directly shocking the Baseline Price $\tilde{P}_j$ itself.

[12] Gaubert and Robert-Nicoud (2025) provide a general form for the supply system with γ_j-independent A_j. Their supply function is $H_j^s = A_j K(P_j/r, \eta_j)$, where the elasticity of supply to prices is increasing in η_j. Herkenhoff, Ohanian and Prescott (2018) uses a Cobb-Douglas in land and capital. However, they model land use restrictions as a land-augmenting parameter. Parkhomenko (2023) employs a Cobb-Douglas in land and capital, augmented with a TFP which also depends on regulations. However, the average TFP shifter and land supply cannot be innocuously normalised. See Appendix C for a discussion of how to accommodate this feature by Parkhomenko (2023).

nology (Glaeser and Gyourko, 2025).[13] While this characterisation solves scale dependency, the Baseline Effect is not independently characterised from the Elasticity Effect, similarly to price function (II). Moreover, the characterisation assumes that highly regulated locations always have the smallest Baseline Effects.

Remark. Notice how price functions (I) to (IV) impose arbitrary values on the Baseline Effect, whether identified or not. Specifically, no flexibility exists to separately characterise the Baseline and Elasticity Effects. In fact, information on prices and either population (I) or price-demand elasticities (II, III and IV) is sufficient to estimate the Baseline Effect.

Well-characterised Price Function Finally, the supply-demand system (V) provides just enough flexibility to independently characterise and calibrate the Baseline Effect, while retaining tractability. The resulting house price function is

$$P_j = \underbrace{(1+\gamma_j)^{1+\alpha_j(1+\gamma_j)} \frac{r}{A_j}}_{\bar{P}_j} \left(\frac{l_j}{\bar{l}_j} g \right)^{\gamma_j}, \tag{2}$$

where α_j captures how prices respond to changes in the price-demand elasticity γ_j at the baseline level of demand $\bar{l}_j$. $\alpha_j > 0$ implies that TFP is decreasing in γ_j. For example, regulations could directly or indirectly prevent the use of technologies that are more overall productive. Conversely, $\alpha_j < 0$ means that obstacles to housing supply increase TFP. For example, by increasing the marginal product of land (as in a Cobb-Douglas, where the expenditure shares sum to one). Conceptually, this characterisation is close to how "regulatory distortions" affect the "developer revenue multiplier" in Babalievsky et al. (2023) and, thus, the baseline price at which developers are willing to supply housing at for a given level of demand. This function is also close to how Parkhomenko (2023) allows regulations to affect both housing TFP and

[13] Glaeser and Gyourko (2025) uses γ_t as a (dis)preference parameters for density, which determines optimal land demand and housing costs. Their pricing function is $P_j = A_j D_j^{\gamma_t}$, where higher density can be intended as higher capital input. This function's Baseline Price and Baseline Effect are consistent with the ones of system (IV) as long as density D is exogenous and individuals only optimise on land ownership.

the price-demand elasticity. Moreover, unlike Greaney, Parkhomenko and Van Nieuwerburgh (2025), it assumes that price-demand elasticity shocks can have both Elasticity and Baseline Effects.

The Baseline Effect of this price function is

$$\text{Baseline Effect} = \frac{\partial \ln(\overline{P}_j)}{\partial \gamma_j} = \alpha_j(1+\ln(1+\gamma_j)) + \frac{1}{1+\gamma_j} + \frac{\partial \alpha_j}{\partial \gamma_j}(1+\gamma_j)\ln(1+\gamma_j). \tag{3}$$

Equation (3) provides two insights. First, a sufficiently negative α_j leads to price-demand elasticity shocks having negative Baseline Effects. That is, additional regulations *reduce* baseline prices $\overline{P}_j$. This would be a paradox. Hence, we can use economic intuition to establish a lower bound for $\alpha_j = -(1+\gamma_j)^{-1}$, which implements a null Baseline Effect. Second and most importantly, this specification nests both characterisations (II) and (IV), clarifying their implicit assumptions. System (II) implicitly assumes that the Baseline Effect is exactly zero. The reason is that TFP falls when regulations are relaxed by the exact amount necessary to compensate the increase in the marginal productivity of capital. Conversely, the capital-augmenting system (IV) (Glaeser and Gyourko, 2025) assumes $\alpha_j = 0$, meaning that housing TFP is not affected by γ_j. Hence, relaxing regulations reduces Baseline Prices, since the marginal product of capital increases.

4 Quantitative Implications

I quantify how estimates of housing supply policy effects are affected by different characterisation of the house price function. Using the spatial equilibrium model of Hsieh and Moretti (2019), I replicate their policy counterfactual of reducing housing supply regulations in the three most productive US commuting zones. I then report the change in GDP as a consequence of the counterfactual policy. I repeat the exercise for each characterisation of the house price function reported in Table 1. I report the counterfactual results in Table 2.

Function (I) yields a negative GDP gain (-0.34%) and lacks identification due to scale dependency on population L. In fact, doubling aggregate population L leads to a policy effect of -0.27%. A paradox, since L is supposed to be a mere normalisation. Similarly, the effects of function (III) are not identified due to scale dependency on the average TFP level A. Doubling the average TFP halves the expected policy effects from 0.16% to 0.09%.

Employing function (II), Greaney (2025) fixes scale dependency but obtains a near-zero GDP effect (+0.02%). This result could be interpreted as a short-term policy effect, as it implicitly assumes that baseline prices can never fall unless $l_j g > \bar{l}_j$.[14]

Finally, I study different calibrations of the demand/supply system (V). Setting $\alpha_j = -(1+\gamma_j)^{-1}$, its lower-bound that ensures non-negative Baseline Effects, replicates function (II), with a GDP gain of 0.02%. Hence, it must be that employing function (II) provides a *lower bound* of aggregate housing supply policy gains.

For $\alpha_j = 0$, system (V) replicates a capital-augmenting technology. In this case, the policy effects are over three times as large (+0.07%) as when α_j is set at its lower bound. As we increase α_j, we start assuming that supply restrictions and regulations reduce TFP. Hence, relaxing them can have important Baseline Effects. For example, regulations could reduce economies of scale in the construction sector (D'Amico et al., 2024). Ultimately, α_j determines the share of the total γ_j policy effect that comes from Baseline Effects. Since the Elasticity Effect does not depend on α_j, higher shares of GDP gains coming from the Baseline Effect also imply larger overall policy effects.

The simulations show that the aggregate effect of the considered housing supply policy is increasing in α_j, being 0.26% for $\alpha_j = 1$ and 2.25% for $\alpha_j = 10$. To understand the underlying

[14]To see why, consider how the Baseline Effect is zero whenever developers' incentives to build are not sufficient to trigger new housing supply, assuming a fixed level of demand. This would be an unreasonable result if we expect regulations to also change the cost of supplying the existing housing stock, but not if we assumed it as "given", which is a reasonable assumption until longer-term redevelopment can take place. Alternatively, Greaney, Parkhomenko and Van Nieuwerburgh (2025) interpret this result as shocks to price-demand elasticity *alone* delivering small aggregate gains when $\bar{l}_j \approx l_j$.

channel behind these estimates and how they are affected by α, in Appendix D I provide additional estimates for the Baseline Effect on house prices.

Table 2: Policy Counterfactual Simulations

Function	α_j	GDP Gain	$L' = 2L$	$A'_j = 2A_j$
Implicit Price Functions				
$(I)\ P_j = \tilde{P}_j(L_j)^{\gamma_j}$		−0.34%	−0.27%	
$(II)\ P_j = \tilde{P}_j \left(\frac{l_j g}{\bar{l}_j}\right)^{\gamma_j}$		0.02%		
Supply/Demand Systems				
$(III) \begin{cases} H_j^s = A_j^{\frac{\gamma_j}{1+\gamma_j}} K^{\frac{1}{1+\gamma_j}} \\ H_j^d = \left(\frac{l_j g}{\bar{l}_j}\right) \end{cases}$		0.16%		0.09%
$(V) \begin{cases} H_j^s = (1+\gamma_j)^{-\alpha_j} (A_j K)^{\frac{1}{1+\gamma_j}} \\ H_j^d = \left(\frac{l_j g}{\bar{l}_j}\right) \end{cases}$	$-(1+\gamma_j)^{-1}$	0.02%		
	0	0.07%		
	1	0.26%		
	2	0.45%		
	5	1.08%		

Notes: "Function" details the model's characterisation. α_j is the parameter introduced by characterisation (5), controlling whether TFP falls ($\alpha_j > 0$) or increases in γ_j. "GDP Gain" is the counterfactual GDP increase. Columns $L' = 2L$ and $A'_j = 2A_j$ report the effects of re-normalising population and TFP, respectively. For further information on the underlying model, see Appendix B.

4.1 Estimating the Baseline Effect parameter α

Ultimately, the precise estimation of $\alpha = [\alpha_1, \ldots, \alpha_J]$ is outside the scope of this paper, as its calibration depends on the specific model, country, geographical scope the housing price function, and normalisation of $\bar{l}_j$. Instead, the scope of this paper is to provide a new tool for researchers to correctly design their models to estimate the housing supply policy effects, and a framework (the Baseline/Elasticity Effect) to assess the implicit assumptions of their modelling choices.

Nevertheless, in this section I provide an example of how the estimation of the parameters related to the Baseline Effects are unrelated to the way the price-demand elasticity is estimated. This example reinforces the message that using information on the Elasticity Effect to inform the Baseline Effect is the main source of bias in the estimation of the aggregate effects of housing policies. In particular, I take estimates of γ_j "as given" by matching the estimates by Saiz (2010), and proceed to match other empirical evidence to calibrate α.

I now review existing empirical evidence on the TFP effects of housing regulations, and how they can be used to inform plausible values of α and, thus, quantify the effects of housing policies. These values are indeed positive, larger than the theoretical lower bound, and lead to policy effect estimates larger than the comparable literature.

However, recall that - since baseline demand $\bar{l}_j$ is normalised to an arbitrary value - calibrating α_j to the sole "direct" TFP effects may underestimate the total effect of reducing regulations. The reason is that calibrating $\bar{l}_j \approx l_j$ and $g \approx 1$ always reduces the size of the Elasticity Effect, relative to assuming a reference point where housing demand $\bar{l}_j$ is considerably different from the "current one $l_j g$ (for example, a year further back in the past). See the next section for an insight of why this may be the case.

Empirical Evidence for α. D'Amico et al. (2024) show that zoning regulations in the US have reduced the economies of scale of construction companies. They estimate that 1SD additional regulations, calculated using a modified Wharton Index, reduce revenue per employee by 0.13 log-points, and capital input per employee by 0.118 points. Using the supply function underlying Equation (2) and an (unweighted) average price-demand elasticity of $\gamma = 0.525$ for the US (Saiz, 2010), these estimates correspond to a 0.053 log-points fall in TFP.[15] Matching this change at the average level of elasticity implies $\alpha = 1.75$.

Notice that this estimate is likely to underestimate the fall in construction output for two reasons. First, prices and, hence, revenue increase with regulations. Second, as shown by D'Amico et al. (2024), unit output scales approximately 30% faster than revenue with firm size.[16] By

[15] The results arises from computing the total derivative of log-revenue, $\ln(P_j \times H_j^s(P_j, z))$, for z being the level of regulations, assuming prices are constant. Inverting the formula for the change in TFP yields $\Delta \ln(TFP) = 0.130 - 0.118 \times (1+\gamma)^{-1} = 0.053$.

[16] See Figure 10, "Output and Revenues per Employee" in D'Amico et al. (2024), pg. 35.

applying the multiplier to the causal findings in revenue falls, we find that the fall is per-worker construction output is up to $0.130 \times 1.3 = 0.169$ log-points for a 1SD additional regulations. Subtracting the fall in capital input, TFP falls by 0.092 log-points. Matching this change at the average level of elasticity implies $\alpha = 2.5$.

The hypothesis that regulations change housing TFP is also supported by Parkhomenko (2023), who finds that TFP falls by approximately 8.6% for a 1SD increase in the Wharton Index, consistent with $\alpha_j \approx 2.2$.[17]

Quantitative Effects. Including the 90% C.I. behind the aforementioned parameter estimates suggests that $\alpha \in [1.2, 3.1]$ (D'Amico et al., 2024) or $\alpha \in [0.7, 3.9]$ (Parkhomenko, 2023). Applying these values of α to the Hsieh-Moretti model implies that aligning regulations in the three most productive commuting zones to the US mean would improve GDP by 0.20% ($\alpha = 0.7$) to 0.85% ($\alpha = 3.9$). For $\alpha = 2.5$, the policy would improve GDP by 0.56%. While somewhat small in absolute terms, there are three considerations to make.

First, the effect obtained with $\alpha = 0.7$ is three times larger than choosing $\alpha = 0$, and one order of magnitude larger than setting it at the theoretical lower bound. The estimates achieved using the most optimistic estimate of $\alpha = 3.9$ is 12 to 42 times larger than alternative well-identified characterisations.

Second, the model does not include agglomeration economies, nor other externalities such as learning, or GE effects such as up-skilling of individuals who expect to be able to move to city jobs. Hence, these results should be interpreted as a comparison of effect sizes within the same model, not as absolute upper bounds.

Third, the counterfactual involves a moderate reduction of regulations in only three commuting

[17] Parkhomenko (2023) calibrates TFP as $\exp(\bar{\chi}_j + \hat{\chi} z_j)$. The parameter $\hat{\chi}$ is set to -0.32, matching the results of an IV estimation. Their normalisation of the Wharton Index imposes a mean of 1 and a SD of 0.27. Hence, the effect of a 1SD change in regulations is $-0.32 \times 0.27 = -0.0864$ log-points.

zones. Extending the policy to the next 7 most productive US MSAs and reducing the regulation level to the one of the Huston MSA, as in Parkhomenko (2023), would double long-run GDP gains to 0.5-1.5%, depending on the choice of α.

5 Alternative Counterfactuals and Extensions

In the previous sections I have analysed the implicit assumptions and quantitative implications of a specific counterfactual: changing the demand-supply elasticities by changing regulations. However, one may want to study different counterfactuals. In this section, I argue that the Baseline-Elasticity framework provides a general tool to understand the implicit assumptions behind these alternatives counterfactuals. Uncovering these assumptions is crucial to understand whether the function is suitable for the specific counterfactual a researcher wants to performs. Importantly, some price functions may be suitable for a counterfactual, but not for another.

A common alternative counterfactual to shocking demand-supply elasticities is to directly shock Baseline Prices (Duranton and Puga, 2023; Greaney, Parkhomenko and Van Nieuwerburgh, 2025). However, depending on how the housing function is characterised, such counterfactual can assume different economic interpretations.

For example, consider a change in the price constant $\tilde{P}_j$ in price function (II), as in Greaney, Parkhomenko and Van Nieuwerburgh (2025). It is evident how the shock yields a positive Baseline Effect ($\partial \overline{P}/\partial \tilde{P}_j = 1$) and a null Elasticity Effect. While both effects are well-identified, this assumption is exactly specular to the one made when shocking γ_j in function (II). Hence, it may suffer from identical issues.

To see why, consider how the partial-equilibrium increase in log-prices induced by increasing

γ_j to $\gamma_{j'}$, when keeping $\tilde{P}_j$ constant, is[18]

$$(\gamma_{j'} - \gamma_j)\ln\left(\frac{l_j g}{\bar{l}_j}\right).$$

Hence, whenever the Baseline Price is treated as a constant relative to γ_j, the policy effect of a γ_j shock depends on the normalisation of $\bar{l}_j$, which is arbitrary. Since $\tilde{P}_j$ is usually calibrated as the residual necessary to match observed prices, after having normalised $\bar{l}_j$ and estimated γ_j, the Baseline Effect suffers from scale effects in $\overline{l_j}$. While not necessarily a problematic assumption per se, this result suggest that the economic interpretation of each $\tilde{P}_j$ and γ_j counterfactual is not straightforward when it is not possible to explicitly calibrate their relative size. That is, it can be hard to build a counterfactual experiment able to match the effects of real-world policies, if these have effects of *both* the Baseline and the Demand-induced components of Price.[19]

Duranton and Puga (2023) performs a similar counterfactual by fixing the endogenous "permit price" of housing (part of the Baseline price). By clearly separating the "permit price" component of housing from the actual supply cost, they provide a clear economic interpretation of a counterfactual that has only Baseline Effects. On the other hand, shocks to "land productivity" (z_j in their notation) and supply-demand elasticity parameters (γ and θ) are not well-identified. I provide a proof and further discussion of Duranton and Puga (2023) in Appendix E.

[18]Using hat-algebra notation, the General Equilibrium price change would be $\gamma_{j'}\ln(\hat{l}_j) + (\gamma_{j'} - \gamma_j)\ln\left(\frac{l_j g}{\bar{l}_j}\right)$.

[19]As a practical example, consider two locations j and j' that had a price ratio $P_j/\tilde{P}_{j'} = 0.8$ in 2025. If we chose as reference demand the one of year 2025, then we would calibrate $l_j/\bar{l}_j = l_{j'}/\bar{l}_{j'} = 1$ and $\tilde{P}_j/\tilde{P}_{j'} = 0.8$. Hence, we would conclude that removing the price gap between the two locations requires a 20% "productivity" increase in location j'. Suppose instead we calibrate reference demand to 1970, finding that the difference in demand-induced price increases between 1970 and 2025 explains all the difference in price. That is,

$$\left(l_j g/\bar{l}_j\right)^{\gamma_j} \times \left(l_{j'} g/\bar{l}_{j'}\right)^{-\gamma_{j'}} = 0.8.$$

Then, the two locations must have identical Baseline Prices $\tilde{P}_j = \tilde{P}_{j'}$. If we were to interpret $\tilde{P}_j$ as a pure productivity parameter we would now conclude that housing productivity is already identical in the two locations. The apparent paradox comes from the implicit assumption that there is no interaction between the determinants of the location price constant $\tilde{P}_j$ and the ones of the price-demand elasticity γ_j, which is equivalent to assuming $\alpha_j = (1+\gamma_j)^{-1}$ in price function (V). When there is no interaction between the two Effects, the relative size of γ_j and $\tilde{P}_j$ counterfactuals is scale-dependent on the chosen reference demand level $l_j g/\bar{l}_j$. For an even stronger example, suppose we chose the year 1800 as our reference point for baseline demand. Then, most of house price level in US West Coast cities in 2025 would be explained by the excess demand component $(l_j g/\bar{l}_j)^{\gamma_j}$. If we chose 2025 as the reference year, all price differences would be explained by differences in Baseline Prices.

In Appendix C I provide an extension to the price-demand system (V) that allows for a higher degree of flexibility in the separability between Baseline and Elasticity Effects, accommodating for counterfactuals and Baseline-Elasticity Effect interdependencies (or lack thereof) such as those by Parkhomenko (2023) and Greaney, Parkhomenko and Van Nieuwerburgh (2025), as well as intermediate cases. Using the Baseline/Elasticity Effect framework, I show that this generalised price function is well-characterised for several counterfactuals, allowing to study policies that affect only the Baseline Price, as well as policies that create both Baseline and Elasticity effects.

6 Conclusions

When analysing how housing supply policies (e.g., zoning reforms) affect the economy as a whole, researchers need to characterise the housing sector in a location choice model. Problematically, many popular characterisations introduce hidden assumptions on the "Baseline Effect": how much the cost to supply a reference level of housing changes in response to such policies. These hidden assumptions often generate puzzles and lack of identification.

This paper introduces a characterisation that allows for a separate characterisation Baseline and Elasticity effects and nests other common characterisations, making their underlying assumptions explicit. A quantitative analysis suggests that common well-characterised specifications underestimate, potentially by one order of magnitude or more, the productivity gains from relaxing housing supply regulations.

Ultimately, the effects of housing supply policies depend on a number of factors not considered in this paper, such as agglomeration, congestion and learning externalities. Nevertheless, I show that the productivity gains from relaxing housing supply regulations are unlikely to be small, even in absence of these factors.

These results will help researchers to assess the implicit assumptions introduced by their characterisations, and what policy counterfactuals can be performed with them. Computing Baseline and Elasticity effects is a useful check to understand whether a policy effect is well-identified, and what are the implicit assumptions behind its characterisation and calibration.

Finally, this paper highlights the importance of further research on how construction TFP and the long-run cost of satisfying the existing demand is affected by regulations, e.g., via scale, patenting, or other restrictions. Understanding how regulations reduce the efficiency of providing *any* level of housing, rather than just additional units, is crucial to understand their aggregate misallocation effects. At the same time, it is important to account for the potential interactions between TFP and price-elasticity effects of regulations.

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Appendix

A Proof of Greaney (2025) Price Puzzle

In this section, I prove that, when using price function (2) (see Table 1 in the main text), there exists a set of counterfactual price elasticities $\{\gamma_i\}_{i\in\{1,\dots,N\}}$ such that: $l_i' = l_i$, $\gamma_i' < \gamma_i$, $\forall i$, and $P_i' = P_i$.

I use Greaney (2025)'s 2-locations analytical model, which I report below for convenience, modified to include Greaney's price function. The model can be summarised through the following equilibrium equations:

$$\text{Wages: } W_i = \mathscr{A}_i L_i^{\frac{1-\alpha-\eta}{\eta-1}},$$

$$\text{House Prices: } P_i = \overline{P}_i L_i^{\gamma_i},$$

$$\text{Population share: } \frac{L_i}{L} = \frac{\left(W_i Z_i P_i^{-\beta}\right)^{\theta}}{\sum_j \left(W_j Z_j P_j^{-\beta}\right)^{\theta}},$$

$$\text{Market clearing: } L = \sum_i L_i.$$

Let $\alpha = \beta = Z_i = 1$, $A_1 > 1$, $A_2 = 1$. Call l_i the population share of a location: $l_i = L_i/(L_1 + L_2)$. Assume $g = 1$, and $L_1 + L_2 = 1$. The equilibrium system is

$$W_i = A_i,$$

$$P_i = \overline{P}_i \left(\frac{l_i}{l_{i,1970}}\right)^{\gamma_i},$$

$$V = \frac{W_i}{P_i},$$

$$L = L_1 + L_2,$$

$$Y = A_1 l_1 + A_2 l_2.$$

In equilibrium,

$$A_1 \left(\frac{l_1}{l_{1,1970}}\right)^{-\gamma_1} \overline{P}_1^{-1} = \left(\frac{1-l_1}{1-l_{1,1970}}\right)^{-\gamma_2} \overline{P}_2^{-1}. \tag{A.1}$$

Equivalently, taking logs and calling $l = l_1$,

$$\gamma_1 \ln(l) - \gamma_2 \ln(1-l) = \ln(A_1) + \ln(\overline{P}_2) - \ln(\overline{P}_1) + \gamma_1 \ln(l_{1970}) - \gamma_2 \ln(1 - l_{1970}). \tag{A.2}$$

Consider the case where $\frac{\partial \overline{P}_i}{\partial \gamma_i} = 0$. Then, the total derivative of Equation (A.2) with respect to l, γ_1 and γ_2 is

$$\left(\frac{\gamma_1}{l} + \frac{\gamma_2}{1-l}\right)\frac{dl}{d\gamma_1} = \ln\left(\frac{l_{1970}}{l}\right) + \frac{d\gamma_2}{d\gamma_1}\ln\left(\frac{1-l}{1-l_{1970}}\right). \tag{A.3}$$

Now, consider a potential counterfactual where $d\gamma_1 \neq 0$ but $dl = 0$. Then, it must be that $d\gamma_2$ satisfies

$$\frac{d\gamma_2}{d\gamma_1} = \frac{\ln\left(\frac{l_{1970}}{l}\right)}{\ln\left(\frac{1-l_{1970}}{1-l}\right)}. \tag{A.4}$$

For the particular case where $l_{1970} = l$, notice that $\frac{d\gamma_2}{d\gamma_1} = 1 > 0$. That is, when we consider the economy in its 1970 steady state, there exists a set of $\gamma_1' < 0, \gamma_2' < 0$ (looser regulations in both locations) such that $l' = l = l_{1970}$. Then, the counterfactual price of each location is

$$P_i' = \overline{P}_i\left(\frac{l_i'}{l_{i,1970}}\right)^{\gamma_i'} = P_i. \tag{A.5}$$

Hence, for any small $d\gamma_1$ there is a set of $\gamma' = \{\gamma_1', \gamma_2'\} = \{\gamma_1 + d\gamma_1, \gamma_2 + d\gamma_1\}$, which yields a counterfactual equilibrium where $l_i' = l_i = l_{1970}$ and $P_i' = P_i$, $\forall i$. In other words, despite having relaxed regulations in all locations, prices do not change in either locations.

This proves that the price formula in Greaney (2025) does not capture how looser regulations should shift the long-run price downwards for any population *level*. Instead, the effects are only proportional to the *change* in population between 1970 and 2009, $\frac{l_{ig}}{l_{i,1970}}$. As discussed in the main text, this result arises from the implicit assumption that TFP is increasing in γ_j.

B Quantitative Simulations

B.1 Model

I follow Greaney (2025) in replicating the model by Hsieh and Moretti (2019) (henceforth, "HM") in hat-algebra form.

Consider HM's imperfect mobility model:

$$\text{Wages: } W_j = \mathscr{A}_j L_j^{\frac{1-a-\eta}{\eta-1}},$$

$$\text{House Prices: } P_j = \overline{P}_j L_j^{\gamma_j},$$

$$\text{Population share: } \frac{L_j}{L} = \frac{\left(W_j Z_j P_j^{-\beta}\right)^{\theta}}{\sum_i \left(W_i Z_i P_i^{-\beta}\right)^{\theta}},$$

$$\text{Market clearing: } L = \sum_j L_j.$$

Expressing with x' the counterfactual value of a variable x, and using hat notation (Dekle, Eaton and Kortum, 2008) to express $\hat{x} = x'/x$, a change in the elasticity of housing supply yields a price change

$$\hat{P}_j = \hat{\overline{P}}_j \hat{l}_j^{\gamma_j'} \left(l_j L\right)^{\gamma_j' - \gamma_j}. \tag{B.1}$$

I consider four different variants of the model. Each of them differs only for the characterisation of the price function, which I report in Table B.1 both in level and in hat-algebra form. Then, for each variant, I perform the same counterfactual exercise as the one in Section IV.C in HM. Specifically, I assign to the commuting zones of New York, San Francisco and San Jose the regulation-induced housing elasticity component of the median US commuting zone.

Table B.1: Baseline Effects of Different Supply Functions

Model	Price Function P_j	Price change $\hat{P}_j$
Hsieh and Moretti (2019)	$\overline{P}_j(Ll_j)^{\gamma_j}$	$\hat{l}_j^{\gamma'_j}\left(l_{j,2009}L\right)^{\gamma'_j-\gamma_j}$
Greaney (2025)	$\tilde{P}_j\left(\frac{l_j}{l_{j,1970}}g_{1970}\right)^{\gamma_j}$	$\hat{l}_j^{\gamma'_j}\left(\frac{l_{j,2009}}{l_{j,1970}}g_{1970}\right)^{\gamma'_j-\gamma_j}$
Cobb-Douglas	$(1+\gamma_j)\frac{r}{A_j^{\gamma_j}}\left(\frac{l_j}{l_{j,1970}}g_{1970}\right)^{\gamma_j}$	$\hat{l}_j^{\gamma'_j}\left(\frac{l_{j,2009}}{l_{j,1970}}\frac{g_{1970}}{A_j}\right)^{\gamma'_j-\gamma_j}$
Well-Characterised	$(1+\gamma_j)^{1+\alpha_j(1+\gamma_j)}\frac{r}{A_j}\left(\frac{l_j}{l_{j,1970}}g_{1970}\right)^{\gamma_j}$	$\hat{l}_j^{\gamma'_j}\left(\frac{l_{j,2009}}{l_{j,1970}}g_{1970}\right)^{\gamma'_j-\gamma_j}\frac{(1+\gamma'_j)^{1+\alpha_j(1+\gamma'_j)}}{(1+\gamma_j)^{1+\alpha_j(1+\gamma_j)}}$

Notes: "Price Function" shows the characterisation of the housing price function in each model. L is total population, L_j location j's population, and l_j location j's population share. $l_{j,x}$ is the population share in location j in year x. g_{1970} is population growth from 1970 to 2009. A_j is the non-capital factor (e.g., land) in the Cobb-Douglas case, in most models calibrated as a productivity scale parameter given the supply parameter γ_j, while in the Agnostic model it is the capital-augmenting productivity parameter. Variables with a hat, e.g., $\hat{l}$, use hat notation (Dekle, Eaton and Kortum, 2008) to express $\hat{x} = x'/x$.

Then, the change in wages, prices and population shares can be expressed as

$$\hat{W}_j = (\hat{l}_j)^{\frac{1-a-\eta}{\eta-1}}$$

$$\hat{P}_j = \hat{l}_j^{\gamma'_j} \times M_j$$

$$\hat{l}_j = \frac{\left(\hat{W}_j(\hat{P}_j)^{-\beta}\right)^{\theta}}{\sum_j l_{j,2009}\left(\hat{W}_j(\hat{P}_j)^{-\beta}\right)^{\theta}}$$

Finally, I calculate the relative size of the counterfactual and baseline production using hat-algebra:

$$\hat{Y} = \sum_j y_j \hat{W}_j \hat{l}_j,$$

where y_j is the share of output of location j before the policy shock.

B.2 Calibration

I follow HM's calibration, besides the one of the elasticity counterfactual parameters, for which I follow Greaney (2025), who uses changes consistent with the estimating equations of Saiz (2010). The parameters are calibrated as described in Table B.2.

Table B.2: Parameters Calibration

Parameter	Target	Value
a	Labour Share	0.65
η	Capital Share	0.25
β	Expenditure Share of Housing	0.40
r	Interest Rate	0.05
θ^{-1}	Idiosyncratic Preferences Scale	0.30
g	1970-2009 Population Growth	2.04
$\bar{l}_j$	1970 Population Shares	Varies
l_j	2009 Population Shares	Varies

Notes: The table reports the calibrated values of the parameters. There are identical as those used by Hsieh and Moretti (2019) and Greaney (2025).

B.3 Counterfactual Estimation

I estimate each counterfactual allocation as follows:

1. Start from step $k = 1$.
2. Take a guess of the hat-algebra change in population shares for each location, $\hat{l}^k = \{\hat{l}^k_j\}_{j\in J}$.
3. Estimate $\hat{W}^k_j$ and $\hat{P}^k_j$.
4. Derive the implied population shares $\hat{l} = \{\hat{l}_j\}_{j\in J}$, with $\hat{l}_j = \dfrac{\left(\hat{W}^k_j(\hat{P}^k_j)^{-\beta}\right)^{\theta}}{\sum_j l_{j,2009}\left(\hat{W}^k_j(\hat{P}^k_j)^{-\beta}\right)^{\theta}}$.
5. If $\hat{l}^k = \hat{l}$, $\hat{l}$ is the equilibrium set of population shares. Otherwise, select a new guess $\hat{l}^{k+1} = \frac{1}{2}\hat{l}^k + \frac{1}{2}\hat{l}$ and repeat steps 2-5 until convergence.

I estimate the following counterfactuals:

1. For the model using the housing price function by Hsieh and Moretti (2019), I estimate a standard counterfactual, as well as one where I double population. This allows me to show the scale-dependency issue of the model.

2. For the model using the housing price function by Greaney (2025), I estimate a standard counterfactual.

3. For the model using the Cobb-Douglas housing production function, I estimate a standard counterfactual, as well as one where I double housing TFP A_j. This allows me to show the scale-dependency issue of the model.

4. For the model using the Agnostic price function, I estimate four different counterfactuals:

   (a) One setting $\alpha_j = -(1+\gamma_j)^{-1}$, replicating the result by Greaney (2025);

   (b) One setting $\alpha_j = 0, \forall j$, representing a capital-augmenting production function;

   (c) One for each $\alpha \in [1,2,5]$, representing cases where TFP is decreasing in the supply elasticity parameter (for example, due to regulations forcing the adoption of inefficient production methods, reducing housing output more than merely reducing the returns to scale of the capital input).

C Housing Supply Function Generalisation

Consider the following generalised demand-supply system:

$$\begin{cases} H_j^s = (1+\gamma_j)^{-\alpha_j} \exp\left(A_j - \frac{\beta_j}{\delta\gamma_j}\right)\left(A_j^K K\right)^{\frac{1}{1+\gamma_j}}, \\ H_j^d = \left(\frac{l_j g}{\bar{l}_j}\right). \end{cases} \tag{C.1}$$

This represents a generalisation of the well-characterised function described in the main text, which can nest additional price functions from the literature. In this function, both the parameters β_j and γ_j should be considered as policy parameters. γ_j represents an elasticity policy parameters that affects the marginal product of labour (and, hence, the price-demand elasticity), while β_j represents a TFP policy parameter.

For example, for $A_j^K = 1$, $\alpha_j = 0$ and $\delta = \gamma_j^{-1}$, we obtain a supply function of the same family as Parkhomenko (2023),

$$H_j^s = e^{A_j - \beta_j} K^{\frac{1}{1+\gamma_j}}$$

which yields an equilibrium price function

$$P_j = \frac{r(1+\gamma_j)}{A_j^{\gamma_j}} \exp\left[(\beta_j - A_j)\gamma_j\right] \left(\frac{l_j g}{\bar{l}_j}\right)^{\gamma_j}.$$

Notice that this price function suffers from the same issue of system (3), where the baseline effect is non-identified due to the non-innocuous normalisation of $\exp\left(A_j - \frac{\beta_j}{\delta\gamma_j}\right)$. To see why, consider the Baseline Effect of log-prices:

$$\frac{\partial \overline{P}_j}{\partial \gamma_j} = \beta_j - A_j + \frac{1}{1+\gamma_j}.$$

The log-TFP scaling factor $\beta_j - A_j$ depends on the normalisation chosen for A_j and β_j. However, A_j represents a mere scaling parameter, meaning that its normalisation is arbitrary. Hence, the policy effects are not identified.

I now discuss when function (C.1) leads to a well-characterised housing price function.

A flexible, well-characterised price function. Assume that $A_j = 0$ and $\delta = 1$. From Equation (C.1) we obtain the price function

$$P_j = \frac{r(1+\gamma_j)^{1+\alpha_j(1+\gamma_j)}}{A_j^K} \exp\left(\beta_j\right) \left(\frac{l_j g}{\bar{l}_j}\right)^{\gamma_j}.$$

Taking logs:

$$\ln(P_j) = \underbrace{\beta_j + \ln\left(\frac{r}{A_j^K}\right) + (1+\alpha_j(1+\gamma_j))\ln(1+\gamma_j)}_{\overline{P}_j} + \gamma_j \ln(g) + \gamma_j \ln\left(\frac{l_j}{\bar{l}_j}\right). \tag{C.2}$$

In price function (C.2), the Baseline Effects arising from the "factor mix" (γ_j) and the "TFP effect" (β_j) are perfectly separable. In fact, taking derivatives of the Baseline Price $\overline{P}_j$ to find the Baseline Effects with respect to γ_j and α_j we obtain:

$$\frac{\partial \overline{P}_j}{\partial \gamma_j} = \frac{1}{1+\gamma_j} + \alpha_j\left(\frac{1}{1+\gamma_j} + \ln(1+\gamma_j)\right) + \frac{\partial \alpha_j}{\partial \gamma_j}(1+\gamma_j)\ln(1+\gamma_j),$$

$$\frac{\partial \overline{P}_j}{\partial \beta_j} = 1.$$

Similarly, the price-demand elasticity is

$$\frac{\partial \ln(P_j)}{\partial \ln(l_j g)} = \gamma_j,$$

and the Elasticity Effect of the γ_j counterfactual is:

$$\frac{\partial^2 \ln(P_j)}{\partial \ln(l_j g)\partial \gamma_j} \ln\left(\frac{l_j g}{\bar{l}_j}\right) = \ln\left(\frac{l_j g}{\bar{l}_j}\right).$$

Hence, the log-price function (C.2) features:

1. Well-identified policy effects (no scale dependency),
2. Separable characterisations of the Baseline and Elasticity Effects,
3. Separability of the Baseline Effect into the role of the "factor mix" (γ_j) and "TFP" (β_j) policy effects, as in Parkhomenko (2023).
4. For $\alpha_j = -\frac{1}{1+\gamma_j}$, the Baseline prices do not depend on γ_j, meaning that the Baseline Effect (fully characterised by β_j) and Elasticity Effects are perfectly separable, as in Greaney, Parkhomenko and Van Nieuwerburgh (2025).

To conclude, this generalised price function (C.2) can be used to separately study the effects of policies that *only* affect TFP (e.g.,micro-power of local councils over designs and other regulatory matters, which reduce economies of scale as in D'Amico et al. (2024)) and the policies that affect the factor mix of housing but may also affect the Baseline Prices (e.g., height limits and minimum lot sizes).

D Quantifying the Baseline Effect

To understand how different levels of α_j lead to substantially different policy effects, I simulate the Baseline Effect for different values of α. Consider that for an initial elasticity value γ_j and a counterfactual value γ_j' the log-ratio of the counterfactual and initial Baseline Prices $\overline{P}_j'$ and

$\overline{P}_j$ is

$$\ln\left(\frac{\overline{P}'_j}{\overline{P}_j}\right) = \ln\left(\frac{(1+\gamma'_j)^{1+\alpha_j(1+\gamma'_j)}}{(1+\gamma_j)^{1+\alpha_j(1+\gamma_j)}}\right).$$

Assume $\gamma_j = 0.525$, the (simple) average value from Saiz (2010) elasticities across US Commuting Zones (MSAs). I then calculate, for different levels of α_j, the partial equilibrium Baseline Effect of a location when regulations fall by an equivalent of 0.05 elasticity points ($\gamma'_j = 0.475$), similar to the average fall in regulations simulated by Hsieh and Moretti (2019).

I report the results in Table D.1. As predicted, for α_j being equal to the lower bound ($-(1+\gamma_j)^{-1} \approx -0.65$), the Baseline Prices are unchanged following a reduction in regulations by 0.05 elasticity points. For $\alpha_j = 0$, Baseline Prices fall by -0.033 log-points. $\alpha_j = 1$ corresponds to a -0.10 log-points fall in Baseline Prices, $\alpha_j = 2$ to a -0.17 fall, increasing up to a -0.385 log-points fall (equivalent to a -32% in baseline prices) for $\alpha_j = 5$.

Table D.1: Policy Counterfactual Simulations and Baseline Effect, by α_j

α_j	Simulated Baseline Effect	
	$\ln\left(\overline{P}'_j/\overline{P}_j\right)$	$\overline{P}'_j/\overline{P}_j - 1$
$-(1+\gamma_j)^{-1}$	0	0%
0	-0.033	-3.27%
1	-0.104	-9.84%
2	-0.174	-16.00 %
5	-0.385	-31.96%

Notes: The table reports the results of a partial-equilibrium simulation exercise where $\gamma_j = 0.35$, $\gamma'_j = 0.30$ and $g = 1$, for different values of α_j. The Baseline Effect, here reported as a log-ratio between two values rather than as a derivative, captures the fall in prices necessary to make so that developers do not supply any new housing unit under the new supply technology level γ'_j.

Remark on the expected size of the Baseline Effect. Recall that the price-demand elasticity is not related to the Baseline Price. Hence, it would be incorrect to interpret a Baseline Effects larger than the change in the price-demand elasticity (-0.05 in the example above) as improbable "more-than-elastic" variations. By definition, demand is unchanged in the calculation of the Baseline Effect. The Baseline Effect represents the counterfactual change in prices that would lead to developers being unwilling to supply any further (or less) housing units in response to a policy. The price-demand elasticity represents how much prices respond to additional demand. Hence, the Baseline Effect cannot be compared to a change in price-demand elasticity.

E Baseline and Elasticity Effects in Duranton and Puga (2023)

I now show that the endogenous approach in Duranton and Puga (2023) provides a separate characterisation of the Baseline and Elasticity effects and well-identified housing supply policy effects. The house price in the Duranton-Puga model is

$$P_j(x) = p_j + \hat{P}_j(x)$$

where p_j is a permitting cost paid to move to buy a plot of land and build in location j, and $\hat{P}_j(x)$ is the actual price of a house in location j at a distance x from the city centre. House prices are decreasing in x due to the presence of commuting costs.

By the arbitrage principle, consumption at the city centre and outside of it must be equal. Hence, normalising the price of land to zero, it must be that the price at the city centre $P_j(0)$ is

$$\begin{aligned} P_j(0) &= p_j + \hat{P}_j(\bar{x}_j) \\ &= p_j + \tau_j \bar{x}_j^{\gamma} \\ &= p_j + \tau_j (z_j N_j)^{\gamma} \\ &= p_j + \tau z_j^{\gamma} N_j^{\gamma+\theta} \end{aligned}$$

where $\tau_j \bar{x}_j^{\gamma}$ is the commuting cost from the edge of the city $\bar{x}_j$ to the city centre $x = 0$ and z_j is the dimension of the plots of land necessary to generate one unit of housing (capturing geographical restrictions). γ captures how much commuting costs scale with distance, θ how much commuting costs scale with congestion (population) in a city, and τ is the absolute commuting technology.

In terms of this paper's Baseline and Elasticity Effects characterisation, and assuming permit costs are exogenous,[20] we can approximate the price function as

$$P_j(0) \approx \underbrace{p_j + \tau z_j^{\gamma} \overline{N}_j^{\gamma+\theta}}_{\overline{P}_j} + (\gamma+\theta)\tau z_j^{\gamma} N_j^{\gamma+\theta-1} \Delta N_j.$$

In the Duranton and Puga (2023) world, incumbents are landowners and receive a share N_j^{-1} of the total land rents of the city, meaning that they have an incentive to set permit costs to limit a city's population and maximise their consumption. Hence, the (direct) policy instrument is a change in permit costs p_j.

Keeping demand constant and changing the permit cost, I derive the Baseline Effect of a p_j counterfactual:

$$\text{Baseline Effect} = \frac{\partial \overline{P}_j}{\partial p_j} = 1.$$

That is, a reduction in the price of the permit maps into an identical fall in the total house price.

In this model there is no Elasticity Effect from reducing housing permit. While population changes in General Equilibrium, changing congestion and thus the city-centre price, recall that the Baseline and Elasticity effects are calculated in Partial Equilibrium.

Hence, Duranton and Puga (2023) perform a counterfactual where policies can reduce the Baseline Price, but have no Elasticity Effects. However, this assumption is justified by the fact that the counterfactual only regards the permit cost of housing (e.g., urbanisation taxes paid to the city council) rather than the actual housing construction technology.

E.1 Alternative Policy Counterfactuals

As a pedagogical discussion, notice that a price function may be well-suited for a specific policy counterfactual, but may not be well-suited for others. This is why it is important to check the

[20] When we do not consider permits as exogenous, the endogenous equilibrium is implemented. In this scenario, no policy would be allowed - since it would require to set an exogenous p_j. See Duranton and Puga (2023) for a derivation of the equilibrium.

feasibility of the counterfactual exercise against the Baseline and Elasticity effects of policies and, more generally, proper identification.

Assume that a policymaker decided to perform an "indirect" supply policy in large cities in the Duranton-Puga model by reducing the geographical restrictions that hold back the expansion of the city. For example, by reducing the minimum lot size necessary to build one unit of housing, z_j, via a height limits expansion or lot size reduction. Then, assuming that the permit cost is constant, calculate the Baseline and Elasticity effects of the policy:

$$\text{Baseline Effect} = \frac{\partial \overline{P}_j}{\partial z_j} = \gamma \tau z_j^{\gamma-1} \overline{N}_j^{\gamma+\theta}, \tag{E.1}$$

$$\text{Elasticity Effect} = \frac{\partial^2 P_j}{\partial N_j \partial z_j} \Delta N_j = \gamma(\gamma+\theta)\tau z_j^{\gamma-1} \overline{N}_j^{\gamma+\theta-1}(N_j - \overline{N}_j), \tag{E.2}$$

Notice that since $\overline{N}_j$ and N_j represent total population, the policy counterfactual would suffer from scale effect issues like Hsieh and Moretti (2019).[21] Hence, even if the permit counterfactual exercise is well-identified in the Duranton and Puga (2023) model, alternative counterfactuals may not be. This issues is clearly and formally uncovered after deriving Equations (E.1) and (E.2).

[21] See the discussion in Section 3 in the main text.