# The Impact of Commercial Real Estate Regulations on U.S. Output *

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**Abstract**

Commercial real estate is roughly 20% of the U.S. fixed asset stock and is highly regulated. However, little is known about the quantitative impact of these regulations on economic activity or consumer welfare. This paper develops a spatial general equilibrium model with commercial real estate regulations, congestion effects, and amenities, and uses the near-universe of CoreLogics's commercial, parcel-level, property tax records to construct a quantitative index of commercial real estate regulations for every commercial property. We use our regulation index to rank zoning codes by their stringency, and we use the model to evaluate the positive and normative impacts of local zoning deregulations. Moderately relaxing commercial regulations across all U.S. cities yields large allocative efficiency effects, with output gains of about 3 percent to 6 percent and welfare gains of about 1 percent to 3 percent of lifetime consumption. These findings are robust to 40 percent of the workforce working remotely.

**JEL codes:** K2, R38

**Keywords:** Regulation, Zoning, Spatial Policy, Labor Reallocation, General Equilibrium, Commercial Land Regulation

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# 1 Introduction

The simultaneous occurrence of low productivity growth (e.g. Fernald (2015) and Syverson (2017)), rising house prices in productive regions (e.g. Ganong and Shoag (2017)), and declining worker reallocation across U.S. states (e.g. Molloy, Smith, and Wozniak (2014)) has spurred a large and growing literature that uses equilibrium conditions and microeconomic data to measure the aggregate effects of residential zoning restrictions (e.g. Hsieh and Moretti (2019), Herkenhoff, Ohanian, and Prescott (2018), Martellini (2019), and Colas and Morehouse (2020) among others). Across a range of methodologies, estimated welfare gains from moderate reductions in the stringency of residential real estate regulations are large, commensurate with the $36 trillion dollar value of existing residential housing.[1]

While *residential* regulations have been studied and debated extensively, *commercial* regulations have attracted less attention despite the $17 trillion dollar value of commercial real estate.[2] Regulations such as height limits, setbacks[3], and floor area ratios[4] apply to commercial as well as residential structures. Commercial structures are also an important factor of production for most goods and services, comprising nearly 20% of the U.S. fixed asset stock.[5] We hypothesize that just as high apartment rents deter talented workers from America's most productive cities, high rental payments for commercial buildings do the same for businesses. In this paper, we develop a theory that allows us to measure the effects of commercial real estate regulations on welfare, productivity, and the spatial allocation of workers and business activity across the U.S. We use our theory to estimate address-level regulatory distortions from the near-universe of commercial property tax records. Moderately loosening commercial regulation across all U.S. cities yields welfare gains worth 0.9% to 2.8% of lifetime consumption.

Our paper makes three contributions. First, we develop a model of optimizing landlords that yields an intuitive formula for identifying the extent to which commercial real estate investment decisions are distorted by zoning codes and other regulations.[6] Regulations enter the problem by distorting the amount of commercial building square footage that is placed on a plot of land. Optimization of commercial landlords implies an intuitive formula for identifying the degree to which commercial real estate is distorted: properties with a very high total value but disproportionately low improvement values are more distorted. The primary benefit of this formula is that it relies on simple statistics available in a number of datasets. Crucially, our regulatory distortions do not directly enter factor prices, which means they are not commingled with factors that affect rents per building square foot (such as a desirable location) or the cost of improvements (such as the physical difficulty of building in certain locations). Our measures of distortion aggregate very cleanly, and can be used to study the of land use regulations. We

[1]This is the 2020 value as estimate by Zillow, which can be found at https://www.zillow.com/research/zillow-total-housing-value-2020-28704/

[2]See NAREIT (2019).

[3]These require a landlord to "set back" the building from the perimeter of the property line, forcing them to build on only a subset of their land.

[4]These are restrictions on the ratio between the floor area of the entire building and the area of the plot of land on which it is built.

[5]See NIPA Table 1.1, "Current-Cost Net Stock of Fixed Assets and Consumer Durable Goods,' at US Bureau of Economic Analysis (2021b).

[6]Building codes, review boards, etc. are policies captured by our address-level regulatory distortions.

study these consequences by embedding our measures of regulation in a new dynamic, spatial, general equilibrium model where commercial buildings are combined with capital and labor to produce goods and services, and where congestion generates negative externalities.

Our second contribution is to apply our theory to the near-universe of commercial property tax records from CoreLogic in order to develop a model-consistent index of commercial regulations. We base our analysis on a rich source of address-level, a.k.a. *parcel-level*, micro-data: municipal tax assessments compiled by CoreLogic. It includes the market- and assessment- based estimates of the total parcel value, land value, and structure value (a.k.a. *improvement* value) as well as building square footage and alphanumeric zoning codes, among other fields. Despite CoreLogic's comprehensive coverage of the commercial real estate market, we face three major measurement challenges: (1) most regulatory restrictions are unobserved in our data, and zoning codes are only observed in roughly half of our sample, (2) even among properties with non-missing zoning codes, zoning codes have different meanings in different locations (e.g. zoning code *C1* in city A has height limits, whereas *C1* in city B does not), and (3) most regulatory restrictions are *highly* multi-dimensional, with zoning codes alone taking on many different attributes (including height limits, setbacks, floor-area-ratios, etc.).

Our theory provides the insights necessary to address these challenges by showing that commercial regulations are identified from land and improvement values alone. Applying our formula to each individual commercial property in the CoreLogic database, we obtain an address-level index of commercial regulatory distortions. This index collapses the multidimensional heterogeneity of zoning laws and building regulations, of which it is near-impossible to determine the facets that may be binding, into a single, model-consistent metric.

We validate our index of commercial regulations in several ways. Among a subset of cities for which zoning codes are available, we hand-collected zoning code attributes, and we show that our index of commerical regulations is correlated with statutory floor area ratios (which restrict the ratio of building square footage to land square footage) and height limits (which restrict the physical height of the building).[7] These correlations between our regulatory index and statutory zoning restrictions are positive, yet imperfect, implying that floor-area ratios and height limits alone are insufficient to summarize the myriad distortions generated by complex zoning laws and other forms of regulation.

We then examine how our commercial regulations compare across cities. Our results confirm the common prior that metro areas in Texas such as Dallas-Fort Worth and Houston face significantly weaker commercial real estate regulation than metros in California, and more generally we find that coastal cities face the most severe distortions to commercial real estate production. Houston provides a useful litmus test since it famously lacks zoning laws, and we do identify Houston as a relatively undistorted city. However, while Houston lacks zoning laws, city ordinances and private deed restrictions distort commercial real estate investment, and these zoning-code-workarounds are reflected in our index. According

[7] Note that for many cities, the details of zoning code laws are not available online. Moreover, most zoning code handbooks are technical and opaque legal documents. These factors prevent systematic compilation of zoning codes across the U.S., even for a small subset of characteristics. The extent of regulations (including zoning codes) also cannot be extracted from construction costs indices (which include building codes), such as RSMeans. This is partly due to their limited sampling of buildings across cities, and partly because—as we will discuss in Section 2.1.1—regulations need not influence costs directly.

to our data, the least distorted city is Midland, Texas while the most distorted city is Urban Honolulu, Hawaii.

Unlike many other attempts to measure the strength of local real estate regulations, such as the Wharton Land Use Regulatory Index of Gyourko, Saiz, and Summers (2008), our measurement derives the strength of regulations from a micro-founded model. We use a production-function based approach and treat regulations as a distortion in the parcel-level builder's problem. This allows us to distinguish regulatory factors from demand factors that affect rents per building square foot and differential costs of building across locations. Unlike the qualitative questions in Gyourko, Saiz, and Summers (2008), from which principal component analysis yields the headline regulatory factor, our approach also allows us to express zoning and other regulatory distortions in real terms, making it easily incorporated in quantitative models. Lastly, our method yields a time series of commercial regulations, providing future researchers with the opportunity to evaluate the effectiveness of zoning and regulatory reforms.

Our third contribution is quantitative: we use our distortion measure and our benchmark equilibrium model to evaluate the effect of both national and local changes to commercial regulations. Crucially, we endogenize amenities (which dictate the cost of sending workers to a particular region) in our model and allow them to depend negatively on congestion, and in the process contribute a novel identification of the congestion costs of density. Since our model is invertible in steady-state, our estimation recovers MSA-level amenity values. Ex-post, recovered amenity values are free to be flexible functions of local characteristics. We specify a log-linear relationship between amenities and business district congestion (workers per downtown-land-square-foot), and use a novel strategy based on model-generated instruments to recover this relationship.

In our primary exercise, we raise average city-level regulations up to a deregulated benchmark (Midland, Texas) and solve for the new steady state, while leaving the dispersion of parcel-level regulations unaltered.[8] National output increases by 2.9% as commercial investment booms and workers reallocate from the midwest to the now-less-regulated states of Florida, California, Oregon, and Minnesota. Notably, the building stock increases by 17%. Because removing these regulations improves the allocative efficiency of the economy, the measured Solow residual increases by 2.3%. At the same time, landlord profits fall as building supply expands and rental rates of commercial real estate decline.

Our framework also allows for very granular counterfactuals within narrowly defined geographies. Because we recover regulatory distortions at the parcel-level, we can project our distortions down onto specific features of zoning codes such as floor area ratios and study what happens when we change those features individually. We use New York City as a test case and simulate moving all zoning codes up to the highest permissible floor area ratio in our sample, and find that doing so raises metro area GDP by 1.8 percent.

[8]Similar to the misallocation literature (e.g. Hsieh and Klenow (2009)), we treat (a) the average level of regulatory distortions and (b) dispersion of parcel-level distortions as separate objects over which we conduct counterfactuals. We view our primary exercise as conservative since it focuses on the average regulatory distortion and ignores dispersion, thus deregulation does not improve the allocation of improvements within a city. As in models of misallocation like Hsieh and Klenow (2009), the efficiency gains from reduced misallocation can potentially be large but can also be biased upwards by mismeasurement. We nevertheless explore the impact of reducing dispersion in a different counterfactual.

Our counterfactual exercises continue to yield large output gains from commercial deregulation if we recalibrate the economy so that 40% of the workforce is in a remote-work sector which does not rely on commercial buildings to produce. We also show that that using exogenous amenities yields near-identical aggregate results to our baseline counterfactual. In the baseline, amenities improve in regions that lose workers, offsetting the congestion costs in regions that gain workers; hence, the nation-wide impact of these regulations does not depend to any significant degree on whether we treat amenities as endogenous or not.

Lastly, while we do not explicitly model the adoption of zoning code regulations (e.g. see models with endogenous local residential regulations by Parkhomenko (2018) and Bunten (2017) among others), disamenities from congestion and landlord profits may provide a rationale for the existence of commercial regulatory distortions. Nonetheless, we estimate large welfare gains from moderate levels of deregulation even with both mitigating factors at play.

**Literature** We contribute to a burgeoning literature on the aggregate effects of spatial policy. Hsieh and Moretti (2019) argue that land use regulations cause significant spatial misallocation. Diamond (2016) combines a shift-share instrument with estimated housing supply elasticities from Saiz (2010) to recover the external effects of worker composition on amenities and productivity. Fajgelbaum and Gaubert (2020) study optimal spatial transfers in the presence of heterogeneous skill types, congestion, and agglomeration. Rossi-Hansberg, Sarte, and Schwartzman (2019a) study spatial redistribution in the presence of heterogeneous industries and occupations with variable patterns of spillovers, with an emphasis on the role of "cognitive non-routine" workers. Fajgelbaum, Morales, Suarez, and Zidar (2019) find that heterogeneity in state taxes leads to significant misallocation across regions. Martellini (2019) develops a model with learning spillovers and agglomeration effects in job search, quantifies their impact on the urban wage premium, and studies their implications for the gains from housing deregulation. Colas and Morehouse (2020) study how land use regulations affect carbon emissions. Herkenhoff, Ohanian, and Prescott (2018) use a similar production-function based approach and identify housing supply restrictions as distortions in the first-order condition of the local housing sector. We build on this by working with parcel-level microdata directly. Cun and Pesharan (2020) study the interaction of land use regulations with migration. Grossman, Larin, and Steger (2020) find that low productivity growth in the housing sector is partly to blame for an increase in the ratio of house wealth to income. Relative to existing work, we provide the first, to our knowledge, macroeconomic analysis of commercial zoning regulations, combining administrative micro-data with a spatial general equilibrium model. We then quantify how commercial regulations distort capital and building investment decisions as well as the spatial allocation of labor.[9]

Our paper also contributes to the field of leximetrics, or the quantification of the "strength" of regulations, in the vein of La Porta, Lopez de Silanes, Shleifer, and Vishny (1998). We are not the first to bring a leximetric approach to real estate regulations—an important antecedent is the Wharton Land Use Reg-

[9]Moreover, by abstracting from taste shocks, our model avoids the recent criticism of optimal place-based policy articulated by Davis and Gregory (2021).

ulation Index of Gyourko, Saiz, and Summers (2008), which focuses on residential buildings (and more recently, Gyourko, Hartley, and Krimmel (2021)). However, the Wharton Index measures the strength of local land use regulations in a fundamentally different way, by itemizing qualitative responses into categories and then taking the principal component of those categories. We provide a complementary approach and infer the strength of regulations using a model of optimizing real-estate firms.

We contribute to an extensive literature that attempts to measure land use regulations and quantify their impact. Glaeser, Gyourko, and Saks (2005a) use construction cost data for residential structures, and they find a significant and positive gap between price and cost. They argue that the difference is due to zoning restrictions. The aforementioned Saiz (2010) attempts to measure physical constraints on housing buildup. Tanure Veloso (2020) focuses on residential real estate but employs a complementary method in which he regresses a Census tract-level housing supply productivity term on the tract-level share of houses zoned as single-family units. This method links observed features of zoning codes to housing supply productivity, which he exploits in counterfactual analysis. Delventhal, Kwon, and Parkhomenko (2021) is, to our knowledge, the only other paper that studies commercial land use regulations, although their focus is on one city (Los Angeles) and their discrete choice model and identification strategy are more similar to Tanure Veloso (2020). Furth (2021) also identifies residential regulations at the parcel level and measures the strength of multiple facets of land use regulations. Rivera-Padilla (2021) models residential land use distortions as equivalent to a tax, rather than a productivity shifter, and identifies them from the difference in rents between rural and urban regions in India. Tan, Wang, and Zhang (2020) argue that the land share of residential building values is informative about regulatory strictness, and they show that it is indeed correlated with floor area ratio restrictions in China. This paper's identification strategy is the closest to our own. Our contributions are to (1) develop a theory that allows us to measure the effects of commercial real estate regulations on welfare, productivity, and the spatial allocation of workers and business activity across the U.S., (2) to use our theory to estimate address-level regulatory distortions from the near-universe of commercial property tax records (which is made possible by the fact that our formula for regulations *only* requires the land share of total building value), and (3) to estimate welfare gains from both national and local commercial deregulations.

An important precedent for our work is Davis and Heathcote (2007). They find that the value of land, and the land share of housing prices, has been rising. They speculate that part of the reason for the trends in land values may be due to cities that "implemented policies to slow further development". Interestingly, they find very high land shares in cities where housing is thought to be heavily regulated, such as San Francisco or San Jose, and they find low land shares in Houston, which is generally thought to be lightly regulated. We formalize that intuition, and argue that variations in the land share are informative about the strictness of land use regulations. Tan, Wang, and Zhang (2020) also identify residential regulatory stringency using the land share of building value, although their focus is on one specific dimension of regulation. We argue that the commercial land share is informative about a broader range of regulations and distortions, as we discuss in greater detail in Section 2.1.1, and we show that these distortions can aggregate tractably in a general equilibrium model.

Our identification of amenities relies on using the model itself to generate instruments. It builds on a tradition begun by Anderson and van Wincoop (2003), developed in Allen, Arkolakis, and Takahashi (2020), and applied in Walsh (2019).

Finally, our model features parcels with heterogeneous *distortions* and productivities, and is therefore related to a wide class of firm dynamics models where firms have heterogeneous *markups* and productivities. It permits an aggregation result similar to, for example, Peters and Walsh (2021): we can separate the impact of land use regulations into one term equivalent to an average "wedge" and a second term that captures the effect of misallocation (or mismeasurement) across parcels.

**Outline** The paper proceeds as follows: In Section 2 we develop our model of building supply and our method of identifying land use regulations. We validate our model-based measures of regulation in Section 3 by showing that they correspond well with statutory measures of regulation. In Section 4, we embed our regulations into a novel general equilibrium spatial model appropriate for conducting policy counterfactuals. In Section 5, we perform several counterfactuals that demonstrate the flexibility of our approach. We conclude the paper with Section 6, and consign certain proofs, computational algorithms, and a more detailed description of our data to the appendices.

## 2 A Model of Distorted Building Supply

This section introduces our measure of distortion and explains how we identify land use regulations. We do so by focusing initially on the partial-equilibrium problem of landlords, taking prices as given for now.

### 2.1 Individual Landlords

Within each city $j$, there are a finite number of differentiated parcels of land endowed to landlords.[10] We index parcels of land by $i$, where $i$ maps to an address in the CoreLogic data. Parcel $i$ in city $j(i)$ is described by its fixed land square footage $x_i$, parcel productivity $z_i$, and building cost $q_i$, and its time-varying building square footage $BSF_{i,t}$. The parcel productivity term $z_i$ is meant to capture the fact that a unit of building square footage may not be equally useful in all parts of the city (consider a warehouse on the outskirts of a metro area compared to one in the central city), and it allows us to match the variation in price-per-building square foot observed in the data. The time-invariant building cost $q_i$ differs across parcels and captures the relative difficultly of building in some locations than others. These differences may be due to differences in soil quality and unionization rates of local construction workers, for example. Note the lack of time subscripts on $x, z$, and $q$, which are immutable. We refer to the sum of productivity-weighted building square feet on parcel $i$ simply as the *building* $B_i$ placed on parcel $i$. That is, $B_{i,t} = z_i \cdot BSF_{i,t}$. We denote the stock of buildings in city $j$ as $B_{j,t}$.

The landlords rent their buildings out at the start of each period, earning $r_{b,j,t}B_{i,t}$ on parcel $i$ in city $j$. For both realism and tractability, we assume "one-hoss-shay" depreciation (Luttmer (2011)): building

[10] As the number of parcels is very large and each one comprises a small share of overall building value, we assume that landlords act as price-takers.

square footage is constant ($BSF_{i,t} = BSF_i$) until the building fully depreciates all at once (i.e. the building is torn down), where the probability of full depreciation is a constant $\delta_b$. We denote the discounted stream of rental payments made to each efficiency-weighted building square foot as $p_{j,t}$:

$$p_{j,t} = \sum_{s=t}^{\infty} (\beta(1-\delta_b))^{s-t} r_{b,j,t}$$

The building fully depreciates with probability $\delta_b$ after its use in production but before the start of the next period. At the end of the period, if the current building has depreciated, the landlord may combine the underlying land with improvements in order to create a new building that can be rented out in subsequent periods. The building cost $q_i$ determines the efficiency with which the numeraire good is converted to improvements $m_{i,t}$ on parcel $i$. For example, purchasing one unit of the numeraire good yields $1/q_i$ units of improvements on parcel $i$. The total cost of improvements $MV_{i,t}$ in units of the numeraire is $q_i m_{i,t}$. We denote the new efficiency-weighted building square footage built on a parcel at period $t$ as $B^N_{i,t}$. The building technology is Cobb-Douglas, and the improvement share in production is $\gamma$:

$$B^N_{i,t} = z_i \underbrace{m^{\gamma}_{i,t} x^{1-\gamma}_i}_{BSF_{i,t}} \tag{1}$$

The building is also subject to a regulatory distortion $\tau_{i,t} \in [0,1]$, which includes all policies that cause landlords to purchase fewer improvements than they would optimally like to, given factor prices. At the extremes, $\tau_{i,t} = 1$ is completely deregulated; $\tau_{i,t} = 0$ effectively forbids construction.

Note that, because improvements are combined with depreciated parcels in this period but do not begin earning rents till next period, the builder discounts these flow payments. We also denote the net present value of payments made to the entire building as *building value*, $BV_{i,t}$. Unlike our data object *total value*, $TV_{i,t}$, it does not include the option value of rebuilding after depreciation.

$$BV_{i,t} = \sum_{s=t}^{\infty} (\beta(1-\delta_b))^{s-t} r_{b,j,t} B_{i,t} \tag{2}$$

We are now ready to write out the problem of a landlord with a depreciated parcel.

$$\max_{m_{i,t}} \beta\tau_i \underbrace{p_{j,t+1} z_i (m_{i,t})^{\gamma} x^{1-\gamma}_i}_{BV_{i,t}} - \underbrace{q_i m_{i,t}}_{MV_{i,t}} \tag{3}$$

We denote $i \in j$ as the set of parcels $i$ in city $J$. We can now write out the law of motion for the aggregate city-level building stock $B_{j,t}$:

$$B_{j,t+1} = (1-\delta_b) B_{j,t} + \sum_{i \in j} B^N_{i,t}$$

### 2.1.1 Different Interpretations of The Regulatory Distortion $\tau_{i,t}$

Broadly speaking, $\tau_{i,t}$ is meant to capture any regulation that prevents landlords from building as much as they would want to, given factor prices. These might include height restrictions, floor area ratios, or setbacks. None of these regulations raise building costs or lower the rents that owners can earn per building square foot; instead, they push landlords away from their optimality condition.

This model is isomorphic to one where landlords pay a tax $1/\tau_{i,t}$ on each dollar of improvement and rebate it to the representative household. Therefore, $\tau_{i,t}$ also captures costs that do not show up in the price of improvements or in the value of the building. This may include the costs of hiring lawyers to navigate the approval process or securing a variance, or paying for improvements in local infrastructure to secure approval for construction.

Alternatively, $\tau_{i,t}$ may also capture the possibility that some projects are denied or delayed by local zoning boards or in environmental reviews, especially if (as seems reasonable) the probability of rejection is rising in how much the landlord builds on the parcel.

This specification rules out regulations that directly enter factor prices and productivities, which means it avoids some potential pitfalls in trying to measure regulation but does not capture all possible dimensions of land use regulations.[11] Taxes and demand-side factors such as desirable locations will be capitalized into the parcel-level price per building square foot $p_{j,t}z_i$, and will not show up in $\tau_{i,t}$. However, restrictions on what buildings may be used for will also be capitalized into $p_{j,t}z_i$, and so our measure will not capture these kinds of regulations. Likewise, if different locations are inherently harder or easier to build on (due to differences in soil quality, for example) this will be picked up in $q_i$ and not $\tau_{i,t}$. This does, however, mean that restrictions on building techniques will not be captured by this specification. Schmitz (2020) studies bans on the use of prefabricated construction for residential buildings—our method would not pick up the impact of such restrictions for commercial buildings. Hence, our results will be a lower bound on the distortions imposed by land use regulations.

Notably, we do not model $\tau_{i,t}$ as a hard cap on development. In practice, zoning regulations typically allow local governments to grant variances, which allow builders to exceed statutory restrictions on floor area ratios and other restrictions. Our measure $\tau_{i,t}$ also incorporates the difficulty of getting variances.

## 2.2 Aggregation

This model admits aggregation up to a representative city-level builder.[12] The representative city-level builder's problem makes clear how regulatory distortions $\tau_{i,t}$ lower the quantity of improvements and cause misallocation across parcels.

In what follows, it will be convenient to define a time-invariant parcel-level productivity term:

$$C_i = z_i^{\frac{1}{1-\gamma}} x_i q_i^{\frac{-\gamma}{1-\gamma}} \tag{4}$$

[11]Our regulatory distortion $\tau_{i,t}$ is not capitalized into the value of the *building*, which we call $BV_{i,t}$. However, it is capitalized into the total value of a *parcel*, our data object $TV_{i,t}$, as it reduced the option value of rebuilding. We make this distinction clear in Appendix B.2.

[12]Appendix B.1 contains more details on the aggregation results outlined in this section.

It is also useful to note that $C_i$ is directly related to improvement value. We can show this by solving Equation (3) for $q_i m_{i,t}$, the quantity of improvement demand expressed in units of the final good. We label this as improvement value, $MV_{i,t}$:

$$(\tau_{i,t} p_{j,t} \beta \gamma)^{\frac{1}{1-\gamma}} C_i = \underbrace{q_i m_{i,t}}_{MV_{i,t}} \tag{5}$$

We now define the problem of the representative builder in region $j$,

$$\max_{m_{j,t}} \beta T_{j,t} p_{j,t} \underbrace{D_{j,t} m_{j,t}^{\gamma} (\delta_b C_j)^{1-\gamma}}_{B_{j,t}^N} - \underbrace{m_{j,t}}_{MV_{j,t}} \tag{6}$$

where the solution to this builder's problem coincides with the aggregated solutions of all the individual landlords' problems in region $j$ when $C_j$, $D_{j,t}$, and $T_{j,t}$ take the following values:

$$C_j = \left( \sum_{i \in j} C_i \right) \tag{7}$$

$$D_{j,t} = \left( \frac{\sum_{i \in j} \tau_{i,t}^{\frac{\gamma}{1-\gamma}} C_i}{\sum_{i \in j} C_i} \right) \Bigg/ \left( \frac{\sum_{i \in j} \tau_{i,t}^{\frac{1}{1-\gamma}} C_i}{\sum_{i \in j} C_i} \right)^{\gamma} \tag{8}$$

$$T_{j,t} = \frac{\sum_{i \in j} \tau_{i,t}^{\frac{1}{1-\gamma}} C_i}{\sum_{i \in j} \tau_{i,t}^{\frac{\gamma}{1-\gamma}} C_i} \tag{9}$$

The term $C_j$ is a measure of productivity, and does not depend on regulatory distortions. It is policy-invariant (hence the lack of time subscripts—all the characteristics contained in $C_j$ are immutable and fixed) and we do not focus on it moving forward.

The term $D_{j,t}$ captures the allocative efficiency losses arising from dispersion in regulatory distortions, under the assumption that $\tau_{i,t}$ are measured correctly. A simple application of Jensen's inequality reveals that this term is weakly less than 1, and is only equal to 1 if all $\tau_{i,t}$ are equal. $D_{j,t}$ also does not change if we scale each $\tau_{i,t}$ up or down by a constant. Hence, eliminating dispersion in $\tau_{i,t}$ while keeping the aggregate $T_{j,t}$ fixed will lead to productivity gains (note that $D_{j,t}$ enters directly into the output quantity $B_{j,t}^N$, and therefore affects total factor productivity, whereas $T_{j,t}$ does not.) As in models of misallocation like Hsieh and Klenow (2009), these gains will be overstated if there is measurement error or misspecification in our parcel-level measures of regulatory distortion. Note that $D_{j,t}$ can be estimated if improvement values $MV_{i,t}$ and regulatory distortions $\tau_{i,t}$ are known, by substituting Equation (5) into Equation (8):

$$D_{j,t} = \left( \frac{\sum_{i \in j} MV_{i,t} / \tau_{i,t}}{\sum_{i \in j} MV_{i,t} / \tau_{i,t}^{\frac{1}{1-\gamma}}} \right) \Big/ \left( \frac{\sum_{i \in j} MV_{i,t}}{\sum_{i \in j} MV_{i,t} / \tau_{i,t}^{\frac{1}{1-\gamma}}} \right)^{\gamma} \tag{10}$$

The term $T_{j,t}$ is a measure of the average regulatory distortion in the economy. It takes on value 1 only if all $\tau_{i,t}$ are equal to 1. We can substitute Equation (5) into Equation (9) to show that $T_{j,t}$ can be expressed as a weighted average of improvement values:[13]

$$T_{j,t} = \frac{\sum_{i \in j} MV_{i,t}}{\sum_{i \in j} MV_{i,t} / \tau_{i,t}} \tag{11}$$

We will focus much of our attention on $T_{j,t}$ going forward—it is an intuitive measure of regulatory distortion, and it is not inflated by parcel-level measurement error. In other words, we focus on *systematic* differences in the weighted average building value across regions.

We will also find it convenient, going forward, to write out the building supply curve in terms of a supply shifter $\Psi$, which we derive in Appendix B.1:

$$p_{j,t} B_{j,t}^{N} = p_{j,t}^{\frac{\gamma}{1-\gamma}} \delta_b \cdot \underbrace{D_{j,t}^{\frac{1}{1-\gamma}} T_{j,t}^{\frac{\gamma}{1-\gamma}} C_j (\beta\gamma)^{\frac{\gamma}{1-\gamma}}}_{\Psi_j} \tag{12}$$

Note that, because $\tau$ is a constant, $\gamma$ alone controls the price elasticity of supply. We discuss the implications of this in Appendix G.

### 2.3 Identifying Parcel-Level Parameters

In this section we describe how we recover building depreciation $\delta_b$, the improvement share of building value $\gamma$, and parcel-level regulatory distortions $\tau_i$.

Our primary data source comes from CoreLogic, a major private provider of real estate data. This dataset consists of county tax assessors' data on the near universe of commercial parcels in the United States, from 2009 to 2018. It includes the total value of the parcel $TV_i$, derived from either assessments, appraisals, or market transactions. This value is subdivided into land value $LV_i$ and improvement value $MV_i$. For a smaller subset of buildings, which still comprise a large share of overall total value, the data also includes building square footage $BSF_i$, the alphanumeric zoning code $z(i)$ to which the building is subject (example names include "C8" and "OR1"), and building age $a_i$. We describe our data in more detail in Appendix A.1.

As shown in Appendix B.2, we can recover the product of our aggregate measure of regulatory distortion $T_j$ and the scale parameter $\gamma$ as follows:

[13] This is mathematically and conceptually similar to a cost-weighted average markup, which Edmond, Midrigan, and Xu (2021) show is the correct way to aggregate markups. To see the similarity, define $\mathcal{M} \equiv 1/T$ and $\mu \equiv 1/\tau$ and compare to the definitions of $\mathcal{M}$ and $\mu$ in that paper. Here, improvements correspond to costs.

$$\gamma \cdot T_j = \frac{\left(\frac{1-\beta(1-\delta_b)}{1-\beta}\right)\frac{\sum_{i\in j} MV}{\sum_{i\in j} TV}}{\beta\left(1+\frac{\delta_b}{1-\beta}\frac{\sum_{i\in j} MV}{\sum_{i\in j} TV}\right)} \tag{13}$$

We get $TV$ and $MV$ from our CoreLogic sample. Under our depreciation assumption, $\delta_b$ is the inverse of the average building age in our sample.[14] We use a standard value of 0.96 for $\beta$, the last value needed to identify $T_j\gamma$.

Unsurprisingly, we cannot separate $T_j$ and $\gamma$ without more assumptions or information. Regulatory distortions cause landlords to spend too little on improvements as a share of total value, hence disentangling distortions from the true improvement share is challenging. However, under the assumption that $T_j \leq 1$ for all $j$ (i.e. that no city has "negative" regulations), every city-level observation of the left-hand term in Equation (13) provides a lower bound for $\gamma$. Our approach is to treat the city with the highest value of $\gamma \cdot T_j$ as a "deregulated benchmark", with $T_j$ assumed to be equal to 1. In practice, we find that the benchmark is Midland, Texas, a small metropolitan area with a large oil-producing sector. Our assumption that $T_{\text{Midland}} = 1$ yields an implied $\gamma$ of 0.92.[15]

Even though our value of $\gamma$ is likely an underestimate, it is very close to 1 and suggests that the building production function is nearly linear in improvements. This is not dramatically out of line with what other studies have found: Epple, Gordon, and Sieg (2010) estimate an improvement share of 0.84 for residential buildings in Allegheny County, Pennsylvania, and they do not take into account regulatory distortions. Combes, Duranton, and Gobillon (2021) finds a slightly lower share of 0.64 for single-family homes in France, although they also do not directly measure regulation and only try to infer it from observed (not statutory) floor area ratios.[16] Glaeser, Gyourko, and Saks (2005b) find that construction costs per building square foot are relatively flat across dramatically different residential building sizes, which is consistent with a high improvement share in production. Moreover, a near-linear production function is intuitively reasonable: roughly speaking, it suggests that a builder can double the number of floors on a building for only slightly more than double the cost. In Appendix G, we explore the implications of such a high $\gamma$ and argue that the very high implied building supply elasticities are not as far out of line with the literature as they seem.

A fixed, rather than city-specific, $\gamma$ is crucial for our identification and ability to compare distortions across regions. It is important to remember that our building supply elasticity is conceptually different from the city-specific elasticities in Saiz (2010): that paper is concerned with the *extensive* margin of construction into currently-undeveloped lots, whereas we focus on the *intensive* margin of construction

[14] Our calibrated value of 0.02 is fairly close to what Davis and Palumbo (2008) find under less stark assumptions about depreciation.

[15] Note that if Midland has any degree of regulation—that is, if the true $T_{\text{Midland}}$ is less than 1—we will underestimate $\gamma$ and therefore overstate the degree of decreasing returns to replicable factors. Hence, we will underestimate the gains from deregulation.

[16] Both of these papers also argue that the production function for buildings is reasonably well-approximated by a Cobb-Douglas function in land and other inputs, which lends further support to our modeling choices. Ahlfeldt and McMillen (2014) also argue that a Cobb-Douglas production function is a good approximation, and that some earlier estimates of a less-than-unitary elasticity of substitution were biased downwards.

Figure 1: Distribution of $MV/TV$

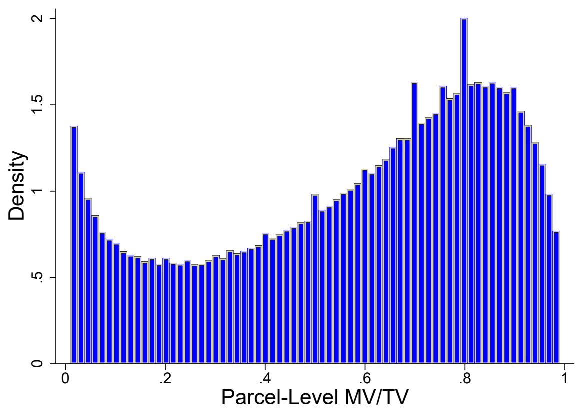
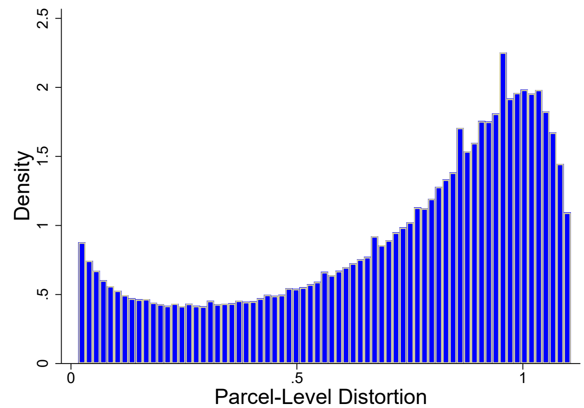



Figure 2: Distribution of $\tau$




*Notes*: Figure 1 displays the ratio of the improvement value of each parcel to its total value. We exclude values above 0.99 and below 0.01, treating them as noise. We also drop parcels designated by CoreLogic as public property. Figure 2 uses the same data and displays $\tau$ as calculated in Equation 14. Both figures use unweighted counts of parcels.

on already-developed land. The former is clearly affected by city-specific factors like geography, but the latter measures the curvature of costs with respect to building height, which is not obviously city-specific.

After having calibrated $\gamma$, we can recover $T_j$ at the MSA level, and by modifying Equation (13) into Equation (14), we can recover $\tau_i$ at the parcel level as well.

$$\tau_i = \frac{\left(\frac{1-\beta(1-\delta_b)}{1-\beta}\right)\frac{MV_i}{TV_i}}{\gamma\beta\left(1+\frac{\delta_b}{1-\beta}\frac{MV_i}{TV_i}\right)} \tag{14}$$

After having recovered $\tau_i$, it is straightforward to use Equations (4) and (8) to get $D_j$.

Finally, we estimate $p_j$ from the subset of buildings $j_b$ with a recorded value for building square footage $BSF$:

$$p_j = \frac{\sum_{i\in j_b} BV_i}{\sum_{i\in j_b} BSF_i}$$

### 2.3.1 Identifying $\tau$ from $MV/TV$

We can illustrate the variation in the data that allows us to estimate $\tau_i$, and therefore also $T_j$ and $D_j$. We plot $MV/TV$, the key moment that identifies regulatory distortions, across all parcels in our sample in Figure 1. We find that, for most parcels, this measure is significantly lower than what we would expect to see in a world with no regulatory distortions and no measurement error.

Alongside the distribution of the data object $MV/TV$, we also plot the distribution of the model object $\tau$ and show that—as one might expect from Equation (14)—the two distributions are quite similar in shape.

Figure 3: Distribution of $T_j$

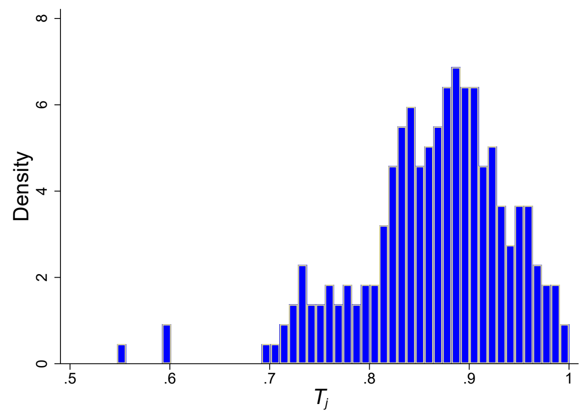
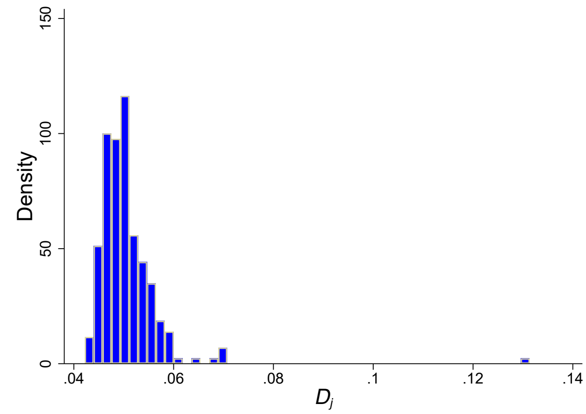



Figure 4: Distribution of $D_j$




*Notes*: Figure 3 displays the distribution of $T_j$ across cities, with $T_j$ calculated as in Equation 9. Figure 4 uses the same data and displays $M$ as calculated in Equation 8. See the caption of Figure 1 for details on sample selection.

# 3 Results and Validation

In this section, we display some of the results of our empirical analysis. We begin by plotting the distribution of $T_j$ and $D_j$, the level and dispersion of regulatory distortions in each MSA.

We next perform several validation exercises that test the central argument of this paper, which is that the improvement share of total value provides information about the degree of land use regulation in a given city. We test this argument by comparing our measure of regulation against several real-world, statutory measures of regulation, and we compare our measures across regions where we expect *a priori* to find differences in regulations. We find that our model-derived measure of regulation align well with these real-world measures. We also examine the threat to our identification posed by differences in building age and argue that it is not a first-order concern.

## 3.1 The Distribution of $T_j$ and $D_j$

In Figures 3 and 4, we plot the distribution of the "average" regulatory distortion $T_j$ and the dispersion in distortions $D_j$ at the MSA level. Most cities are clearly far from the deregulated benchmark, and in most cities $\tau$ is quite dispersed across parcels. $D_j$ takes on a maximum value of 1.0 if all parcels have the same regulatory distortion, and it is isomorphic to productivity in the construction sector. Hence, these plots suggest that both the level and dispersion of $\tau$ may induce significant inefficiencies.

## 3.2 Zoning Code Dimensions

In this section, we plot our measure of regulatory distortion against two dimensions of statutory zoning code strictness: floor area ratios in New York City, and height restrictions in Washington, DC. We chose these cities and measurements because a high share of the parcels in these cities had non-missing zoning codes, and because their websites made it easy for us to manually collect and clean these zoning code features. [17]

We first project parcel-level regulatory distortions $\tau_i$ down onto zoning codes, and recover a code-level regulatory distortion $\tau_z$. Denoting $i \in z$ as the set of parcels subject to zoning code $z$, we write:

$$\tau_z = \frac{\sum_{i \in z} MV_i}{\sum_{i \in z} MV_i / \tau_i} \tag{15}$$

We expect a positive correlation between the model-derived measure and the statutory measures, but we do not expect it to be perfect. We plot $\tau$ against only one dimension of zoning codes, and we do not attempt to account for variances given to individual buildings.

We plot a binscatter of zoning-code level $\tau_z$ against these two statutory measures of regulation in Figures 5 and 6. To construct the red best-fit line, we weight each zoning code by the sum of building value subject to that code. We find a positive relationship in both cases, as expected.

Figure 5: FAR in NYC

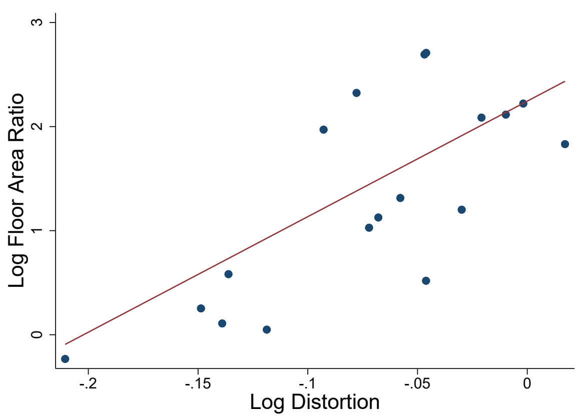
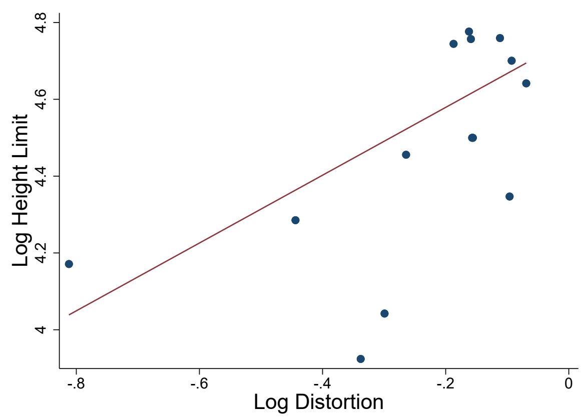



Figure 6: Height Limits in DC




*Notes*: In Figures 5 and 6, the horizontal axis is the logarithm of the zoning code-level distortion $\tau_z$, as calculated in Equation 15. The vertical axes are the logarithm of the regulation associated with each zoning code, namely floor area ratios in Figure 5 and height limits in 6. Floor area ratios are the maximum building floor area per ground area and are expressed as a ratio; height limits are expressed in feet. Both Figures 5 and 6 are binscatters where the constituent zoning codes of each bin are weighted by the sum of the value of the buildings (see Equation 2) in each code.

### 3.3 Downtowns

We next provide another graphical illustration of our measure of regulatory distortion and how it maps onto the real world.

In Figures 7 and 8, we map the most and least distorting zoning codes in San Francisco, and contrast this to statutory height restrictions provided in San Francisco Planning (2021). More specifically, we rank all parcels by their code-level regulatory distortion $\tau_z$[18] and map the top decile (least-regulating,

[17] The original data is available at City of New York (2021) and DC Office of Zoning (2021a), respectively. We go into greater detail in Appendix A.2.

[18] We use this aggregated measure of $\tau$ instead of the individual parcel-level $\tau$ in order to reduce the impact of outliers and measurement error, and to address issues with older buildings that we explain in greater depth in Section 3.5.

Figure 7: Model Zoning Distortion

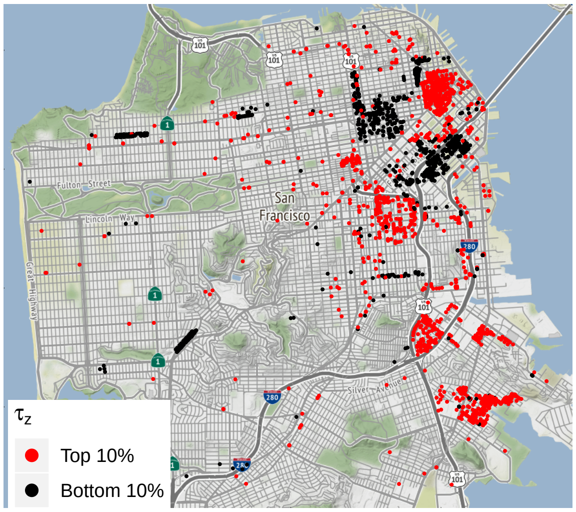
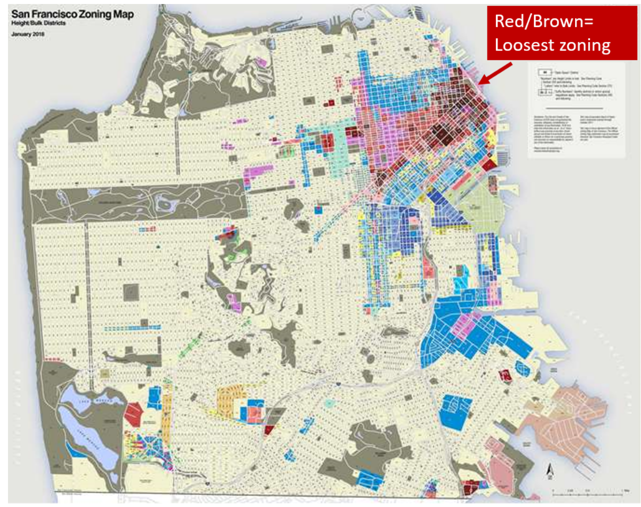



Figure 8: SF Height Limit Zoning Map, 2021




*Notes*: In Figure 7, we plot zoning code-level distortions $\tau_z$ in San Francisco for the most- and least- distorted zoning codes. We rank zoning codes by their $\tau_z$, take the most- and least- distorting 10 percent of zoning codes, and put in a dot denoting each building subject to those codes. Red dots correspond to buildings with the highest (least regulating) $\tau_z$, and black dots correspond to buildings with the lowest (most regulating) $\tau_z$. In Figure 7, we provide a map of height limits taken from San Francisco Planning (2021) and highlight downtown San Francisco, noted for having the largest concentration of high-rise office buildings in the city.

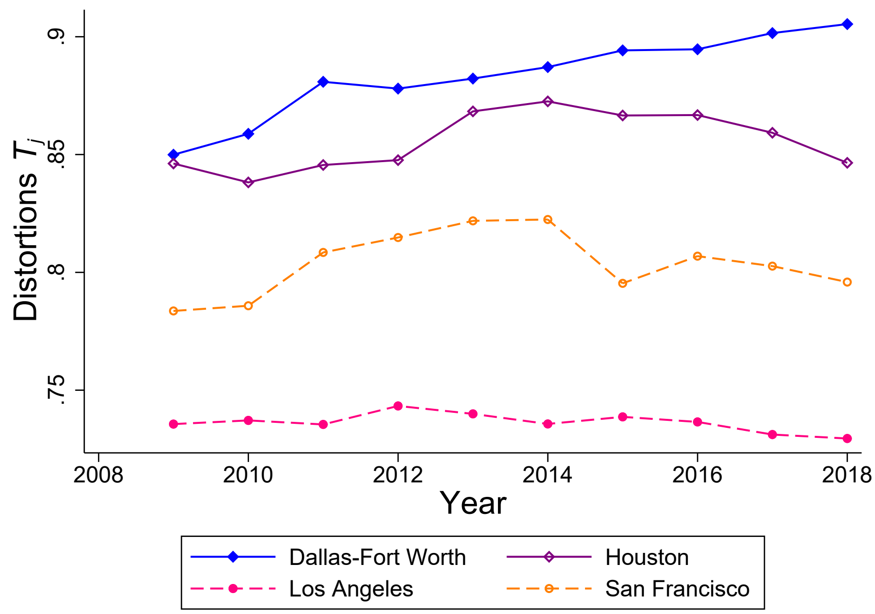
in red) and bottom decile (most-regulating, in black.) We find that our model identifies downtown San Francisco, the site of many of its most iconic skyscrapers, as relatively deregulated. We also find that our measure of regulatory distortion tracks reasonably well with statutory measures of regulation, even within a single jurisdiction where demand-side factors should be relatively similar. This suggests that our measure is picking up underlying regulations rather than simple demand-side factors.

### 3.4 Cities in California and Texas

Much of the prior literature on land use regulation has argued that Texas is less regulated than California. In general, we expect to find that liberal coastal states should have stricter regulations than more conservative states. We show in this section that this is the case for our measure of regulation.

In Figure 9, we plot our measure of regulation $T_j$ for each of the ten years in our sample (2009-2018) in the largest MSAs in those two states (Dallas and Houston in Texas; San Francisco and Los Angeles in California.) We find that, as expected, the major cities in California are more regulated than those in Texas. Indeed, Los Angeles is one of the most tightly regulated major cities in our sample. Figure 9 also demonstrates that our measure of regulation is, reassuringly, stable across years.

Figure 9: Cities in Texas and California




*Notes*: This plot shows $T_j$ for a set of 4 cities, two in California and two in Texas. In each year, we recalculate $T_j$ using all tax assessments from that year, rather than using buildings first assessed in that year.

### 3.5 Older Buildings

One possible issue with our identification strategy is that it might systematically overestimate regulation for older buildings.[19] If improvement value $MV$ is fixed, or perhaps even declining as the building ages, but the option to rebuild becomes more valuable as the economy grows, then older buildings should have a low measured $\tau$ even if they are not truly more regulated.

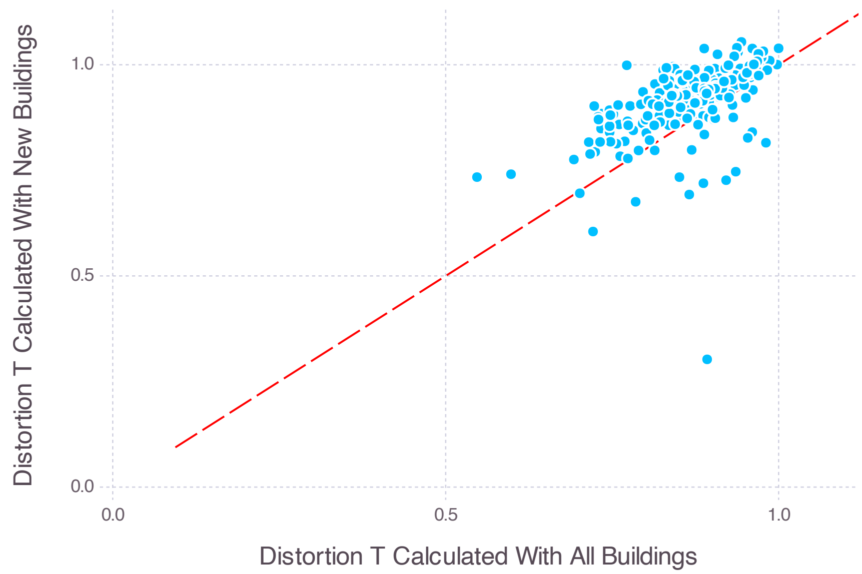
We offer a few responses to this potential criticism. First, we show that $T$ is not as tightly connected to age as one might expect, perhaps because older buildings get renovated. In Figure 10, we plot our baseline $T_j$ against an alternative $T_j$ calculated only with buildings from the last 10 years. The two series are highly correlated, and the alternative $T_j$ are clustered roughly along the 45 degree line. As described in Appendix A.1, only 57 percent of the buildings in our filtered sample even have a recorded age, and these are likely not selected at random, so the tight correlation in spite of these sources of noise is reassuring. In Appendix C, we also show that age is not very predictive of parcel-level distortions $t_i$.

More importantly, we have not used the parcel-level $\tau$ directly in our validation exercises and we do not use them in our counterfactuals[20]. We aggregate them up and treat zoning codes or MSAs as our units of observation. Older buildings may drive down the average $\tau$ and drive up its dispersion *within* a

[19]We thank Salim Furth for a very helpful conversation on this topic.

[20]In Appendix F, we follow Furth (2021) and use only buildings less than 10 years old to compute our counterfactuals, which yields results that are smaller than but still comparable to our baseline specification.

Figure 10: $T$ Calculated From New Buildings




*Notes*: In this Table, we compare our city-level distortions $T_j$ as calculated with all parcels on the horizontal axis with an alternative measure of $T_j$ calculated using only buildings from the last 10 years. We only have 235 matched MSAs in this sample, as no buildings in 6 MSAs have a recorded age.

zoning code or MSA, but we remove these effects in our counterfactual by using more-aggregated units of observation. Stated differently, dispersion in the measured $\tau$ due to building aging will be picked up more in $D$ than $T$. This leaves differences in the impact of aging on the level and dispersion of $\tau$ *across* our units of observation, but these differences may actually pick up on the effects of regulation if builders in more-regulated MSAs or zoning codes rebuild less frequently.

# 4 General Equilibrium Model

In order to calculate the consequences of our measured land use regulations for output and welfare, we need an equilibrium model where prices are allowed to vary. In this section we introduce just such a model, building on Herkenhoff, Ohanian, and Prescott (2018). This section also demonstrates the ease with which our measures of regulation can be incorporated into a macroeconomic model.

In what follows, $t \in \{0, 1, ..., \infty\}$ indexes time and $j \in \{1, 2, ..., N\}$ indexes regions, corresponding to 241 major metropolitan statistical areas, plus a remote work sector (denoted $j = r$) and a rest-of-country aggregate. Locations ("cities") are differentiated on amenities $a_j$ and TFP $A_j$. A stand-in household sends workers to cities to earn wages, allocates capital, and receives profits from landlords and final goods producing firms. The final goods firms hire workers and rent capital from the representative household, rent buildings from landlords, and combine these factors to produce a numeraire final good. Landlords combine a fixed factor ("land") with the final good to produce buildings, and they rebate their profits to the stand-in household.

### 4.1 Households

The stand-in household has preferences over consumption $c_t$ and regional labor supply $L_{j,t}$. These preferences feature city-specific disutilities of labor.[21] Amenities $a_j$ decrease the marginal disutility of sending workers to a given city. We parametrize amenities as a function of "congestion", or the quantity of workers per unit of commercial land $L_{j,t}/X_j$. This gives rise to one possible rationale for zoning regulations: the representative household takes these amenities as given when choosing where to send workers, but in doing so they generate unpriced externalities. The household invests $i_t$ in capital and allocates both workers $L_{j,t}$ and capital $K_{j,t}$ across regions. The wage rate in region $j$ is given by $w_{j,t}$, and we make the assumption that capital is perfectly mobile, implying a single national rental rate of capital $r_{k,t}$. The household also receives profits from landlords $\pi_{j,b,t}$ and from final goods firms $\pi_{j,f,t}$. The household solves the following optimization problem:

$$\max_{c_t,i_t,K_{j,t},L_{j,t}} \sum_{t=0}^{\infty} \beta^t \left( \frac{c_t^{1-\sigma}}{1-\sigma} - \frac{1}{1+\frac{1}{\eta}} \sum_{j=1}^{N} \left( \frac{L_{j,t}}{a_j(L_{j,t}/X_j)} \right)^{1+\frac{1}{\eta}} \right) \tag{16}$$

subject to:

$$c_t + i_t = \sum_{j=1}^{N} \left( \pi_{j,b,t} + \pi_{j,f,t} + w_{j,t}L_{j,t} + r_{k,t}K_{j,t} \right)$$

$$K_{t+1} = i_{k,t} + (1-\delta_k)K_t$$

$$\sum_{j=1}^{N} K_{j,t} = K_t$$

### 4.2 Final Goods

Final goods firms combine labor $L_{j,t}$, buildings $B_{j,t}$, capital $K_{j,t}$ at the city level to produce the numeraire final good.[22] We assume they operate constant returns to scale Cobb-Douglas production technologies with city-specific total factor productivity $A_j$. The building share $\chi_j$ is assumed to be zero in the remote work sector ($\chi_r = 0$) and both constant and positive across all other non-remote regions ($\chi_j > 0 \; \forall j \neq r$). Firms pay a national rental rate for capital $r_{k,t}$. They pay city-specific wages $w_{j,t}$ and building rents $r_{b,j,t}$. They maximize the following static profit function and rebate all profits (which will be zero in equilibrium) to the household:

[21] Similar to Herkenhoff, Ohanian, and Prescott (2018), these preferences stand-in for idiosyncratic preferences for a given city and other forces that limit inter-regional mobility. As $\eta \to 0$, it becomes more costly to send all workers to a given region. See Berger, Herkenhoff, and Mongey (2019) for discrete choice micro-foundations of related firm-specific preferences.

[22] As we will explain in more detail later, $B_{j,t}$ maps into productivity-weighted building square feet supplied by the landlords.

$$\pi_{j,f,t} = \max_{K_{j,t},L_{j,t},B_{j,t}} \underbrace{A_j L_{j,t}^{\alpha} B_{j,t}^{\chi_j} K_{j,t}^{1-\alpha-\chi_j}}_{Y_{j,t}} - w_{j,t}L_{j,t} - r_{k,t}K_{j,t} - r_{b,j,t}B_{j,t}$$

### 4.3 Representative Landlord

As described in Section 2.2, our model admits a representative city-level landlord. This landlord purchases the final good $m$ at cost $1/q_j$ and combines it with newly-depreciated land to create new buildings $B_j^N$, as in Equation 6, which we rewrite below:

$$\max_{m_{j,t}} \beta T_{j,t} p_{j,t} \underbrace{D_{j,t} m_{j,t}^{\gamma} (\delta_b C_j)^{1-\gamma}}_{B_{j,t}^N} - \underbrace{m_{j,t}}_{MV_{j,t}}$$

The stock of buildings in each city grows according to a standard law of motion:

$$B_{j,t+1} = (1-\delta_b)B_{j,t} + B_{j,t}^N$$

Note that we incorporate our measures of regulation $T$ and $D$ in a fully model-consistent manner. This is one major advantage of our approach relative to Gyourko, Hartley, and Krimmel (2021).

### 4.4 Equilibrium

An equilibrium in this economy consists of prices $\{\{r_{b,j,t}, w_{j,t}\}_{\forall j}, r_{k,t}\}_{t=0}^{\infty}$, quantities $\{\{Y_{j,t}, K_{j,t}, L_{j,t}, B_{j,t}\}_{\forall j}, \{m_{i,t}\}_{\forall i}, i_t, c_t\}_{t=0}^{\infty}$, and decision rules for investment, consumption, and labor supply, such that, given prices, the stand-in household maximizes utility, firms maximize profits, markets clear, and the resource constraint holds:

$$c_t + i_{k,t} + \sum_j \left( \sum_{i \in j} q_i m_{i,t} \right) = \sum_j Y_{j,t}$$

### 4.5 Identification

We now identify the other parameters of the general-equilibrium model, again assuming a steady state and dropping time subscripts. We set a subset of these parameters externally, using standard values, and summarize these parameters in Table 1. We discipline the factor shares in production, region-level total factor productivity, and productivity in the building sector using external data from the 2018 American Community Survey (Ruggles, Flood, Goeken, Grover, Meyer, Pacas, and Sobek (2020) ) and the Bureau of Economic Analysis, as summarized in Table 2.

We allocate labor supply across regions, and to the remote work sector, using the ACS. The variable TRANWORK asks “How did this person usually get to work LAST WEEK?" (emphasis original), and we define a remote worker as someone who answers “worked from home." We calculate the share of remote

Table 1: External Parameters

| Parameter | Description | Value | Source |
|---|---|---|---|
| $\beta$ | Discounting | 0.96 | Standard, i.e. Herkenhoff and Raveendranathan (2023) |
| $\sigma$ | CRRA | 2 | Standard, i.e. Friend and Blume (1975) |
| $\eta$ | Labor Curvature | 2 | Standard, i.e. Keane and Rogerson (2012) |
| $\delta_k$ | Non-Structures Depreciation | 0.032 | Standard, i.e. McGrattan (2020) |
| $\alpha$ | Labor Share | 0.594 | Penn World Table (Feenstra, Inklaar, and Timmer (2015)) |

*Notes*: This Table reports the parameters which we set externally. We use standard values in all cases, and we provide sources from the literature that support our choices.

Table 2: Additional Data Sources

| Variable | Description | Source |
|---|---|---|
| $Y$ | Aggregate GDP | US Bureau of Economic Analysis (2021b) |
| $Y_j$ | MSA GDP | US Bureau of Economic Analysis (2021a) |
| $i_k$ | Equipment+IP Investment | US Bureau of Economic Analysis (2021b) |
| $L_j$ | MSA Labor Supply | ACS |
| $\rho^L \equiv L_r/\sum_j L_j$ | Remote Labor Supply Share | ACS |
| $\rho^W \equiv w_r L_r/\sum_j w_j L_j$ | Remote Wage Bill Share | ACS |

*Notes*: This Table reports our key sources of data outside of CoreLogic. We get data on national output, metro-level output, and investment from the Bureau of Economic Analysis; and we get metro-level labor supplies, the share of workers who work remotely, and the wage bill share of remote workers from the American Community Survey. We define a remote worker as anyone who lists their primary commuting mode as "worked from home" in response to the questions in variable TRANWORK.

workers $\rho^L$ and set $L_{\text{remote}}$, the labor supply in the remote work region, as $\rho^L$ times the aggregate labor supply. We multiply each non-remote region's labor supply by a factor $1-\rho^L$ to avoid double-counting workers.

We assume that the labor share is constant in the remote work and traditional regions. This means that remote workers' share of GDP will be proportional to their share of the wage bill. Analogously to our procedure for labor supplies, we therefore calculate remote workers' share of the aggregate wage bill $\rho^A$, set $Y_{\text{remote}}$ to $\rho^A$ times aggregate GDP, and multiply regional GDP in every other region by a factor $1-\rho^A$ to avoid double-counting output.

We next turn to non-structures capital. We pin down the rate of return $r_k$ using standard parameters and set $r_k = \frac{1-\beta(1-\delta_k)}{\beta}$. The aggregate capital stock is such that investment $i_k$ exactly offsets depreciation, hence $K = i_k/\delta_k$.

We can recover $\chi_n$, commercial buildings' factor share in non-remote regions, by noting that factor payments to non-structures capital are equal to $(1-\alpha-\chi_n)Y_j$ in non-remote regions $j \neq r$, and $(1-\alpha)Y_r$ in the remote region $r$. A little algebra yields: $\chi_n = \left((1-\alpha)\sum_j Y_j - r_k \sum_j K_j\right) / \left(\sum_{j\neq r} Y_j\right)$. With the factor share in hand, we can now calculate regional capital stocks:

$$K_j = (1 - \alpha - \chi_j) Y_j / r_k \tag{17}$$

We recover the level of the building stock $B_j$ and the level of the supply shifter $\Psi_j$ from the region-$j$ final goods firm's first-order condition—that is, we set the value of the building stock $p_j B_j$ equal to the net present value of factor payments made to these buildings, $B_j = \chi_j Y_j / p_j(1 - \beta(1 - \delta_b))$. This then pins down the shifter $\Psi_j = B_j / p_j^{\frac{\gamma}{1-\gamma}}$ We do not take the value of the building stock $BV_j \equiv p_j B_j$ directly from CoreLogic for several reasons. First, we use a filtered subset of all parcels as described in Appendix A, as we do not have full information on the universe of buildings in our data. Second, the value of the building stock will be depressed relative to true factor payments because of property taxes. Third, state policies like Proposition 13 in California may cause assessment values to be biased downwards—see Office of the Assessor, County of Santa Clara (2021) for details. Note that while the *level* of improvement value and total value may be artificially low, especially in California, we do not use the level directly and are instead concerned with improvement value's *share* of total value. The share should not be systematically biased by any of the factors we describe above, unlike the level. Likewise, property taxes should be capitalized into the parcel-level price per building square foot $p_j z_i$, as discussed in Section 2.1.1, and are not a direct threat to our identification.

We recover the total amount of resources expended in improvements from the first-order condition of the aggregate builder and the steady-state condition that new buildings replace depreciation, so $p_j B_j^N = \delta p_j B_j$. Usefully, this also yields the demand curve for materials:

$$m_j = \gamma \beta T_j \delta_b p_j B_j \tag{18}$$

Next we can recover total factor productivity from the production function of the final goods firms, $A_j = Y_j / \left( L_j^{\alpha} B_j^{\chi_j} K_j^{1-\alpha-\chi_j} \right)$. We then use ACS data on $L_j$ and BEA data on $Y_j$ to recover wages from the first-order condition of the final goods firms, giving us $w_j = \alpha Y_j / L_j$. Next we recover consumption by subtracting investment in improvements and capital from output, giving us $c = \sum_j \left( Y_j - \delta_k K_j - m_j \right)$. We then recover amenities from the household's first order condition:

$$a_j = \exp\left( \frac{\sigma \log c + \frac{1}{\eta} \log L_j - \log w_j}{1 + \frac{1}{\eta}} \right)$$

Our analysis will overstate the gains from deregulation if there are countervailing benefits to these regulations. One possibility is that more commercial development would lead to more congestion and therefore a lower quality of life. As noted earlier, the fact that many most regulated towns are famous for their natural amenities lends some credence to this theory. In our preferred specification, captured in Equation (19), we regress amenities $a_j$ against a measure of congestion: the ratio of workers $L_j$ to the sum of commercial land square footage $X_j$.[23]

One might be concerned, however, that this procedure would yield biased results: a place with high

[23] We sum land square footage $x_i$ across all parcels with a non-missing value, not only the ones in our filtered sample.

exogenous amenities will draw a lot of workers in, meaning that $L/X$ would be correlated with $e$. We therefore use the model itself to generate instrumental variables, in a manner similar to papers like Anderson and van Wincoop (2003), Allen, Arkolakis, and Takahashi (2020), and Walsh (2019).We resolve the model setting TFP and amenities to their average value and turning off zoning distortions, meaning that the only reasons why populations would differ across regions are the land supply shifters $\Psi$.[24] This is particularly close to the "model-implied IV" of Rossi-Hansberg, Sarte, and Schwartzman (2019b). We store this counterfactual value of $L/X$ and denote it as $\widehat{L/X}$, and use that counterfactual as an instrument for $L/X$ in Equation (19). We report the measured coefficient and standard error below:

$$\log a_j = \underbrace{\mu}_{\substack{-0.53^{***} \\ [0.07]}} \log(L_j/X_j) + e_j \tag{19}$$

We drop the remote work sector and the rest-of-country aggregator from this regression. There are 241 MSAs in this analysis, some of which are very small, so we weight the regression by the true population of each MSA. We also use robust standard errors. The first-stage F-statistic is 191. This small but statistically significant negative relationship between amenities and our measure of congestion suggests that the increased labor supply attracted to a region by a larger building stock might make a place less desirable. This provides one possible rationale for zoning regulations.

# 5 Counterfactuals

We can use our model for large-scale counterfactuals that illustrate the aggregate consequences of commercial land use regulation, and we can use the same framework to simulate detailed local counterfactuals. In this section, we provide some examples of both. We explain how we compute counterfactuals in Appendix E, and we explain how we incorporate endogenous amenities into these counterfactuals in Appendix E.1.

## 5.1 Aggregate Counterfactuals

This first set of counterfactuals demonstrates that land use regulations are consequential for both aggregate output and the distribution of economic activity across space. The first experiment shifts the "average" level of regulation in each city up to the benchmark by setting $T_j = 1$, the second experiment reduces dispersion in zoning codes; the third experiment tests whether there are still meaningful gains from deregulation in a world where remote work is more common, the fourth experiment studies how local counterfactuals can have aggregate effects, and the fifth experiment tests whether congestion externalities meaningfully reduce the welfare gains from deregulation. We summarize the counterfactuals in Table 3 and explain them in greater detail in the next few sections.

[24] We report the results of other approaches in D. This specification yielded the most pessimistic estimate of the negative effects of congestion, so we use it as our baseline to make our results more conservative.

Table 3: Aggregate Counterfactuals: Description

| **Counterfactual** | $T$ | $D$ | **Amenities** |
|---|---|---|---|
| Baseline | Set to 1.0 | Unchanged | Baseline |
| Less Dispersion | Unchanged | max[Second Highest, $D_j$] | Baseline |
| More Remote | Set to 1.0 | Unchanged | Set so $\rho^L = 0.4$ |
| Local Deregulation | $\tau_{cf} = \max[\tau, \min[\text{Median in FIPS}, 2\tau]]$ | | Baseline |
| No Congestion | Set to 1.0 | Unchanged | Exogenous |

*Notes*: This Table provides a guide to each of our five aggregate counterfactuals. The first column explains how we change the aggregate distortion $T_j$, the second explains how we change the dispersion term $D_j$, and the third explains whether we endogenize amenities as in our baseline case or treat them as exogenous. For the "Local Deregulation" counterfactual, we do not change $T_j$ and $D_j$ directly but rather change zoning code level $\tau_z$ and then re-aggregate.

Table 4: Aggregate Counterfactuals: Results

| | **Baseline** | **Less Dispersion** | **More Remote** | **Local Deregulation** | **No Congestion** |
|---|---|---|---|---|---|
| $\%\Delta Y_j$ | 3.0% | 6.0% | 1.5% | 3.1% | 2.9% |
| $\%\Delta L_j$ | -0.8% | -2.8% | -0.8% | -2.3% | -1.0% |
| $\%\Delta K_j$ | 2.6% | 5.2% | 0.4% | 2.6% | 2.5% |
| $\%\Delta B_j$ | 17.4% | 60.0% | 19.2% | 26.2% | 16.6% |
| %Δ Landlord Profits | -2.8% | 7.6% | -1.1% | 11.0% | -2.9% |
| $\%\Delta c$ | 2.2% | 6.1% | 1.0% | 4.0% | 2.1% |
| %Δ Consumption Equiv. | 1.5% | 3.1% | 0.8% | 1.7% | 1.5% |

*Notes*: In Table 4, we display the results of our five aggregate counterfactuals. $\%\Delta X$ is the percent change in variable $X$ relative to the baseline, where $X$ stands for output $Y$, aggregate labor supply $L$, capital $K$, building stock $B$, landlord profits, and consumption. The final row is the percent change in consumption relative to the baseline needed to make the stand-in household indifferent between moving to the counterfactual steady state or not.

We report the major results from these exercises in Table 4. We calculate the percent change in GDP $Y$, labor supply $L$, capital stock $B$, and (efficiency-weighted) building stock $B$, aggregate landlord profits (given by the rental payments made to buildings $\sum_j \chi Y_j$ less the cost $\sum_j m_j$ needed to offset depreciation), and consumption.

Finally, we compute the percentage change in consumption in the original steady state needed to make the representative household equally well-off as in the new steady state. We derive this analytically in E.2.

### 5.1.1 Baseline

In our baseline exercise, we simply set $T_j = 1$ in all regions and keep all other parameters the same. This is an extremely conservative exercise that treats all of the dispersion in $\tau$ within a region as measurement error; in other words, it leaves $D_j$ unchanged. We report the results in the first column of Table 4. We find that this leads to a nearly 3 percent increase in GDP, and a notably smaller increase in consumption. This

Table 5: Most and Least Regulated Cities

| | **Distortion** $T_j$ | **Change in** $Y_j/L_j$ | **Change in** $L_j$ |
|---|---|---|---|
| Midland, TX | 1.000 | 0.1% | -3.5% |
| Shreveport-Bossier City, LA | 0.998 | 0.1% | -3.4% |
| Monroe, LA | 0.987 | 0.4% | -3.2% |
| Tuscaloosa, AL | 0.985 | 0.4% | -3.2% |
| Baton Rouge, LA | 0.983 | 0.4% | -3.2% |
| Lebanon, PA | 0.701 | 8.3% | 3.2% |
| Myrtle Beach-Conway-North Myrtle Beach, SC-NC | 0.693 | 8.6% | 3.4% |
| Ocean City, NJ | 0.598 | 12.3% | 6.3% |
| El Centro, CA | 0.597 | 12.3% | 6.3% |
| Urban Honolulu, HI | 0.547 | 14.5% | 8.1% |

*Notes*: This table shows the five cities with the highest and lowest values of $T_j$, corresponding to the lowest and highest degrees of regulation. The first column reports the city-wide distortion $T_j$, the second column represents the change in GDP per worker in our baseline counterfactual where we set $T_j = 1 \; \forall j$, and the third column reports the change in city-level labor supplies in that same counterfactual.

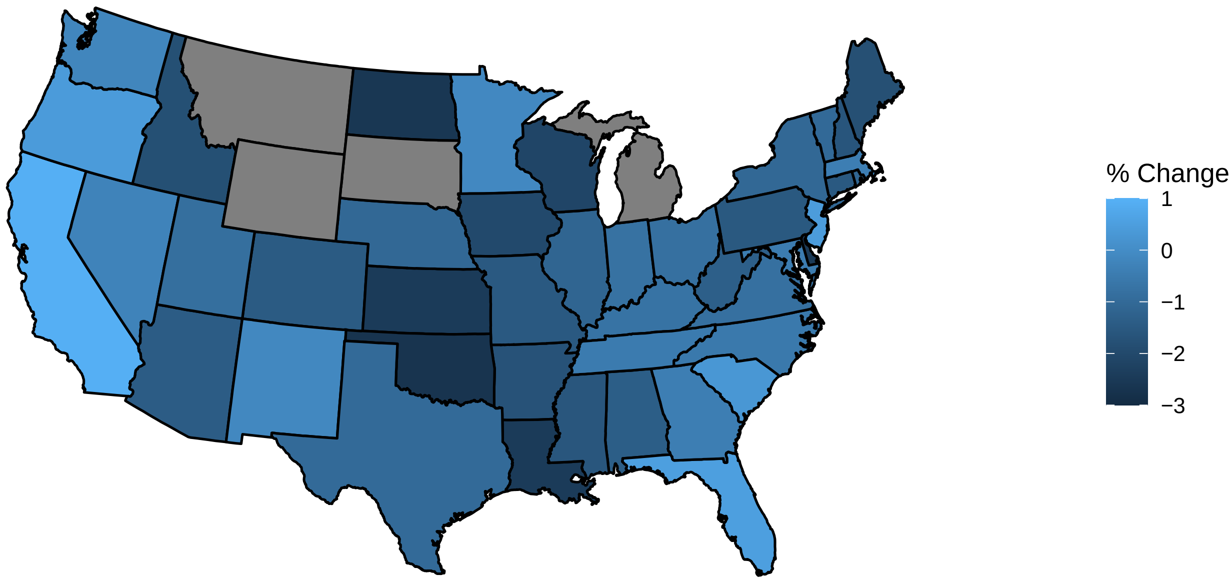
discrepancy arises because removing regulatory distortions leads landlords to invest more resources in their building stock, leaving fewer to rebate to the household for consumption. The stand-in household in the original steady state would be indifferent between a 1.5 percent increase in consumption and switching to the counterfactual steady state. Interestingly, we find that landlord profits fall in the new steady state due to the drop in price per building square foot. This is not surprising: regulations in this model effectively force landlords to spend “too little" on construction. which saves them money directly and indirectly leads to higher equilibrium prices per building square foot. Higher construction expenditures for landlords also leave fewer resources available for consumption, explaining why consumption and welfare increase less than output. We speculate that part of the reason why these regulations persist is because, while each individual landlord would be better off if their $\tau_i$ were set to its maximal value of 1, deregulating *every* parcel would lower prices and profits for all landlords.[25]

In Table 5, we show what MSAs grow and shrink the most in our baseline deregulation. We report the regulatory distortion $T_j$, along with the change in GDP per capita and the change in labor supply after the deregulation. We find that the least regulated cities are generally in the South, and that many of the most regulated cities are beach towns. We speculate that certain cities with desirable natural amenities might use these restrictions to avoid over-developing and lowering the value of those amenities. Interestingly, our finding that Honolulu is the most regulated city mirrors what Gyourko, Saiz, and Summers (2008) found for residential buildings: Honolulu singlehandedly pushed Hawaii to the top of their rankings of most-regulated states.

We also find that, as expected, deregulation generally shifts labor from cities in initially less-regulated states like Texas to cities on the more-regulated coasts. In Figure 11, we show the change in labor supply

[25]However, landlord profits do increase under counterfactuals where we allow $D_j$ to change.

Figure 11: Metropolitan Labor Supply Changes Across States in Baseline Counterfactual




*Notes*: This table reports the change in labor supply $L_j$ across the 241 cities in our baseline counterfactual, with the cities combined into their constituent states. Cities and towns in the rest-of-country aggregator are not included, and we omit Alaska and Hawaii for readability.

in all cities within a state.[26]

In Appendix F, we test how the results of this counterfactual vary as we change our data sample and parametrization.

### 5.1.2 Reducing Dispersion

In this exercise, we take our measure of dispersion more seriously and perform an exercise inspired by Hsieh and Klenow (2009): we move dispersion $D_j$ up to a minimally-dispersed benchmark and recalculate the equilibrium. That is, we leave the *average* level of regulation in a city ($T_j$) fixed but reduce the dispersion of regulation. We interpret "reduced dispersion" as allowing more-equal development within a city as opposed to clustering commercial real estate in business districts.

$D_j$ is tightly concentrated in a range of 0.04-0.07, with a single outlier observation (namely Yuma, AZ) at roughly 0.13. Hence, we move $D_j$ in all regions up to the maximum of their pre-reform $D_j$ or the *second* highest $D_j$ in our sample (Youngstown-Warren-Boardman, OH-PA), so that the one outlier does not skew our results.

[26] But note that we do not include the rest-of-country aggregator or remote work sector in this figure.

We find that the gains from this exercise are very large: output goes up by 6%, and consumption-equivalent welfare rises by 3%.

However, the benefits from this form of deregulation depend heavily on agglomeration and congestion externalities. If de-centralizing commercial real estate reduces congestion by spreading out employment, this exercise may understate the benefits of reducing dispersion. If agglomeration externalities have an increasing elasticity with respect to economic activity (that is, if reallocating activity from business districts to the outskirts causes a net weakening of agglomeration forces), then moving such activity away from the central business district will lessen the benefits of agglomeration, and so this exercise would overstate the benefits of reducing dispersion. This is an interesting avenue for future research.

#### 5.1.3 Expanded Remote Work

In the wake of the COVID-19 pandemic and the shift to remote work, one might wonder whether commercial real estate regulations are as important. We have taken an extreme stance by setting the factor share of buildings in the remote work sector to zero, and can therefore use our model to calculate a "worst case" scenario for the gains from deregulation. Dingel and Neiman (2020) argue that almost 40 percent of jobs can be done from home, a number we treat as a rough upper bound for the near-future impact of remote work. We now ask what happens to the benefits of deregulation after a large shift to remote work.

This is deliberately a very extreme interpretation of the impact of remote work: as noted in Table 8, office buildings account for less than one-fifth of the total value of our sample, and yet we assume that commercial buildings (including warehouses and factories) are not an input at all into production done at home.

We first use the counterfactual algorithm detailed in Appendix E to compute a new initial steady state where remote work comprises 40% of the labor force. To do so, we scale down amenities $a_j$ in all non-remote regions by a common factor $v$, recalculate the steady-state share of remote work, and continue scaling down until we find the $v^*$ that delivers our desired remote work share.

Next, we start from the new high-remote work benchmark and perform our baseline deregulation. We report the results in the second column of Table 4. We find that the gains from deregulation are attenuated, but still amount to an 0.8% consumption equivalent gain in welfare in a world where four in ten jobs are done remotely.

#### 5.1.4 The Aggregate Consequences of Local Reforms

We next consider a simple counterfactual conducted at the local level: what if every county up-zoned its most regulated buildings by moving every $\tau_z$ up to the median? Our goal is to understand whether relatively conservative, easy-to-interpret policy changes at the local level can aggregate up and have significant consequences at the national level. We also use this counterfactual to demonstrate that our method can be used to perform detailed, specific policy counterfactuals and give granular advice to local policymakers.

We first project regulatory distortions down onto zoning codes and recover $\tau_z$ as in Equation (15), and treat buildings in each zoning code as if there was no dispersion in distortions. We now recalculate Equations (10) and (11) after projecting down onto zoning codes:

$$MV_z \equiv \sum_{i \in z} MV_i \tag{20}$$

$$D_j = \left( \frac{\sum_{z\in j} MV_z/\tau_z}{\sum_{z\in j} MV_z/\tau_z^{\frac{1}{1-\gamma}}} \right) \Big/ \left( \frac{\sum_{z\in j} MV_z}{\sum_{z\in j} MV_z/\tau_z^{\frac{1}{1-\gamma}}} \right)^{\gamma} \tag{21}$$

$$T_j = \frac{\sum_{z\in j} MV_z}{\sum_{i\in j} MV_z/\tau_z} \tag{22}$$

The misallocation term $D_j$ does not stay the same—it gets closer to 1.0 as this procedure removes any within-zoning-code dispersion in $\tau$. The average dispersion $T_j$ is unchanged after we project regulatory distortions down onto zoning codes—this is immediately apparent after substituting Equations (20) and (15) into Equation (22) and contrasting it with Equation (11). To perform this counterfactual, we change $\tau_z$, recalculate $T_j$ and $D_j$ in Equations (22) and (20), and use the algorithm in Appendix E.

We emphasize that, due to our data limitations, this is an extremely conservative exercise. Some counties do not report their zoning codes at all in the datasets that CoreLogic compiles, hence these counties would see no change in the extent of their regulation in our counterfactual. We do not allow any $\tau_z$ to go up by more than a factor of 2, and we also cap $T_j$ and $D_j$ at 1.0 to prevent any city from having "negative" average regulation or dispersion. Our results indicates that this modest reform could increase output by roughly 3%.

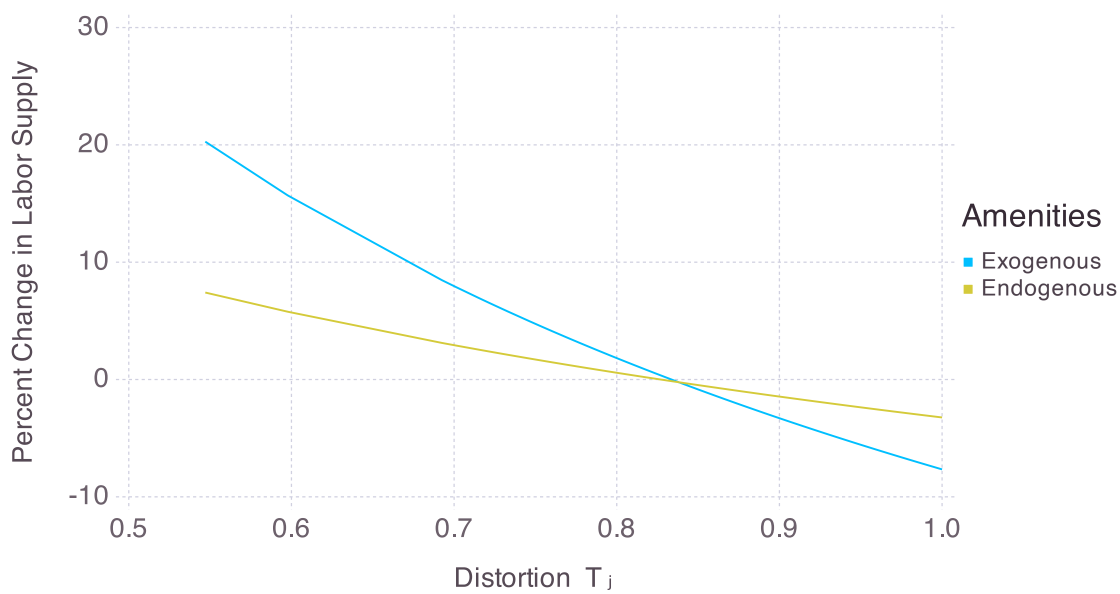
#### 5.1.5 Exogenous Amenities

We report the results of this counterfactual in the third column of Table 4. Perhaps surprisingly, we find that aggregate outcomes barely change. Upon closer inspection, we find that this is because increases in congestion in initially more-regulated cities, which gain more workers when we loosen regulations, are offset in the aggregate by decreases in congestion in initially less-regulated cities. We show in Figure 12 that these responses differ greatly between the benchmark case with endogenous amenities and the case with exogenous amenities. In the baseline case, amenities worsen in cities with larger increases in $T_j$ and greater labor supply increases, but they improve in cities that lose workers. Endogenizing amenities therefore dampens the labor supply response to deregulation, with only a minor effect on aggregate outcomes.

### 5.2 Local Counterfactual

We can also use our framework to perform detailed counterfactuals that change individual parcel-level regulatory distortions, and can therefore provide advice to local policymakers. Below, we provide an

Figure 12: Exogenous vs Endogenous Amenities




*Notes*: This table compares the change in labor supplies across cities in our baseline counterfactual with endogenous amenities and an alternative with exogenous amenities. The horizontal axis corresponds to a city's distortion $T_j$ in the baseline, and the vertical axis corresponds to the percentage change in $L_j$ relative to the baseline in a counterfactual steady state where $T_j = 1$ in all cities.

examples of a fine-grained counterfactual within New York City: moving all buildings up to the highest floor area ratio that we observe.

We first regress $\tau_z$ on $FAR$ at the zoning code level, weighting zoning codes by their summed $BV$:

$$\log \tau_z = \underbrace{\alpha}_{\substack{0.0343^{***} \\ [0.00433]}} \log FAR_z$$

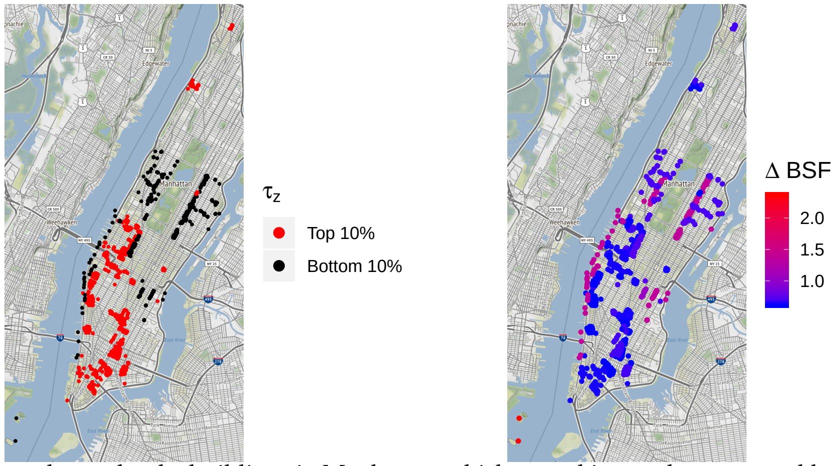
This projects our measure of regulatory distortion down onto a real measure of regulation, and captures the impact of one dimension of regulation on zoning code strictness. We can use this projection to estimate a counterfactual $\tau_{z,cf}$ in the case where we raise all buildings[27] to the highest observed floor area ratio, which we denote as $FAR_{\max}$:

$$\log \tau_z^{CF} = \alpha \log(FAR_{\max}) + \epsilon_z$$

We then use Equations (21) and (22) to calculate $M$ and $T$ under the new $\tau_z^{CF}$, and use them to

[27] We "cap" the zoning codes at 1, preventing us from having negative regulations, in the following sense: If $\tau_z > 1$, we do not change it in the counterfactual. If $\tau_z < 1$ but $\tau_z^{CF}$ would be greater than 1, we set $\tau_z^{CF} = 1$.

Figure 13: Zoning and counterfactual NYC




*Notes*: In the left panel, we plot the buildings in Manhattan which are subject to the most- and least- regulating ten percent of zoning codes. In the right panel, we plot the change in their square footages in the new steady state after counterfactually moving all FAR up to the highest that we observe. We only plot Manhattan to improve readability, and because Manhattan is likely more familiar to most readers than the rest of NYC.

compute a counterfactual.[28]

We find nontrivial local gains from this counterfactual, on the order of one percentage point of metro-area GDP[29]. We summarize these results in Table 6. Note that the metro-level (efficiency-weighted) building stock goes up only slightly when increase FARs in the largest city in the MSA. This suggests that FARs do not bind for many buildings. Indeed, most buildings in our sample are not particularly close to their statutory floor area ratio. This illustrates another advantage of our method: we can project our measure $\tau$ onto statutory characteristics of regulations such as floor area ratios, and figure out which of these characteristics are truly distortionary and which ones are not.

In Figure 13, we provide a graphical illustration of what this exercise would entail for NYC. We focus on Manhattan and plot the buildings in the most- and least-regulating ten percent of zoning codes in NYC, alongside the change in their building square footage in the new steady state following the counterfactual. Business activity moves from Midtown (already built-up) to the Upper East and West sides (mostly residential neighborhoods known for their opposition to development.) Note that the least regulated buildings *shrink* in the new steady state due to decreases in the equilibrium price per building square foot in the NYC metro area.

## 6 Conclusion

Our paper makes three contributions. First, we develop a model of the U.S. economy in which commercial real estate is a productive, regulated, and potentially misallocated component of the capital stock.

[28]We only use the subsample of buildings where we can find a floor area ratio for this exercise. See Appendix A.2 for details.

[29]Note also that the counterfactual takes place in New York City proper, whereas (to preserve compatibility with the rest of our model and analysis) we calculate changes in GDP at the level of the New York City MSA. Hence, these percentage gains are diluted by the many cities and suburbs in the NYC metro that do not deregulate in this counterfactual.

Table 6: NYC Counterfactual

| **Outcome:** | $Y_{NYC}$ | $B_{NYC}$ | $L_{NYC}$ | $P_{NYC}$ |
|---|---|---|---|---|
| Change Rel. to Baseline | +1.8% | +6.0% | +0.0% | -8.5% |

*Notes*: This Table reports the results of moving all buildings in NYC We report the change in metro-level GDP $Y$, commercial building supply $B$, labor supply $L$, and price per building square foot $P$ in the new steady state.

Importantly, our model yields an intuitive formula for identifying the extent to which commercial real estate investment decisions are distorted by zoning codes and other local regulations.

Second, we apply our theory to the near-universe of commercial property tax records from CoreLogic in order to measure a model-consistent index of commercial regulations. Our analysis uses rich address-level micro-data: municipal tax assessments compiled by CoreLogic. We validate our index of commercial regulations by hand-collected zoning code attributes and showing that our index of commercial regulations is correlated with statutory floor area ratios and height limits. We then examine how our commercial regulations compare across cities. Our results confirm the common prior that metro areas in Texas such as Dallas-Fort Worth and Houston face significantly weaker commercial real estate regulation than metros in California, and more generally we find that coastal cities face the most severe distortions to commercial real estate production.

Third, we use our distortion measure and our benchmark equilibrium model to evaluate the effect of both national and local changes to commercial regulations. In our primary exercise, we raise average city-level regulations up to a deregulated benchmark (Midland, Texas) and solve for the new steady state, while leaving the dispersion of parcel-level regulations unaltered. National output increases by 3.0% as commercial investment booms and workers reallocate from the midwest to the now-less-regulated states of Florida, California, Oregon, and Minnesota.

One benefit of our framework is that it allows for very granular counterfactuals within narrowly defined geographies. Because we recover regulatory distortions at the address-level, we can project our distortions down onto specific features of zoning codes such as floor area ratios. We apply this counterfactual to New York City and find that doubling floor area ratios would reallocate business activity toward the Upper West Side of Manhattan, and yield local output gains of 0.5%.

Our framework opens a number of avenues for future research. The model and empirical exercises can be extended to include residential zoning, heterogeneous workers, and intangible capital, and transition dynamics. Our framework is also well-suited for studying how regulations distort the allocation of resources and workers not only *across* cities but *within* a given city, and to study phenomena such as the interaction between inequality, homelessness and zoning distortions.

## References


AHLFELDT, G. M., AND D. P. MCMILLEN (2014): *New estimates of the elasticity of substitution between land and capital*. Lincoln Institute of Land Policy.

ALLEN, T., C. ARKOLAKIS, AND Y. TAKAHASHI (2020): "Universal Gravity," *Journal of Political Economy*, 128(2), 393–433.

ANDERSON, J. E., AND E. VAN WINCOOP (2003): "Gravity with Gravitas: A Solution to the Border Puzzle," *American Economic Review*, 93(1), 170–192.

BAUM-SNOW, N., AND L. HAN (2021): "The Microgeography of Housing Supply," Manuscript.

BERGER, D. W., K. F. HERKENHOFF, AND S. MONGEY (2019): "Labor market power," Discussion paper, National Bureau of Economic Research.

BUNTEN, D. M. (2017): "Is the rent too high? Aggregate implications of local land-use regulation," .

CITY OF NEW YORK (2021): "Zoning: Districts Guide," https://www1.nyc.gov/site/planning/zoning/districts-tools/commercial-districts-c1-c8.page, Accessed: 2021-02-13.

COLAS, M., AND J. M. MOREHOUSE (2020): "The Environmental Cost of Land Use Restrictions," Manuscript.

COMBES, P.-P., G. DURANTON, AND L. GOBILLON (2021): "The Production Function for Housing: Evidence from France," *Journal of Political Economy*, 129(10), 2766–2816.

CUN, W., AND M. PESHARAN (2020): "Land Use Regulations, Migration and Rising House Price Dispersion in the U.S.," Manuscript.

DAVIS, M., AND J. M. GREGORY (2021): "Place-Based Redistribution in Location Choice Models," Discussion paper, National Bureau of Economic Research.

DAVIS, M. A., AND J. HEATHCOTE (2007): "The price and quantity of residential land in the United States," *Journal of Monetary Economics*, 54(8), 2595 – 2620.

DAVIS, M. A., AND M. G. PALUMBO (2008): "The Price of Residential Land in Large U.S. Cities," *Journal of Urban Economics*, 63 (1), 352–384.

DC OFFICE OF ZONING (2021a): "Summary of Zone Districts," https://dcoz.dc.gov/page/summary-zone-districts, Accessed: 2021-08-02.

——— (2021b): "Title 11 Subsection K," https://dcoz.dc.gov/sites/default/files/dc/sites/dcoz/publication/attachments/SubtitleK_0.pdf, Accessed: 2021-08-02.

DELVENTHAL, M. J., E. KWON, AND A. PARKHOMENKO (2021): "Zoning and the Density of Urban Development," Unpublished Manuscript.

DIAMOND, R. (2016): "The Determinants and Welfare Implications of US Workers' Diverging Location Choices by Skill: 1980-2000," *American Economic Journal: Macroeconomics*, 106.3, 479–524.

DINGEL, J. I., AND B. NEIMAN (2020): "How Many Jobs can be Done at Home?," *Journal of Public Economics*, 189, 104.

EDMOND, C., V. MIDRIGAN, AND D. Y. XU (2021): "How Costly are Markups?," Manuscript.

EPPLE, D., B. GORDON, AND H. SIEG (2010): "A New Approach to Estimating the Production Function for Housing," *American Economic Review*, 100(3), 905–24.

FAJGELBAUM, P. D., AND C. GAUBERT (2020): "Optimal Spatial Policies, Geography, and Sorting," *Quarterly Journal of Economics*, 135.2, 959–1036.

FAJGELBAUM, P. D., E. MORALES, J. C. SUAREZ, AND O. ZIDAR (2019): "State Taxes and Spatial Misallocation," *Review of Economic Studies*, 86.1, 333–376.

FEENSTRA, R. C., R. INKLAAR, AND M. P. TIMMER (2015): "The Next Generation of the Penn World Table," *American Economic Review*, 105(10), 3150–3182.

FERNALD, J. G. (2015): "Productivity and Potential Output before, during, and after the Great Recession," *NBER macroeconomics annual*, 29(1), 1–51.

FRIEND, I., AND M. E. BLUME (1975): "The Demand for Risky Assets," *American Economic Review*, 65(5), 900–922.

FURTH, S. (2021): "Foundations and Microfoundations: Building Housing on Regulated Land," Manuscript.

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

GLAESER, E., J. GYOURKO, AND R. E. SAKS (2005a): "Why Have Housing Prices Gone Up?," *American Economic Review*, 95(2), 329–333.

——— (2005b): "Why is Manhattan So Expensive? Regulation and the Rise in Housing Prices," *The Journal of Law and Economics*, 48, 331–369.

GROSSMAN, V., B. LARIN, AND T. STEGER (2020): "Das House Kapital," Manuscript.

GYOURKO, J., J. S. HARTLEY, AND J. KRIMMEL (2021): "The local residential land use regulatory environment across US housing markets: Evidence from a new Wharton index," *Journal of Urban Economics*, 124, 103337.

GYOURKO, J., A. SAIZ, AND A. SUMMERS (2008): "A New Measure of the Local Regulatory Environment for Housing Markets: The Wharton Residential Land Use Regulatory Index," *Urban Studies*, 45.3, 693–729.

HERKENHOFF, K. F., L. E. OHANIAN, AND E. C. PRESCOTT (2018): "Tarnishing the Golden and Empire States: Land-use Restrictions and the U.S. Economic Slowdown," *Journal of Monetary Economics*, 93, 89 – 109, Carnegie-Rochester-NYU Conference on Public Policy held at the Stern School of Business at New York University.

HERKENHOFF, K. F., AND G. RAVEENDRANATHAN (2023): "Who Bears the Welfare Costs of Monopoly? The Case of the Credit Card Industry," Working paper.

HSIEH, C.-T., AND P. J. KLENOW (2009): "Misallocation and Manufacturing TFP in China and India," *Quarterly Journal of Economics*, 124(4), 1403–1448.

HSIEH, C.-T., AND E. MORETTI (2019): "Housing Constraints and Spatial Misallocation," *American Economic Journal: Macroeconomics*, 11.2, 1–39.

KEANE, M., AND R. ROGERSON (2012): "Micro and Macro Labor Supply Elasticities: A Reassessment of Conventional Wisdom," *Journal of Economic Literature*, 50(2), 464?476.

LA PORTA, R., F. LOPEZ DE SILANES, A. SHLEIFER, AND R. W. VISHNY (1998): "Law and Finance," *Journal of Political Economy*, 106.6, 1113–1155.

LINCOLN INSTITUTE OF LAND POLICY AND MINNESOTA CENTER FOR FISCAL EXCELLENCE (2021): "50-State Property Tax Comparison Study," https://www.sccassessor.org/index.php/faq/understanding-proposition-13, Accessed: 2021-11-07.

LUTTMER, E. G. (2011): "On the Mechanics of Firm Growth," *The Review of Economic Studies*, 78(3), 1042–1068.

MARTELLINI, P. (2019): "The City-Size Wage Premium: Origins and Aggregate Implications," Manuscript.

MCGRATTAN, E. R. (2020): "Intangible Capital and Measured Productivity," *Review of Economic Dynamics*, 37, S147–S166, The twenty-fifth anniversary of "Frontiers of Business Cycle Research".

MOLLOY, R., C. L. SMITH, AND A. K. WOZNIAK (2014): "Declining migration within the US: The role of the labor market," Discussion paper, National Bureau of Economic Research.

MURPHY, A. (2018): "A Dynamic Model of Housing Supply," *American Economic Journal: Economic Policy*, 10(4), 243–67.

NAREIT (2019): "Estimating the Size of the Commercial Real Estate Market," https://www.reit.com/sites/default/files/Size%20of%20CRE%20market%202019%20full.pdf.

OFFICE OF THE ASSESSOR, COUNTY OF SANTA CLARA (2021): "Understanding Proposition 13," https://www.sccassessor.org/index.php/faq/understanding-proposition-13, Accessed: 2021-08-02.

PARKHOMENKO, A. (2018): "The rise of housing supply regulation in the US: Local causes and aggregate implications," *University of Southern California*.

PETERS, M., AND C. WALSH (2021): "Population Growth and Firm Dynamics," Manuscript.

RIVERA-PADILLA, A. (2021): "Slums, allocation of talent, and barriers to urbanization," .

ROSSI-HANSBERG, E., P.-D. SARTE, AND F. SCHWARTZMAN (2019a): "Cognitive Hubs and Spatial Redistribution," Working Paper 26267, National Bureau of Economic Research.

——— (2019b): "Cognitive Hubs and Spatial Redistribution," Working Paper 26267, National Bureau of Economic Research.

RUGGLES, S., S. FLOOD, R. GOEKEN, J. GROVER, E. MEYER, J. PACAS, AND M. SOBEK (2020): "IPUMS USA: Version 10.0 [dataset].," Discussion paper, IPUMS, Minneapolis, MN:, https://doi.org/10.18128/D010.V10.0.

SAIZ, A. (2010): "The Geographic Determinants of Housing Supply," *Quarterly Journal of Economics*, 125.3, 1253–1296.

SAN FRANCISCO PLANNING (2021): "Zoning Height and Bulk Districts," https://sfplanning.org/resource/zoning-height-and-bulk-districts, Accessed: 2021-08-11.

SCHMITT, A. (2019): "Houston Rolling Back Parking Requirements," Blog Post: StreetsBlog USA.

SCHMITZ, J. A. J. (2020): "Solving the Housing Crisis will Require Fighting Monopolies in Construction," Manuscript.

SYVERSON, C. (2017): "Challenges to mismeasurement explanations for the US productivity slowdown," *Journal of Economic Perspectives*, 31(2), 165–86.

TAN, Y., Z. WANG, AND Q. ZHANG (2020): "Land-Use Regulation and the Intensive Margin of Housing Supply.," *Journal of Urban Economics*, 115, 103199.

TANURE VELOSO, P. (2020): "Housing Supply Constraints and the Distribution of Economic Activity: The Case of the Twin Cities," Manuscript.

URBAN INSTITUTE (2018): "Property Taxes," https://www.urban.org/policy-centers/cross-center-initiatives/state-and-local-finance-initiative/projects/state-and-local-backgrounders/property-taxes, Accessed: 2021-11-07.

US BUREAU OF ECONOMIC ANALYSIS (2021a): "Real GDP by County and Metropolitan Area," https://www.bea.gov/data/gdp/gdp-county-metro-and-other-areas, Accessed: 2021-02-13.

——— (2021b): "Table 1.1.6," https://apps.bea.gov/iTable/iTable.cfm?reqid=19&step=2&isuri=1&1921=survey#reqid=19&step=2&isuri=1&1921=survey, Accessed: 2021-11-07.

WALSH, C. (2019): "Firm Creation and Local Growth," .

# A Data

In this appendix, we provide more details on our data. Appendix A.1 describes CoreLogic's sample of commercial buildings in greater detail,

## A.1 CoreLogic

CoreLogic's dataset is the most comprehensive available source of commercial parcel-level data. However, it is limited by the quality and quantity of the data compiled by local assessors.[30] Not all of these variables are available for all parcels in all cities, particularly building square footage. We restrict our sample to buildings where total value, improvement and/or land value, and land square footage are available. We also find that, for some parcels, $MV/TV$ takes on values outside $[0, 1]$, or in some cases either $MV$ or $LV$ are recorded as 1 dollar. As the improvement share of building value is an important object in our analysis, we drop buildings where the ratio $MV/TV$ is greater than .99 or less than .01. CoreLogic has also harmonized county-level land use codes, which explain what a parcel is primarily used for. Our sample excludes all buildings which CoreLogic has identified as primarily residential; hence, we treat the stock of commercial parcels as fixed and do not explore the decision to build a residential or commercial building on a given plot of land. We also drop buildings identified as public land. The buildings we keep after filtering account for roughly 23 percent of all non-public parcels in CoreLogic's sample, but their total values sum to 73 percent of the total value of all non-public parcels in the unfiltered sample.

Table 7 shows the availability of different variables in the 2018 sample, in both the raw version of the data and the filtered version we use for our analysis. $N$ and $\sum TV$ indicate the share of parcels, and the share weighted by total value, preserved in the filtered sample. The variable $a$ denotes the availability of the age variable in the filtered and unfiltered samples, whereas $\bar{a}$ indicates its mean value. Note that some parcels list only $MV$ or only $LV$. In those cases, we impute the missing value by subtracting the non-missing value from $TV$. We record value availability after doing this imputation. We also record what share of parcels have land square footage $x$, building square footage $BSF$, and an alphanumeric zoning code $z$.

In Table 8, we further break down the buildings in our filtered sample by CoreLogic's one-digit land use codes. "Commercial"[31] includes things as diverse as office buildings, parking lots, and funeral homes; "Industrial" includes factories as expected but also things like warehouses and wineries; "Vacant Land" includes empty lots but also golf courses; "Agriculture" includes things like farms and fisheries; "Recreational" includes things like stadiums and bowling alleys, "Transportation" includes things like harbors but also sweeps in utilities; and the final category includes buildings denoted as "Real property (NEC)" or "Misc" by CoreLogic. Recall that our filtered sample excludes public buildings (encompassing

[30] To give one example of the limitations of using raw assessor data: we manually inspected parts of the data and found that zoning codes "C-3" and "C3", with and without hyphens, coexisted in one jurisdiction. We therefore drop hyphens when we analyze alphanumeric zoning codes.

[31] The notion of "commercial" buildings in our model encompasses all of the categories in this list and is broader than CoreLogic's usage of the term "commercial."

Table 7: Variable Availability

| | Full Sample | Filtered |
|---|---|---|
| $TV$ | .97 | 1.0 |
| $MV$ | .9 | 1.0 |
| $x$ | .97 | .98 |
| $BSF$ | .17 | .63 |
| $a$ | .15 | .57 |
| $z$ | .32 | .39 |
| $N$ | 1.0 | .23 |
| $\sum TV$ | 1.0 | .74 |
| $\bar{a}$ | 49 | 50 |

*Notes*: This table reports the availability of total value $TV$, market value $MV$, land square footage $x$, building square footage $BSF$, age $a$, and zoning code $z$ in the full and filtered sample; the share of buildings $N$ and total building value $\sum TV$ in the filtered sample; and the average age $\bar{a}$ in the full and filtered sample.

Table 8: Building Types

| Code | Type | Share of $TV$ |
|---|---|---|
| 2 | Commercial | .663 |
| 244-247 | Office Buildings | .176 |
| 3 | Industrial | .193 |
| 4 | Vacant | .002 |
| 5 | Agriculture | .096 |
| 7 | Recreational | .027 |
| 8 | Transportation | .016 |
| 9 | Misc | .002 |

*Notes*: This table reports the share of total value $TV$ in the filtered sample by category of building. The numbers do not add up to 1 because of rounding. Office buildings are a subset of commercial buildings.

things like schools, military bases, and property owned by different levels of government), which are listed under code 6. We break out office buildings from the rest of the buildings labeled "Commercial"—this subset of buildings is likely to become less important in the wake of the COVID-19 pandemic and the resulting shift to remote work.

CoreLogic offers multiple measurements of land and total value depending on what information each county tax assessor offers. These include the assessor's estimate of market value, the assessed value used for tax purposes, and estimated values from third-party appraisers. Not all jurisdictions report all three values, and the first two have much better coverage than the third. CoreLogic also provides a "calculated" value based on which of these three they think is the closest to the true market value. We use this "calculated" value but find that this choice is not very consequential—we recalculate our indices using market and assessed values instead of CoreLogic's preferred value, and find that over 90 percent of our observations of $T_j$ and $M_j$ change by less than 10 percent in either direction, and that most do not change at all. We provide more proof that this choice is not very important in Appendix F.

We also highlight one important decision here: we do not treat buildings without an alphanumeric zoning code as unregulated. Several jurisdictions such as Houston do not have any formal zoning codes, and yet they still have land use restrictions such as parking minimums as documented by Schmitt (2019). Also, some jurisdictions such as Chicago (but not all of Cook County, Illinois) do have zoning codes but do not report them in the tax assessments used by CoreLogic. We also do not treat missing zoning codes as an unregulated or minimally-distorting benchmark in jurisdictions where they coexist with non-missing zoning codes.

### A.2 Zoning Code Parameters

We hand-collected zoning code data for New York City and Washington, DC from City of New York (2021) and DC Office of Zoning (2021a), respectively. We also needed to supplement DC Office of Zoning (2021a) with information from DC Office of Zoning (2021b) for zoning codes such as WR-3. We merged them into the CoreLogic dataset, which has some errors in how individual zoning codes were recorded. Hence, we did not get a match for all buildings.

Some zoning codes had a range of parameters associated with them—for example, "C1" districts in New York City have a maximum permissible FAR of 1 or 2 depending on whether the residential buildings in their neighborhoods are in R1-R5 districts or R6-R10 districts. As we do not observe all of the different possible contingencies that may affect the FAR of a given building in a given zoning code, whenever we see a New York City zoning code reported multiple possible FARs, we simply use the midpoint of the highest and lowest values reported in the zoning reference tables in City of New York (2021). We did not include attic allowances.

In DC Office of Zoning (2021a), the set of contingencies was even more complicated. Many zoning codes were associated with a list of height limits, rather than one or two at most in NYC. If a zoning code provided a list of possible height limits, we used either the median height limit or the average of the middle two. STE-19 did not report a height limit, so we listed it as missing. Many codes listed a height limit of 35 feet, or 40 feet if the building adjacent to them was already over 40 feet. We counted these as 35 feet. If a zoning code could apply to residential or non-residential buildings, we only used the height limits associated with non-residential buildings. We also do not count the additional floors allowed for penthouses in STE-7.

# B Aggregation Results

## B.1 Individual and Aggregate Landlords

In this section we establish the connection between the problems of the individual landlord and the aggregate landlord. In order to do so, we solve Equations (3) and (6), and show that they yield the same quantity of improvements demanded and quantity of buildings supplied. We assume a steady state and drop time subscripts.

First, we take the first-order condition of Equation (3) and solve for the optimal quantity of improvements, expressed in units of the final good.

$$\underbrace{q_i m_i}_{MV_i} = (p_j \tau_i \beta \gamma)^{\frac{1}{1-\gamma}} \underbrace{z_i^{\frac{1}{1-\gamma}} x_i q_i^{\frac{-\gamma}{1-\gamma}}}_{C_i}$$

Next, we divide both sides by $q_i$ and use the resulting expression for $m_i$ to solve for the individual landlord's building production function in terms of prices and exogenous parameters:

$$B_i^N = (p_j \tau_i \beta \gamma)^{\frac{\gamma}{1-\gamma}} C_i \tag{23}$$

Only a random share $\delta_b$ of buildings depreciate and are rebuilt in each period, hence we can recover the sum of individual landlords' improvement demand and building supply curves in each period. Note that the improvement demand curve is in units of the final good.

$$\underbrace{\sum_{i \in j} q_j m_j}_{MV_j} = \delta_b (p_j \beta \gamma)^{\frac{1}{1-\gamma}} \sum_{i \in j} \tau_i^{\frac{1}{1-\gamma}} C_i$$

$$\underbrace{\sum_{i \in j} B_i^N}_{B_j^N} = \delta_b (p_j \beta \gamma)^{\frac{\gamma}{1-\gamma}} \sum_{i \in j} \tau_i^{\frac{\gamma}{1-\gamma}} C_i$$

Next we solve Equation (6) for both quantity of improvements demanded and quantity of new construction supplied, mirroring the derivation above. Note that the technology that the representative landlord uses to convert the final good to the improvement good is one-for-one, as $q_i$ is swept into the parcel-level efficiency terms.

$$\underbrace{m_j}_{MV_j} = \delta_b (p_j \beta\gamma)^{\frac{1}{1-\gamma}} D_j^{\frac{1}{1-\gamma}} T_j^{\frac{1}{1-\gamma}} C_j$$

$$B_j^N = \delta_b p_j^{\frac{\gamma}{1-\gamma}} \underbrace{(\beta\gamma)^{\frac{\gamma}{1-\gamma}} D_j^{\frac{1}{1-\gamma}} T_j^{\frac{\gamma}{1-\gamma}} C_j}_{\Psi_j}$$

It is straightforward to use Equations (7), (8), and (9) to replace $C_j$, $D_j$, and $T_j$ in the above two equations and thereby establish that the improvement demand and building supply curve of the representative landlord are identical to the summed-up demand and supply curves of the individual landlords.

### B.2 Estimating $\tau_i$ and $T_j$

In this section, we explain in more detail how we estimate the regulatory distortions $\tau_i$ and $T_j$.

We first recover $\tau_i$. Because we focus on a single parcel in the steady state, we drop time and parcel subscripts.

The total value of the parcel ($TV$) is the net present value of payments made to the building stock $B_i$, plus the option to rebuild on the parcel after the building depreciates. We denote the option to rebuild as $V_f$, and note that it is available with probability $\delta_b$. We may therefore write the total value of the parcel as:

$$TV \equiv V(B,\tau,z,q,x) = r_{b,j}B + (1-\delta_b)\beta V(B,\tau,z,q,x) + \delta_b V_f(\tau,z,q,x)$$

If the building falls, the parcel owner puts improvements on the building today and starts earning rents tomorrow. We denote $m^*$ as the solution to the parcel-owner's problem and write:

$$V_f(\tau,z,q,x) = \beta V(B,\tau,z,q,x) - qm^*$$

In a steady state, $qm^* = MV$, and therefore $MV$ and $B$ are constant every time the building needs to be rebuilt. We can therefore take the infinite sum of payments and get that:

$$TV = \frac{r_{b,j}B}{1-\beta} - \frac{\delta_b qm^*}{1-\beta}$$

Recall:

$$MV = qm^* = \beta\gamma\tau BV_i$$

And by definition, $BV$ is the flow value of payments made to the building:

$$BV = \frac{r_{b,j}B}{1-\beta(1-\delta_b)}$$

Let us rewrite the first expression in TV in terms of BV:

$$\frac{r_{b,j}B}{1-\beta} = \frac{1-\beta(1-\delta_b)}{1-\beta}BV$$

Hence we can add up and rearrange some terms to relate the total value of the parcel to the total value of the building :

$$TV = (\frac{1-\beta(1-\delta_b)-\delta_b\beta\gamma\tau}{1-\beta})BV$$

And let us again substitute $MV$:

$$TV = (\frac{1-\beta(1-\delta_b)-\delta_b\beta\gamma\tau}{1-\beta})\frac{MV}{\tau\beta\gamma}$$

Let us rearrange this expression in order to get $\gamma$ in terms of $TV$, $MV$, and $\tau$:

$$\tau\beta\gamma = (\frac{1-\beta(1-\delta_b)-\delta_b\beta\gamma\tau}{1-\beta})\frac{MV}{TV}$$

$$\tau = \frac{\left(\frac{1-\beta(1-\delta_b)}{1-\beta}\right)\frac{MV}{TV}}{\gamma\beta\left(1+\frac{\delta_b}{1-\beta}\frac{MV}{TV}\right)}$$

This yields Equation (14).

We now turn to $T_j$ and reintroduce the parcel-level index $i$. We can replace $\tau_i$ on the left hand side of Equation (11) with Equation (14) and recover Equation (13):

$$T_j = \frac{\sum_{i\in j} MV_i}{\sum_{i\in j} MV_i\gamma\left(\beta+\frac{\delta_b\beta}{1-\beta}\frac{MV_i}{TV_i}\right) / \left(\left(\frac{1-\beta(1-\delta_b)}{1-\beta}\right)\frac{MV_i}{TV_i}\right)}$$

$$= \frac{\left(\frac{1-\beta(1-\delta_b)}{1-\beta}\right)\sum_{i\in j} MV_i}{\beta\gamma\left(\sum_{i\in j} TV_i + \frac{\delta_b}{1-\beta}\sum_{i\in j} MV_i\right)}$$

We now multiply both the numerator and denominator by $\sum_{i\in j} TV_i$:

$$T_j = T_j^1\frac{\sum_{i\in j} TV}{\sum_{i\in j} TV} = \frac{\left(\frac{1-\beta(1-\delta_b)}{1-\beta}\right)\sum_{i\in j} MV}{\beta\gamma\left(\sum_{i\in j} TV + \frac{\delta_b}{1-\beta}\sum_{i\in j} MV\right)}\frac{\sum_{i\in j} TV}{\sum_{i\in j} TV} = \frac{\left(\frac{1-\beta(1-\delta_b)}{1-\beta}\right)\frac{\sum_{i\in j} MV}{\sum_{i\in j} TV}}{\beta\gamma\left(1+\frac{\delta_b}{1-\beta}\frac{\sum_{i\in j} MV}{\sum_{i\in j} TV}\right)}$$

We now recover Equation (13):

$$\gamma\cdot T_j = \frac{\left(\frac{1-\beta(1-\delta_b)}{1-\beta}\right)\frac{\sum_{i\in j} MV}{\sum_{i\in j} TV}}{\beta\left(1+\frac{\delta_b}{1-\beta}\frac{\sum_{i\in j} MV}{\sum_{i\in j} TV}\right)}$$

# C Age Regressions

We regress parcel-level $\tau$ on age, as well as county fixed effects, for the subset of parcels where we have building age, and report the results in Table 14. We weight parcels by $BV$. Most notably, the regression R-squared is below 5%, suggesting building age explains very little of our zoning distortion. We also find that the impact of age on measured $\tau$ is surprisingly small—a 50-year-old building would on average have a $\tau$ less than 0.1 lower than a brand-new building. Hence, these measured age effects in and of themselves cannot explain much of the variation in $\tau$ seen in Figure 2.[32]

Figure 14: The role of building vintages: Regression of zoning distortion ($\tau$) on age

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | $\tau$ | $\tau$ | $\log \tau$ | $\log \tau$ | $\log \tau$ | $\log \tau$ |
| Age | -0.00189*** | -0.00188*** | -0.00350*** | -0.00350*** | | |
| | (3.44e-06) | (3.48e-06) | (6.96e-06) | (7.20e-06) | | |
| $\log(\text{Age}+1)$ | | | | | -0.105*** | -0.0993*** |
| | | | | | (0.000225) | (0.000227) |
| Constant | 0.910*** | 0.910*** | -0.116*** | -0.116*** | 0.0995*** | 0.0820*** |
| | (0.000162) | (0.000158) | (0.000328) | (0.000327) | (0.000765) | (0.000768) |
| FIPS FE | No | Yes | No | Yes | No | Yes |
| Observations | 4,650,804 | 4,650,787 | 4,650,804 | 4,650,787 | 4,649,281 | 4,649,264 |
| R-squared | 0.061 | 0.212 | 0.051 | 0.171 | 0.044 | 0.163 |

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

*Notes*: This table reports the results of regressions of distortions $\tau$ on age, either in levels or logs, with and without controls for the county in which the parcel is located.

[32] Admittedly, this may understate the impact of aging on $\tau$ if old buildings were far less regulated than new ones.

# D Alternative Amenity Specifications

In this section we consider several alternative specifications for amenities. We consider regressions of amenities $a$ on both $L/X$ ("congestion") and $L$ ("labor supply").

First, in Table X, we report the results of naive regressions of amenities on congestion and labor supply, with and without weights for the

Figure 15: Naive Regressions

| | Log Amenities | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| (Intercept) | 10.090*** | 10.071*** | 8.586*** | 6.526*** |
| | (0.015) | (0.013) | (0.390) | (0.851) |
| Log Labor Supply | 0.288*** | 0.265*** | | |
| | (0.008) | (0.007) | | |
| Log Congestion | | | -0.049** | -0.165*** |
| | | | (0.019) | (0.040) |
| Estimator | OLS | OLS | OLS | OLS |
| Weights | No | Yes | No | Yes |
| $N$ | 241 | 241 | 241 | 241 |
| $R^2$ | 0.829 | 0.885 | 0.023 | 0.151 |

*Notes*: This table reports the results of regressions of the log of amenities $a$ on the log of labor supply $L$ and the log of congestion $L/X$, with and without weighting by the labor supply of each observation. The observations are metropolitan statistical areas—we do not include the rest-of-country aggregator or remote work sector.

Next, in Table 16, we focus on instrumental variable regressions of log amenities on log labor force. The first instrument is the model-generated counterfactual $\hat{L}$. The second is the supply shifter in the regional building supply function $\Psi$, where the assumption is that the ease of building and the availability of commercial land are uncorrelated with exogenous amenities. The third is the supply of commercial land $X$. The fourth is the shifter per unit of land, a rough measure of how easy it is to build on each unit of land. The fourth is a quadratic in the model-generated counterfactual $\hat{L}$. By and large, these coefficients are smaller than the ones in the naive regression in Table 15. However, only one of these regressions has a negative sign on the coefficient of interest, and that one is not significant. This casts doubt on the strength of negative externalities from a growing population.

Figure 16: Instrumenting for Labor Supply $L$

| | Log Amenities | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| (Intercept) | 10.001*** | 10.132*** | 10.075*** | 10.069*** | 10.038*** | 10.114*** | 10.094*** | 10.057*** | 9.838*** | 9.102 |
| | (0.151) | (0.206) | (0.016) | (0.013) | (0.144) | (0.115) | (0.092) | (0.027) | (0.756) | (8.686) |
| Log Labor Supply | 0.231* | -0.080 | 0.278*** | 0.275*** | 0.255** | 0.019 | 0.291*** | 0.348*** | 1.358 | 1.391 |
| | (0.096) | (1.043) | (0.009) | (0.010) | (0.091) | (0.559) | (0.058) | (0.067) | (3.324) | (14.354) |
| Log Labor Supply Squared | | | | | | | | | 0.510 | 0.433 |
| | | | | | | | | | (1.413) | (3.584) |
| Instrument | $\hat{L}$ | $\hat{L}$ | $\Psi$ | $\Psi$ | $X$ | $X$ | $\Psi/X$ | $\Psi/X$ | $\hat{L}, \hat{L}^2$ | $\hat{L}, \hat{L}^2$ |
| Weights | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes |
| $N$ | 241 | 241 | 241 | 241 | 241 | 241 | 241 | 241 | 241 | 241 |
| $R^2$ | 0.797 | -0.617 | 0.828 | 0.883 | 0.818 | 0.123 | 0.829 | 0.798 | -4.328 | -18.448 |
| $F$ | 5.783 | 0.006 | 1007.543 | 775.540 | 7.763 | 0.001 | 24.737 | 27.270 | 0.132 | 0.012 |
| First-stage $F$ statistic | 2.210 | 0.107 | 264.290 | 341.651 | 2.348 | 0.195 | 4.952 | 4.692 | 0.072 | 0.003 |

*Notes*: This table reports the results of instrumental variables regressions of the log of amenities $a$ on the log of labor supply $L$, with and without weighting by the labor supply of each observation. The observations are metropolitan statistical areas—we do not include the rest-of-country aggregator or remote work sector .

Finally, in Table 17, we report the results of a similar set of regressions on $L/X$, our measure of congestion. The only difference is that we use $\widehat{L/X}$ as our instrument. The coefficient declines much more strongly relative to Table 15, providing more support for negative congestion effects.

Figure 17: Instrumenting for Congestion $L/X$

| | Log Amenity | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| (Intercept) | 3.372*** | -1.375 | 3.525*** | -0.891 | 21.796 | 10.300 | 6.521*** | 4.556* | 71.743*** | 55.491 |
| | (0.812) | (1.518) | (0.782) | (1.408) | (19.244) | (5.775) | (1.505) | (1.889) | (17.868) | (31.838) |
| Log Congestion | -0.293*** | -0.528*** | -0.286*** | -0.505*** | 0.568 | 0.008 | -0.146* | -0.255** | 6.244*** | 4.818 |
| | (0.038) | (0.071) | (0.037) | (0.066) | (0.899) | (0.265) | (0.070) | (0.087) | (1.732) | (3.055) |
| Log Congestion Squared | | | | | | | | | 0.156*** | 0.125 |
| | | | | | | | | | (0.042) | (0.073) |
| Weights | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes |
| Instrument | $\widehat{L/X}$ | $\widehat{L/X}$ | $\Psi$ | $\Psi$ | $X$ | $X$ | $\Psi/X$ | $\Psi/X$ | $\widehat{L/X}, (\widehat{L/X})^2$ | $\widehat{L/X}, (\widehat{L/X})^2$ |
| $N$ | 241 | 241 | 241 | 241 | 241 | 241 | 241 | 241 | 241 | 241 |
| $R^2$ | -0.552 | -0.581 | -0.518 | -0.494 | -3.668 | -0.016 | -0.067 | 0.106 | -1.724 | -1.022 |
| $F$ | 59.321 | 55.648 | 61.003 | 59.336 | 0.399 | 0.001 | 4.285 | 8.657 | 18.344 | 30.237 |
| First-stage $F$ statistic | 220.282 | 89.358 | 251.075 | 101.171 | 0.601 | 9.045 | 18.030 | 43.513 | 14.171 | 4.574 |

*Notes*: This table reports the results of instrumental variables regressions of the log of amenities $a$ on the log of congestion $L/X$, with and without weighting by the labor supply of each observation. The observations are metropolitan statistical areas—we do not include the rest-of-country aggregator or remote work sector .

Out of all our regressions, the one that uses $\widehat{L/X}$ as an instrument for $L/X$ implies the strongest negative externality from congestion. We therefore use that one in our baseline specification to make our results as conservative as possible.

# E Computing Counterfactuals

For each counterfactual, we alter a subset of parameters and recompute a new steady state. At a high level, our algorithm takes as an input a vector of $Y_j$, feeds it through all the equilibrium conditions of the model, and gives as output a new guess for $Y_j$.

All of our counterfactuals involve altering the $\tau_i$ terms in Equations (8) and (9), or altering the $\tau_z$ in Equations (21) and (22), and recovering new values for $T$ and $D$. Recall the building supply curve from Equation (12) and denote $\Psi_j^p$ as the pre-counterfactual $\Psi_j$. If we increase $D_j$ by some factor $\Phi_1$ and $T_j$ by some factor $\Phi_2$, we increase $\Psi_j$ as follows:

$$\Psi_j = (\Phi_1)^{\frac{1}{1-\gamma}} (\Phi_2)^{\frac{\gamma}{1-\gamma}} \Psi_j^p$$

Having recovered the new $T, D$, and $\Psi$, we move on to the rest of the counterfactual algorithm. We will proceed by substituting out endogenous variables until we are left with a function that only takes as inputs the vector $Y_j$ and exogenous parameters. We begin by rewriting the consumption equation:

$$c = \sum_j Y_j - \delta_k K_j - m_j$$

In a steady state, $K_j = (1 - \alpha - \chi_j)Y_j / r_k$, hence we can replace $K_j$:

$$c = \sum_j Y_j - Y_j \delta_k (1 - \alpha - \chi_j)/r_k - m_j$$

Recall $m_j = T_j \gamma \delta_b \beta p_j B_j$, and $p_j B_j = \chi_j Y_j / (1 - \beta(1 - \delta_b))$, hence:

$$c = \sum_j Y_j - Y_j \delta_k (1 - \alpha - \chi_j)/r_k - Y_j T_j \delta_b \gamma \beta \chi_j / (1 - \beta(1 - \delta_b)) \equiv \sum_j \theta_j Y_j$$

Recall the labor supply equation:

$$L_j = (a_j^{1+\frac{1}{\eta}} c^{-\sigma} w_j)^{\eta}$$

We can express wages in terms of labor supply, GDP, and factor shares and rewrite this as:

$$L_j^{\frac{1}{\eta}} = (a_j^{1+\frac{1}{\eta}} c^{-\sigma} \alpha Y_j / L_j)$$

$$\frac{L_j^{\frac{1}{\eta}+1}}{(a_j^{1+\frac{1}{\eta}} c^{-\sigma} \alpha)} = Y_j$$

We can also express L in terms of $Y, B$, and $K$:

$$L_j = \left( \frac{Y_j}{A_j K_j^{1-\alpha-\chi_j} B_j^{\chi_j}} \right)^{\frac{1}{\alpha}} \tag{24}$$

We can also use our supply function to recover $B$ in terms of $Y$:

$$BV_j = p_j B_j = \frac{\chi_j Y_j}{1 - \beta(1 - \delta_b)}$$

$$BV_j = p_j B_j = p_j^{\frac{1}{1-\gamma}} \Psi_j$$

$$p_j = \left( \frac{BV_j}{\Psi_j} \right)^{1-\gamma}$$

$$B_j = BV_j / p_j = BV_j^{\gamma} (\Psi_j)^{1-\gamma}$$

$$= \left( \frac{\chi_j Y_j}{1 - \beta(1 - \delta_b)} \right)^{\gamma} (\Psi_j)^{1-\gamma}$$

Because we already solved for K in terms of Y, we can now get labor entirely in terms of a guess for Y:

$$L_j = \left( \frac{Y_j}{A_j \left( \frac{(1-\alpha-\chi_j)Y_j}{r_k} \right)^{1-\alpha-\chi_j} \left( \left( \frac{\chi_j Y_j}{1-\beta(1-\delta_b)} \right)^{\gamma} (\Psi_j)^{1-\gamma} \right)^{\chi_j}} \right)^{\frac{1}{\alpha}}$$

Now we replace $L_j$ in Equation (24) with the above expression to get:

$$\frac{\left( \frac{Y_j}{A_j \left( \frac{(1-\alpha-\chi_j)Y_j}{r_k} \right)^{1-\alpha-\chi_j} \left( \left( \frac{\chi_j Y_j}{1-\beta(1-\delta_b)} \right)^{\gamma} (\Psi_j)^{1-\gamma} \right)^{\chi_j}} \right)^{\frac{\frac{1}{\eta}+1}{\alpha}}}{\left( a_j^{1+\frac{1}{\eta}} \left( \sum_k \theta_k Y_k \right)^{-\sigma} \alpha \right)} = Y_j$$

We rearrange this expression one last time, as we find that this final expression converges more easily:

$$Y_j = \left( \left( A_j \left( K_j \right)^{1-\alpha-\chi_j} \left( B_j \right)^{\chi_j} \right)^{\frac{\frac{1}{\eta}+1}{\alpha}} \left( Y_j ( a_j^{1+\frac{1}{\eta}} \left( \sum_k \theta_k Y_k \right)^{-\sigma} \alpha) \right) \right)^{\frac{\alpha}{\frac{1}{\eta}+1}} \tag{25}$$

Now we can take a guess for the vector $Y$, put it on the right-hand-side of the above equation, and back out a new $Y$ on the left. We use a "damped" algorithm: we start with a guess $Y^G$ on the left, get the new $Y^N$ on the right, calculate a weighted average $Y^W = p * Y^G + (1 - p)Y^N$, and use $Y^W$ as the new $Y^G$ in the next iteration. In practice we set $p = 0.9$.

### E.1 Endogenous Amenities

Here we briefly discuss how we compute the model with endogenous amenities. First, our guess for $Y_j$ also yields a guess for the counterfactual $L_j$, which we now call $L_j^{cf}$ in Equation (24). Second, we have already computed the relationship between amenities and labor supply in Equation (19) and computed the key coefficient $\mu$ in the process. We can combine these expressions, along with the original amenity vector $a_j$ and labor supply vector $a_j$, to calculate how amenities change if the current guess for $Y_j$ is correct. More specifically, we recover the ratio $r_j$ between new and old amenities in Equation (26):

$$r_j = \frac{a_j^{cf}}{a_j} = \frac{\exp(\mu \log(L_j^{cf}/X_j)}{\exp(\mu \log(L_j/X_j)} = \Big(\frac{L_j^{cf}}{L_j}\Big)^{\mu} \tag{26}$$

We multiply amenities in Equation (25) by $r_j$, and keep the algorithm otherwise unchanged. Note that we do not change amenities in the remote work region, and note that $X_j$ divides out of this equation.

### E.2 Certainty Equivalent

Consider a move between steady states A and B. We calculate the consumption-equivalent welfare increase caused by moving from A to B by scaling consumption in A by some factor $\lambda$ such that the consumer is indifferent between it and B. Below we show how to use Equation (16) to get $\lambda$. Note that, in the case where amenities depend on congestion, we must combine this with the method described above in Appendix E.1 to account for the change in amenities.

We know consumption, amenities, and the labor supply in both the original and final steady states. We can therefore write:

$$\frac{(\lambda c^A)^{1-\sigma}}{1-\sigma} - \frac{1}{1+\frac{1}{\eta}} \sum_j \left(\frac{L_j^A}{a_j^A}\right)^{1+\frac{1}{\eta}} = \frac{(c^B)^{1-\sigma}}{1-\sigma} - \frac{1}{1+\frac{1}{\eta}} \sum_j \left(\frac{L_j^B}{a_j^B}\right)^{1+\frac{1}{\eta}}$$

Some algebra yields:

$$\lambda = \left((1-\sigma)\left(\frac{(c^B)^{1-\sigma}}{1-\sigma} + \frac{1}{1+\frac{1}{\eta}} \sum_j \left(\left(\frac{L_j^A}{a_j^A}\right)^{1+\frac{1}{\eta}} - \left(\frac{L_j^B}{a_j^B}\right)^{1+\frac{1}{\eta}}\right)\right)\right)^{\frac{1}{1-\sigma}} \Big/ c^A$$

We record $\lambda - 1$, i.e. the percentage change in consumption needed to equate utility in the old steady state with the new, in Table 4.

# F Robustness Exercises

In this section, we test the robustness of our results to different data filtering choices and calibrations. In particular, we re-do the baseline counterfactual described in Section 5.1.1 and test how much the headline results change. We explain these exercises in more detail below and report their results in Table 9.

Table 9: Robustness Exercises

| | **Baseline** | **Mkt. Value** | **Assd. Value** | $\chi = .13$ | $\chi = .10$ | **No Agriculture** | **Young Buildings** |
|---|---|---|---|---|---|---|---|
| $\%\Delta Y_j$ | 3.0% | 3.2% | 2.9% | 2.5% | 1.9% | 2.9% | 1.4% |
| $\%\Delta L_j$ | -0.8% | -0.8% | -0.8% | -0.7% | -0.5% | -0.8% | -0.4% |
| $\%\Delta K_j$ | 2.6% | 2.8% | 2.5% | 2.2% | 1.8% | 2.5% | 1.3% |
| $\%\Delta B_j$ | 17.3% | 22.7% | 16.1% | 16.9% | 16.3% | 16.8% | 8.4% |
| %Δ Landlord Profits | -2.8% | -3.0% | -2.7% | -3.3% | -4.0% | -2.7% | -1.5% |
| $\%\Delta c$ | 2.2% | 2.3% | 2.1% | 1.8% | 1.4% | 2.1% | 1.0% |
| %Δ Consumption Equiv. | 1.6% | 1.7% | 1.6% | 1.4% | 1.0% | 1.6% | 0.8% |

In our first two robustness exercises, we test whether using CoreLogic's preferred "calculated" values instead of the assessors' "market" or "assessed" values makes a significant difference. We recalculate all regional parameters (TFP $A_j$, amenities $a_j$, regulatory distortions $T_j$, dispersion $D_j$, etc) and recompute the new steady state for each of our alternative data choices. Note that some of these measures are missing in certain MSAs, hence we end up with 193 regions for market value and 233 for assessed, compared to 243 with our preferred measure. The missing MSAs are thrown into the rest-of-country aggregator. We find that our headline results mostly change by less than 10 percent.

We next test the sensitivity of our results to the value of $\chi$. We get $\chi \sim .15$, at least for non-remote regions. Our calibration is based on getting the factor share for non-structures capital, using an off-the-shelf value for the labor share. then assigning the residual factor share to structures. First, let us go through a back-of-the-napkin alternative calibration showing that this is not unreasonable.

Investment in non-residential structures in 2018 was 550 billion dollars per US Bureau of Economic Analysis (2021b). This corresponds to flow investment $MV = \beta\gamma T \delta_b BV$ in our model. Using the average value of .87 for T, we get that $550b = 0.96 * 0.923 * 0.87 * 0.0198 * BV = 0.0152BV$. This suggests a structures capital stock of around 36 trillion, or nearly 1.9 times GDP. Hence we get: $BV = \frac{\chi Y}{1-\beta(1-\delta_b)} \sim \frac{\chi Y}{0.059}$. Using this and the fact that $BV \sim 1.9Y$, we get:

$$1.9 * 0.059 = \chi \sim 0.11$$

So this rough alternative calibration yields a building share only slightly lower than our baseline, which in turn only applies to non-remote work (in remote work, $\chi$ is 0.)

Even this is depressed by property taxes, which are around 2 of assessed building values in many major cities according to Lincoln Institute of Land Policy and Minnesota Center for Fiscal Excellence

(2021). These generate a second wedge, between BV and the true factor share of structures. This may be exaggerated because assessments are lower than true values, so let us be conservative and instead use 1 percent below. That would correspond to 360 billion in commercial property tax, which is around 60 percent of the property tax bill reported in Urban Institute (2018). We do not know what share of property tax revenue comes from commercial properties. Note that 1 percent is not a random number: NAREIT (2019) suggests a value of 15 trillion for the sum of commercial properties, roughly half of what our calibration implies. Building values are depressed by these taxes, as the payments to buildings now comprise factor payments $\chi Y$ less taxes, $0.01BV$. Hence we can write:

$$BV = \frac{\chi Y - 0.01BV}{1 - \beta(1 - \delta_b)} \sim \frac{\chi Y - 0.01BV}{0.059}$$

We can rearrange to get:

$$(1 + 0.01/0.059)BV * 0.059 = \chi Y$$

$$(1.17)BV * 0.059 = \chi Y$$

$$1.17 * 1.9 * 0.059 = \chi \sim 0.13$$

This is not far from the original calibrated value.

Nevertheless, we test how our results change at different values of $\chi$, specifically at $\chi = 0.13$ and $\chi = 0.1$. It remains zero in remote work. We assign the missing factor share to labor, i.e. we set $\alpha$ so that factor shares sum to 1. Starting from Equation (17), we redo our identification and recalculate a new initial steady state. Starting from this steady state, we redo our baseline counterfactual. Unsurprisingly, we find lower output gains at lower values of $\chi$, but even at $\chi = 0.1$ the gains are significant.

We next test whether agricultural parcels (which arguably use a different technology with a different $\gamma$) skew our results. We drop parcels whose primary land use is listed as agriculture, golf, or wild lands, and we drop parcels that are listed as empty space zoned for commercial or industrial uses. That is, we drop all parcels with a CoreLogic land use code starting with "4." We then re-calculate $\gamma$ from this sample based on the least-distorted MSA and find that it is basically unchanged. We recalculate all regional parameters using this slightly smaller sample and recompute the new steady state. Using that as our starting point, we redo our baseline counterfactual. We find that this makes almost no difference, as agricultural parcels are simply not very economically significant.

Finally, we follow Furth (2021) and restrict our sample to buildings less than 10 years old as of 2018. This costs us a large and presumably non-random share of our sample, as not all buildings have their age recorded in CoreLogic's data—recall Table 7. The impact of deregulation falls by roughly half when using this restricted sample.

## G Non-Constant $\tau$ and the Elasticity of Building Supply

We have assumed that $\tau$ is a fixed parcel-level constant, and that it does not get smaller (more restrictive) as the landlord tries to build more on the parcel. We will show here with a simple example that relaxing this assumption changes the price elasticity of building supply, but does not change the counterfactual increase in building supply if *all* regulations are removed.[33]

First, notice that from Equation 23, the price elasticity of supply is $\gamma/(1-\gamma)$, which at our calibrated value of $\gamma = 0.92$ yields a seemingly very high elasticity of 11.5. This seems very high compared to the estimates in, for example, Baum-Snow and Han (2021). However, this elasticity ends up being quite different from what is usually calculated in the literature: we focus only on the quantity of construction on a given parcel. Indeed, when Baum-Snow and Han (2021) try to connect their estimates to the literature on the housing production function, they estimate a price elasticity of 3.5 for floorspace, which is conceptually closer to what we estimate. Their preferred value is still lower than ours, but the magnitudes are more comparable than they first appear. Murphy (2018) shows that current-price elasticities may also be driven down by forward-looking behavior: if higher current prices predict even-higher future prices, they give landlords a reason to wait before building. This forward-looking behavior means that relatively small current-price elasticities are consistent with a very high improvement share in production.

Now we show how making $\tau$ a decreasing function of the level of construction breaks the link between the improvement share and the price elasticity of building supply. We specify $\tau$ as $\tau(m) = \tau_0 m^{-\zeta}$, where $\zeta > 0$. That is, we assume that regulations get more restrictive as the landlord tries to increase the quantity of improvements that they put on a parcel. For clarity, we drop subscripts and focus on a parcel where $\tau_0$, $x$, and $z$ are equal to 1.[34] $B$ is therefore directly equal to building square footage, making our estimates easier to compare to Baum-Snow and Han (2021). We can therefore write the problem of the landlord as:

$$\max_m \underbrace{m^{-\zeta}}_{\tau(m)} \cdot \beta p m^{\gamma} - qm$$

Taking first-order conditions, we get the distorted optimal value of $m$, which we denote $m_1$:

$$m_1 = \left( \frac{(\gamma - \zeta)\beta p_j}{q} \right)^{\frac{1}{1+\zeta-\gamma}}$$

Putting this in the building production function and rearranging we get:

$$B = \left( \frac{(\gamma - \zeta)\beta p}{q} \right)^{\frac{\gamma}{1+\zeta-\gamma}}$$

The price elasticity of supply is now $\gamma/(1+\zeta-\gamma)$, which is smaller than our baseline elasticity (and

[33]We thank Giacomo Ponzetto and Jacob Adenbaum for their feedback on this topic. We combined their suggestions for how a non-constant $\tau$ could work into the example in this Appendix.

[34]The model yields the same first-order conditions as one where $q = \tilde{q}/(\tau_0 z x^{1-\gamma})$, hence this simplification is without loss of generality.

can indeed be arbitrarily close to zero) as long as $\gamma > 1$.

Now let us return to our original model, where $\tau$ is a constant:

$$\max_m \tau \cdot \beta p m^{\gamma} - qm$$

The first-order condition now yields a new value for the distorted optimal $m$, which we denote $m_2$:

$$m_2 = \left(\frac{\tau\gamma\beta p}{q}\right)^{\frac{1}{1-\gamma}}$$

With some algebra we can show that at following value of $\tau$, the distorted optimal $m_2$ will be identical to $m_1$:

$$\tau = \frac{\gamma - \zeta}{\gamma}\left(\frac{q}{(\gamma - \zeta)\beta p}\right)^{\frac{\zeta}{1-\gamma+\zeta}}$$

The quantity of improvements demanded, and therefore also the building square footage and building value, are exactly the same in the model with a constant and non-constant $\tau$. Hence, the two models are observationally equivalent in the cross-section. Because the two models have the same underlying values for $q$ and $p$, they also have the same implications for how much $B$ would change if all regulations were dropped, which is what we do in our baseline counterfactual. We believe that relaxing the assumption of a constant $\tau$ is a promising direction for future work, but it would likely not change our baseline results.