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ABSTRACT

Commercial real estate accounts for roughly 20% of the U.S. fixed asset stock, and commercial land use 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 of the U.S. economy that includes commercial real estate regulations and congestion effects, the latter of which provide a rationale for such regulations. The model is tailored to exploit the near-universe of CoreLogic's commercial, parcel-level, property tax records to construct a quantitative index of commercial real estate regulations for nearly every commercial property. We use the model to evaluate the positive and normative impacts of commercial land use 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 3 percent to 9 percent of lifetime consumption. We also find significant positive and normative gains from deregulation with 40 percent of the labor force working remotely.

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1 Introduction

The value of commercial real estate is roughly \$16 trillion (NAREIT, 2019), accounting for roughly 20% of the U.S. fixed asset stock. Similar to residential real estate, commercial real estate is highly regulated. However, the quantitative impact of commercial real estate regulations on economic activity and consumer welfare remains an open question.

This paper develops a theory 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, and construct quantitative indexes of these distortions across metro locations. We validate the estimates by hand-collecting zoning code attributes in some cities and show that the model's indices are 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). We find that there are quantitatively large commercial land-use distortions in many cities, and that moderately relaxing these distortions across metro locations yields welfare gains worth 1.3% to 2.8% of lifetime consumption, which are similar in size to the welfare gains found in the literature studying residential land use regulations.

This paper makes three contributions. One is the development of a general equilibrium model, with a commercial building sector, that yields a simple method for identifying how much commercial real estate investment decisions are distorted by zoning codes and other regulations that restrict commercial building.¹ We develop a parsimonious and flexible specification of land-use regulations, which combined with a profit-maximizing commercial building sector, generates an intuitive formula for quantifying land-use regulation at the parcel (address) level. Specifically, properties whose total value is largely accounted for by raw land value are identified as being subject to more stringent land-use regulations (e.g., small buildings on very valuable land). An important benefit of this formula

¹Regulations that restrict building are not limited to zoning codes. Other factors include various review boards that can reject a proposed development, actual and/or threatened litigation against large developments, and political and community pressures that negatively affect the permitting process for large developments. These factors, as well as zoning regulations, will be captured in our framework.

is that it relies on statistics available in a number of datasets, and thus the approach can be applied more broadly. Crucially, the model’s regulatory distortions do not directly enter factor prices, which means they are not commingled with variables that affect property rents, such as a desirable location, or the cost of construction, which is affected by many factors, including the physical difficulty of building (e.g. building on a steeply sloped lot versus a flat lot), to the use of high-end versus low-end finishes and amenities.

The second contribution is the application of the regulation formula to the near-universe of address-level commercial property tax records from CoreLogic. These property records include the raw land value of an address, the value of the structure at the address (*improvement* value), and the combined (parcel) value of both land and structures, as well as the amount of building square footage and some alphanumeric zoning codes. Despite CoreLogic’s comprehensive coverage of the commercial real estate market, the analysis faces a number of measurement challenges: (1) many regulations are unmeasured and/or unobserved in the dataset, as zoning codes are only observed in roughly half of the properties, (2) zoning codes can be ambiguous, subject to legal challenges, have different meanings in different locations, and may not be up-to-date in code handbooks, (3) some properties receive one or more zoning exemptions, which means that the *effective impact* of zoning can differ from its legal (statutory) specification, and (4) most regulatory restrictions are *highly* multidimensional, with zoning codes alone taking on many attributes (including height limits, property setbacks², maximum floor-area-ratios, parking requirements, and time-of-day operation limitations, etc.). Our theory is tailored to exploit tax record data on land, improvement, and total property values to distill the multidimensional heterogeneity of effective – as opposed to statutory – zoning and other regulations into a single, model-consistent metric.

The third contribution is to evaluate the effect of both national and local changes to commercial land use regulations by analyzing the model’s distortions within a dynamic, spatial, general equilibrium model with congestion externalities and amenities. Building on [Diamond \(2016\)](#) and [Rossi-Hansberg, Sarte, and Schwartzman \(2019\)](#), we endogenize amenities (which dictate the cost of sending workers to a particular region) in our model and allow them to depend negatively

²Setbacks limit the amount of a lot that can be used by requiring a developer to “set back” the building from the perimeter of the property line.

on congestion. The model's specification also provides a novel identification of the congestion costs of density.³

The model-based identification of land use distortions, and the ability to conduct policy experiments using these distortions within a model economy, complements approaches that measure the stringency of local real estate regulations using survey evidence, such as the Wharton Land Use Regulatory Index of [Gyourko, Saiz, and Summers \(2008\)](#). Our approach also allows us to express zoning and other regulatory distortions into time series measures that make it straightforward to incorporate them in quantitative models, providing future researchers with the opportunity to evaluate the impact of commercial land use regulations in a variety of environments and settings.

Our baseline counterfactual evaluates the positive and normative effects of a national deregulation such that the average level of regulation in all metro areas is equal to that of the least-regulated metro in the dataset (Midland, Texas). We thus compare the steady state of the model with the identified distortions to that of the economy with the Midland, Texas average distortion, while leaving the dispersion of parcel-level regulations unaltered. National output increases by 3.0% as commercial investment booms. Notably, the commercial building stock increases by 18%. The higher wealth arising from this deregulation reduces labor supply, which promotes higher welfare. Labor is modestly reallocated from the Midwest to Florida and California, but this reallocation is not large enough to contribute significantly to the output gain, because higher congestion in areas attracting more workers limits this reallocation. Our results also suggest that rent-seeking may be a factor in the regulatory process: building developer profits decline in the deregulated counterfactual as building supply expands and rental rates of commercial real estate decline.

We also conduct local deregulations. Since the regulatory distortions are identified at the parcel-level, we are able to project these distortions onto hand-collected zoning code features, including floor area ratios, and we analyze what happens when those specific policies are changed. We examine the impact of increasing the floor-area ratio limit in all New York City buildings to the highest observed floor-

³The identification of amenities relies on the model's ability to generate instruments, building on [Anderson and van Wincoop \(2003\)](#), [Allen, Arkolakis, and Takahashi \(2020\)](#), [Walsh \(2019\)](#) and [Rossi-Hansberg, Sarte, and Schwartzman \(2019\)](#).

area ratio level in the city, and find that doing so raises MSA-level output by 1.8 percent. The MSA building stock increases by 6% and business activity relocates from Midtown to the tightly-zoned Upper East- and West- sides of Manhattan.

We conduct several robustness exercises. The counterfactual analyses continue to yield large output gains from commercial deregulation if we (1) recalibrate the economy so that 40% of the workforce is in a remote-work sector⁴, (2) restrict attention to recently developed buildings and thereby address concerns over old/outdated regulations, (3) double the negative congestion externality, (4) assume exogenous amenities, or (5) use alternate property valuations within tax assessor records.

Literature This paper contributes to the structural literature on land regulations and economic activity. The majority of studies focus on residential land regulations (for a review of early work, see [Turner, Haughwout, and Van Der Klaauw \(2014\)](#), and for more recent work see [Herkenhoff, Ohanian, and Prescott \(2018\)](#), [Hsieh and Moretti \(2019\)](#), [Martellini \(2019\)](#), [Colas and Morehouse \(2020\)](#), [Cun and Pesharan \(2020\)](#), [Tanure Veloso \(2020\)](#), [Delventhal, Kwon, and Parkhomenko \(2021\)](#), [Favilukis, Mabile, and Van Nieuwerburgh \(2023\)](#), [Greaney \(2023\)](#)). [Hsieh and Moretti \(2019\)](#) study residential land use regulations in a Rosen-Rosback model, whereas [Herkenhoff, Ohanian, and Prescott \(2018\)](#) conduct their analysis in an optimal growth model. In particular, [Herkenhoff, Ohanian, and Prescott \(2018\)](#) use state-level residential housing data to estimate land distortions, and then they impose the same land distortions in the construction sector and final goods sector. They ease land restrictions in both sectors and find significant gains to reverting to 1980s levels of land regulation. [Ahlfeldt, Redding, Sturm, and Wolf \(2015\)](#) and [Delventhal, Kwon, and Parkhomenko \(2021\)](#) study models featuring commercial land use regulations within specific cities, respectively Berlin and Los Angeles. Relative to existing structural work, we make three contributions: (1) we incorporate parcel-specific commercial real-estate developers in a spatial, optimal growth model of the U.S., (2) we show how the model's structure yields a formula for regulatory distortions, and (3) we estimate parcel-level commercial distortions by combining our model's structure with the universe of commercial tax records in the U.S.

⁴Importantly, remote work primarily affects office buildings, and only 30% of the commercial building stock is office buildings.

We contribute to an extensive empirical literature that relies on a variety of approaches to measure residential land use regulations (Glaeser, Gyourko, and Saks (2005a), Davis and Heathcote (2007), Tan, Wang, and Zhang (2020), Furth (2021), Rivera-Padilla (2021), Zhang (2023)). 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. 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.” Tokman (2023) uses a related model-based approach to infer regulations from the returns to building an additional unit of housing. Zhang (2023) treats land use regulations as a Lagrange multiplier, which is conceptually similar to our approach, and Tan, Wang, and Zhang (2020) argue that the land share of residential building values is informative about regulatory strictness in China. Recent empirical work valuing the commercial building stock post-Covid (e.g. Gupta, Mittal, and Van Nieuwerburgh (2022) and Gupta, Martinez, and Van Nieuwerburgh (2023)) provides an informative discussion of regulations in the sector. Relative to existing empirical work, our contributions are to (1) derive a formula that links commercial land’s share of total property value to regulatory distortions, (2) measure the regulatory distortions using tax records, (3) validate the distortions against observed commercial building height limits and floor-area-ratios, and (4) estimate welfare gains from both national and local commercial deregulations.

Our model also relates to the growing literature on place-based policies (e.g., Fajgelbaum and Gaubert (2020), Fajgelbaum, Morales, Suarez, and Zidar (2019), Rossi-Hansberg, Sarte, and Schwartzman (2019), Davis and Gregory (2021) among others) and 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). An important antecedent to our work is the Wharton Land Use Regulation 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

that infers the strength of regulations from a model of optimizing commercial real-estate firms.

Outline Section 2 describes the developer problem and identification of regulatory distortions. Section 3 validates our measures. Section 4 embeds our regulations into general equilibrium model. Section 5 conducts counterfactuals. Section 6 concludes.

2 Modeling Commercial Building

Before describing the full economic environment, we begin by presenting the commercial building supply “block” of the model to show how we model commercial land use regulations and how we then use the model to empirically identify land use regulations. We later embed this within the full general equilibrium structure.

2.1 Individual Developers

There are j cities (which we will later map into MSAs), and within each city j there are a large, finite number of differentiated parcels of land endowed to developers.⁵ We index land parcels by i , where i maps into a street address in the CoreLogic dataset.

Parcel characteristics. Parcel i in city j is described by its fixed land square footage x_i , parcel productivity z_i , the physical building cost q_i , and its time-varying building square footage $BSF_{i,t}$. The parcel productivity term z_i captures the fact that 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 center of the city), and it allows us to model the variation in price-per-building square foot observed in the data. The time-invariant building cost q_i differs across parcels. For example, these cost differences include variation in the difficulty of building (e.g. building on a flat lot versus a sloped lot, building on bedrock versus loamy soil), differences in the quality of building amenities and finishes, and cost differences such as unionization rates or prevailing wage requirements of local construction

⁵Since the number of land parcels is large and each one comprises a small share of total value, we assume that developers are price takers and that the law of large numbers holds within a city.

workers. Note the lack of time subscripts on x_i , z_i , and q_i , as these are all constant over time.

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 $B_{j,t}$. Depreciation is of the “One-hoss-shay” variety, which facilitates tractability, in which a building depreciates fully with probability δ_b (e.g., [Luttmer \(2011\)](#)).

Building technology. Consider a building that has depreciated at the end of period t . A developer creates a new building $B_{i,t}^N$ by combining the land parcel with improvements $m_{i,t}$ (building a new structure). This new building is rented for commercial use in subsequent periods.⁶ The new building is produced with a Cobb-Douglas technology with improvement share γ :

$$B_{i,t}^N = z_i \underbrace{m_{i,t}^\gamma x_i^{1-\gamma}}_{BSF_{i,t}} \quad (1)$$

This yields a law of motion for the aggregate city-level building stock $B_{j,t}$:

$$B_{j,t+1} = (1 - \delta_b)B_{j,t} + \sum_{i \in j} B_{i,t}^N \quad (2)$$

where $i \in j$ denotes the set of parcels i in city j .

Prices. Developers rent their buildings at the start of each period, earning $r_{b,j,t} B_{i,t}$ on parcel i in city j . We assume that there is a city-level rental rate $r_{b,j,t}$ and that parcel-level differences in rent are captured by building efficiency z_i . We denote the discounted stream of rental payments to each efficiency-weighted building square foot as $p_{j,t}$:

$$p_{j,t} = \sum_{s=t}^{\infty} (\beta(1 - \delta_b))^{s-t} r_{b,j,t} \quad (3)$$

Commercial Building Without Regulations. A developer with an unregulated parcel chooses improvements to maximize profits over the expected life of the

⁶The building fully depreciates with probability δ_b after its use in production but before the start of the next period.

building.⁷

$$\max_{m_{i,t}} \beta p_{j,t+1} z_i m_{i,t}^\gamma x_i^{1-\gamma} - q_i m_{i,t} \quad (4)$$

The first order condition for developing an unregulated parcel is: $q_i = \gamma \frac{p_{j,t+1} B_{i,t}^N}{m_{i,t}}$. Developers choose improvements to equalize the marginal benefit of building ($\gamma \frac{p_{j,t+1} B_{i,t}^N}{m_{i,t}}$) to its marginal cost (q_i). When we turn to the data, we observe that the marginal benefit of building exceeds the marginal cost for almost all commercial parcels. As we discuss in more detail below, we interpret the difference between the marginal benefit and marginal cost as arising from land-use regulations.

Commercial Building with Regulations. Commercial land may be subject to literally hundreds of zoning and other land use regulations that can take many forms (e.g. building height restrictions that limit the number of floors, floor-area ratio restrictions that limit the amount of building square footage relative to the size of the parcel, and building setbacks from the property line are all common zoning restrictions, while other regulations include receiving approvals from environmental and community review boards). It is infeasible to model all of these regulations, not only because of their number but also because some are de facto unmeasured (e.g., environmental reviews or actual or threatened lawsuits by community groups to limit development). Therefore, we need a framework that can (i) capture the many potential regulations facing a developer that limits building size, (ii) be tractably incorporated into a profit maximizing model of commercial development, (iii) be mapped into tax assessor data to quantify the stringency of parcel-level regulations, and (iv) be aggregated from the parcel-level to the city (MSA) level.

Given these requirements, we model parcel-specific regulations as what we call a *virtual distortion* $\tau_i \in [0, 1]$. We refer to τ_i as a virtual distortion because it looks like a tax in the developer's optimization problem below, but unlike a tax, it does not transfer any resources. Our approach captures policies and impediments that cause developers to construct fewer building square feet than they would optimally choose in the absence of regulations, given factor prices. At the two extremes, $\tau_i = 1$ nests the unregulated developer's problem, whereas $\tau_i = 0$ effectively forbids construction.

The problem of a developer facing regulations with a depreciated parcel is

⁷Note that the developer discounts these flow payments because the new building does not begin earning rents until next period.

$$\max_{m_{i,t}} \beta \tau_i p_{j,t+1} z_i m_{i,t}^\gamma x_i^{1-\gamma} - q_i m_{i,t}. \quad (5)$$

This yields the following first order condition for choosing improvements:

$$\gamma \tau_i = \frac{q_i m_{i,t}}{p_{j,t+1} B_{i,t}^N}. \quad (6)$$

For a given building technology (γ), equation (6) shows that regulatory distortions are weaker when the value of improvements ($q_i m_{i,t}$) comprises a larger share of building value ($p_{j,t+1} B_{i,t}^N$). Let $m_{i,t}^*$ denote the optimal choice of improvements. Notably, the virtual distortion τ_i affects the choice of $m_{i,t}^*$, but does not directly enter developer profits:

$$\beta p_{j,t+1} z_i (m_{i,t}^*)^\gamma x_i^{1-\gamma} - q_i m_{i,t}^*$$

Only via affecting $m_{i,t}^*$ does τ_i indirectly enter profits. We provide more discussion of τ_i in Section 2.1.1.

To illustrate how τ_i can capture a broad variety of regulations, we consider as an example the case of a floor-area-ratio restriction on a building. This is a commonly used regulation that limits the amount of building square footage ($BSF_{i,t} = m_{i,t}^\gamma x_i^{1-\gamma}$) that can be placed on the parcel of land x_i . First, we show an explicit model of development subject to a binding floor-area-restriction, and then show how it can be captured by the virtual distortion τ_i .

Let $\frac{\overline{BSF}}{x}$ denote the maximal floor-area-ratio. The developer's problem with this explicit constraint becomes

$$\max_{m_{i,t}} \beta p_{j,t+1} z_i m_{i,t}^\gamma x_i^{1-\gamma} - q_i m_{i,t}$$

subject to:

$$\frac{BSF_{i,t}}{x_i} \leq \frac{\overline{BSF}}{x} \quad (7)$$

The floor-area-ratio restriction in equation (7) distorts the choice of $m_{i,t}$ but does not generate any transfer of resources. It also maps into the Lagrange/Kuhn-Tucker multiplier that alters the optimal choice of $m_{i,t}$.

Note that this floor-area-ratio restriction example, which involves a binding constraint, is captured in our formulation with τ_i , but without any additional

constraints. We simply find the appropriate value of τ_i such that the developer "chooses" the same level of improvements in the formulation with τ_i as in the problem with the binding floor-area-ratio constraint above. See Appendix H for a discussion of when this constant τ_i yields the same implications for counterfactuals as a non-constant distortion.

Accounting for Property Value. Our model decomposes a property's total value into an amount due to improvements (the physical building) and an amount due to land. We denote *total value* as $TV_{i,t}$, *improvement (structure) value* as $MV_{i,t}$, and *land value* as $LV_{i,t}$. We define the identity:

$$TV_{i,t} \equiv MV_{i,t} + LV_{i,t} \quad (8)$$

The total value of a parcel of land consists of two terms: the first is the discounted value of rents, and the second is the discounted cost of redeveloping the property when the structure depreciates.⁸ Suppressing time subscripts, Appendix B derives the corresponding two-term steady-state expression for total value, TV_i :

$$TV_i = \frac{r_{b,j}B_i}{1 - \beta} - \frac{\delta_b q_i m_i^*}{1 - \beta}$$

We define the improvement value $MV_{i,t}$ as the cost of improvements $MV_{i,t} = q_i m_{i,t}$. We define the land value $LV_{i,t}$ as the difference between total value and improvement value: $LV_{i,t} = TV_{i,t} - MV_{i,t}$. We later show how we map this into tax assessor data on total value, land value, and improvements value.

2.1.1 The Regulatory Distortion τ_i

Broadly speaking, τ_i captures policies/regulations that prevent developers from constructing their desired building size, given factor prices. As noted above, these can include height restrictions, floor area ratios, and setbacks. None of these regulations raise building costs or lower the rents that owners can earn per building square foot, however.

This formulation captures regulations that limit size. It is not intended to capture regulations that enter factor prices and productivities, thus avoiding some

⁸Note that the value of the current building ($p_j B_i$) differs from total value, as total value can alternatively be written as the sum of the rents from the current building ($p_j B_i$) plus the future option value of rebuilding. Appendix B.2 contains this alternative formulation.

potential pitfalls that arise in measuring regulations. For example, taxes, and demand-side factors such as location desirability, will be capitalized into the parcel-level price per building square foot $p_{j,t}z_i$, and thus will not be captured in τ_i . Similarly, restrictions on building use (e.g. the type of activity that can be conducted at a location, or time-of-day operation restrictions at a location) will also be capitalized into $p_{j,t}z_i$. Moreover, if different locations are inherently harder or easier to build on (due to differences in soil quality, for example), then this will be reflected in q_i , the construction cost, and not τ_i . Restrictions on building techniques will also not be captured by τ_i . [Schmitz \(2020\)](#) studies bans on the use of prefabricated construction for residential buildings, which would be capitalized into $p_{j,t}z_i$. As our identification strategy does not pick up on such regulations, our results will be a lower bound on the distortions imposed by land use regulations. Notably, we do not model τ_i as a binding constraint. This is important since local governments grant variances and exemptions that allow developers to avoid statutory restrictions. If variances are easy to obtain, τ_i should move closer to 1, correctly reflecting that regulations are not as tight as the statutes might suggest.

2.2 Aggregation of Individual Parcels

We now aggregate the parcel-level optimization problem up to the city-level.⁹ The aggregation allows us to analyze MSA-level policy reforms. It also can address potential parcel-level measurement error and potential model misspecification, which we describe below.

In what follows, it is convenient to define productivity-weighted land (i.e. land adjusted for its productivity and cost of building), which is time invariant, as:

$$C_i = z_i^{\frac{1}{1-\gamma}} x_i q_i^{\frac{-\gamma}{1-\gamma}} \quad (9)$$

Note also that C_i is directly related to improvement value. Using the definition of improvement value, $MV_{i,t} = q_i m_{i,t}$, the first order condition for equation (5) can be written:

$$(\tau_i p_{j,t} \beta \gamma)^{\frac{1}{1-\gamma}} C_i = MV_{i,t} \quad (10)$$

⁹Appendix B.1 contains more details on the aggregation results outlined in this section. Our aggregation is closely related to [Hsieh and Klenow \(2009\)](#), [Edmond, Midrigan, and Xu \(2021\)](#), [Berger, Herkenhoff, and Mongey \(2019\)](#), and [Peters and Walsh \(2021\)](#).

We use the following notation for the aggregation. Let $m_{j,t}$ denote MSA-level improvements. Let T_j denote the average MSA-level regulatory distortion, let D_j denote dispersion in regulatory distortions, and let C_j denote the MSA-level efficiency units of land (which is immutable and thus does not feature a time subscript). We define and interpret these terms below.

Appendix B.1 shows that the first order conditions of the following city-level developer problem yields the same allocations as the individual developer problems:

$$\max_{m_{j,t}} \beta T_j p_{j,t} \underbrace{D_j m_{j,t}^\gamma (\delta_b C_j)^{1-\gamma}}_{B_{j,t}^N} - m_{j,t}. \quad (11)$$

The solution to this developer's problem coincides with the aggregated solutions of all the individual developers' problems in region j when C_j , D_j , and T_j take the following, time-invariant values:

$$C_j = \sum_{i \in j} C_i \quad (12)$$

$$D_j = \left(\frac{\sum_{i \in j} \tau_i^{\frac{\gamma}{1-\gamma}} C_i}{\sum_{i \in j} C_i} \right) / \left(\frac{\sum_{i \in j} \tau_i^{\frac{1}{1-\gamma}} C_i}{\sum_{i \in j} C_i} \right)^\gamma \quad (13)$$

$$T_j = \frac{\sum_{i \in j} \tau_i^{\frac{1}{1-\gamma}} C_i}{\sum_{i \in j} \tau_i^{\frac{\gamma}{1-\gamma}} C_i} \quad (14)$$

The term C_j is a measure of land productivity, and does not depend on regulations. It is policy-invariant, and we do not focus on it below.

The term D_j captures the allocative efficiency losses arising from dispersion in regulatory distortions across an MSA, under the assumption that τ_i are measured correctly. Applying Jensen's inequality shows that this term is weakly less than 1, and is only equal to 1 if all τ_i are equal. D_j also does not change if we scale each τ_i up or down by a constant. Hence, eliminating dispersion in τ_i while keeping the aggregate T_j fixed will lead to productivity gains (note that D_j enters directly into the output quantity $B_{j,t}^N$, and therefore affects total factor productivity, whereas T_j does not.) As in models of misallocation like [Hsieh and Klenow \(2009\)](#), these

gains may be overstated if there is measurement error or misspecification in our parcel-level measures of regulatory distortions. Note that D_j can be estimated if improvement values $MV_{i,t}$ and regulatory distortions τ_i are known, by substituting equation (10) into equation (13):

$$D_j = \left(\frac{\sum_{i \in j} MV_{i,t} / \tau_i}{\sum_{i \in j} MV_{i,t} / \tau_i^{\frac{1}{1-\gamma}}} \right) / \left(\frac{\sum_{i \in j} MV_{i,t}}{\sum_{i \in j} MV_{i,t} / \tau_i^{\frac{1}{1-\gamma}}} \right)^\gamma \quad (15)$$

The term T_j is a measure of the average regulatory distortion in MSA j . It takes on value 1 only if all τ_i are equal to 1. We can substitute equation (10) into equation (14) to show that T_j can be expressed as a weighted average of improvement values:¹⁰

$$T_j = \frac{\sum_{i \in j} MV_{i,t}}{\sum_{i \in j} MV_{i,t} / \tau_i} \quad (16)$$

Measurement error and model misspecification. Our counterfactuals primarily focus on reforms to the common, MSA-wide component of regulations, T_j , rather than the dispersion of regulations within a city, D_j . T_j reflects *systematic* differences in regulatory distortions across cities, and is thus unlikely to be impacted by idiosyncratic measurement error in parcel-level distortions, τ_i .

On the other hand, the dispersion of regulations within a city, D_j , may reflect regulations as well as a variety of unmodeled factors, such as credit constraints. The terms of loans — and thus the degree of credit constraints — in the commercial mortgage market reflect default and prepayment risk and are highly individualized, just as residential mortgage rates are (see [Vandell \(1984\)](#), [Ambrose and Sanders \(2003\)](#)).

Focusing on the city-wide component of regulations, T_j , reduces concerns about the impact of measurement error and misspecification and provides conservative estimates of the effects of regulations on economic activity.

¹⁰This 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 μ in that paper. Here, improvements correspond to costs.

MSA-level building supply. It is convenient to write the building supply curve in terms of a supply shifter Ψ_j , which we derive in Appendix B.1. It incorporates both productivity through C_j and regulations through T_j and D_j . Changes in T_j and D_j in our counterfactuals are captured by changes in Ψ_j (although note that T_j shows up separately in the demand curve for improvements).

$$B_{j,t}^N = p_{j,t}^{\frac{\gamma}{1-\gamma}} \delta_b \cdot \underbrace{D_j^{\frac{1}{1-\gamma}} T_j^{\frac{\gamma}{1-\gamma}} C_j (\beta\gamma)^{\frac{\gamma}{1-\gamma}}}_{\Psi_j} \quad (17)$$

Note that γ alone controls the price elasticity of supply. We discuss the implications of this in Appendix H.

2.3 Quantifying Commercial Land Use Regulations

This section recovers parcel-level regulatory distortions τ_i using the model in conjunction with CoreLogic data. We also address factors that may affect this quantification, including heterogeneous building technologies, differences in valuation methods used by tax assessors, and the possibility that older buildings were subject to outdated regulations, and thus may not be informative for analyzing current regulations. We will show that our regulatory measures are robust to these issues.

Parcel, Land, and Improvement Value Data. We use data from CoreLogic, a large commercial provider of real estate data. They obtained data from county tax assessors on the near-universe of commercial parcels in the United States, including the total value of the parcel $TV_{i,t}$, derived from either tax assessments, market transactions, or CoreLogic’s own calculations. This value is divided into land value $LV_{i,t}$ and improvement value $MV_{i,t}$ according to identity (8). We discuss valuation methods in more detail at the end of this section. The data covers the period 2009 to 2018.

For a subset of buildings, the data also includes building square footage $BSF_{i,t}$, the alphanumeric zoning code $Z_{i,t}$ to which the building is subject (example names include “C8” and “OR1”), and building age $a_{i,t}$. Crucially, our identification does not require knowing $BSF_{i,t}$ or $Z_{i,t}$. We remove parcels in which there appear to be obvious measurement errors, including parcels where improvement value exceeds total value, or improvement value takes a value of one dollar or less. We describe

our data in more detail in Appendix A.1. In the remainder of this paper, we focus on the continental U.S.

Identification. To identify τ_i , we proceed in two steps. In the first step, we identify the production technology scale parameter γ using the aggregate developer’s problem. In the second step, we use the value of γ obtained in the first step to identify τ_i at the parcel level developer’s problem.

Step 1: As shown in Appendix B.2, the first order condition of the aggregate builder’s problem allows us to recover the product of our aggregate measure of regulatory distortion T_j and the scale parameter γ as follows:

$$\gamma \cdot T_j = \frac{\left(\frac{1-\beta(1-\delta_b)}{1-\beta}\right) \frac{\sum_{i \in j} MV_{i,t}}{\sum_{i \in j} TV_{i,t}}}{\beta \left(1 + \frac{\delta_b}{1-\beta} \frac{\sum_{i \in j} MV_{i,t}}{\sum_{i \in j} TV_{i,t}}\right)}. \quad (18)$$

The variables on the right-hand side of equation (18) are easily obtained. We have CoreLogic’s calculated values of TV_i and MV_i . Under our one-hoss shay depreciation assumption, $\delta_b = .02$ is the inverse of the average building age in our sample.¹¹ We assume a standard annual discount value of $\beta = 0.96$.

The left-hand side of equation (18) reveals that T_j and γ are not separately identified without additional assumptions or information. Our approach treats the city with the highest value of $\gamma \cdot T_j$ as a “deregulated benchmark” in which T_j is to equal 1. In practice, we find that the least-regulated (benchmark) city is Midland, Texas, a metropolitan area of about 130,000 population which is known as “the Tall City” because of its very tall commercial buildings (Midland (2023)).

Our assumption that $T_{\text{Midland}} = 1$ yields an implied γ of 0.92. Note that if Midland has any regulation—that is, if the true T_{Midland} is less than 1—we will underestimate γ . If this was the case, then we would also understate the gains from commercial land-use deregulation.¹² This suggests that our evaluations of the gains from deregulation will produce conservative estimates.

Step 2: After having estimated γ , we can recover T_j at the MSA level, and through

¹¹Our calibrated value of 0.02 is fairly close to what Davis and Palumbo (2008) find under standard geometric depreciation.

¹²Moreover, 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 (18) provides a lower bound for γ .

Figure 1: Distribution of $MV_{i,t}/TV_{i,t}$

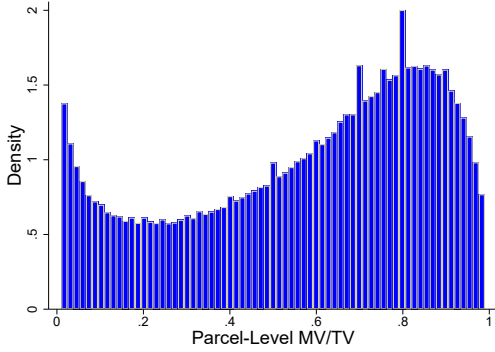
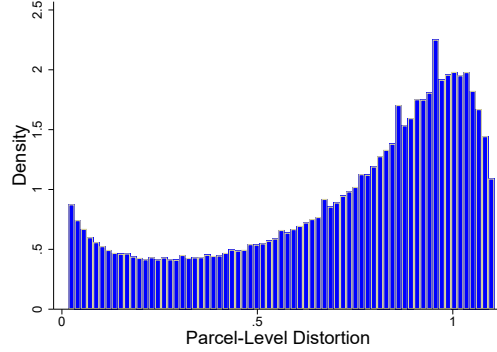


Figure 2: Distribution of τ_i



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 measurement error. We also drop the parcels designated by CoreLogic as public property. Figure 2 displays τ_i as calculated in equation 19. Both figures use unweighted counts of parcels.

simple manipulation of equation (6) (see Appendix B.2), we can recover τ_i at the parcel level as well:

$$\tau_i = \frac{\left(\frac{1-\beta(1-\delta_b)}{1-\beta}\right) \frac{MV_{i,t}}{TV_{i,t}}}{\gamma\beta\left(1 + \frac{\delta_b}{1-\beta} \frac{MV_{i,t}}{TV_{i,t}}\right)}. \quad (19)$$

After having recovered τ_i , it is straightforward to use equations (9) and (13) to obtain D_j .

There is significant variation in the data that we use us to estimate τ_i , T_j and D_j . We plot $MV_{i,t}/TV_{i,t}$, the key moment that identifies regulatory distortions in equation (19), across all parcels in our sample in Figure 1. For most parcels, this measure is considerably lower than what we would observe with no regulatory distortions.

Along with the distribution of the data object $MV_{i,t}/TV_{i,t}$, we also plot the distribution of the model-inferred τ_i and show that—as one might expect from equation (19)—the shape of two distributions is similar.

2.4 The Distribution of T_j and D_j

Figures 3 and 4 plot the distribution of the “average” regulatory distortion T_j and the dispersion in distortions D_j at the MSA level. Most cities are far from the deregulated benchmark, and in most cities τ_i is quite dispersed across parcels. D_j takes on a maximum value of 1.0 if all parcels have the same regulatory distortion, and in this case, is isomorphic to productivity in the construction sector. Hence,

Figure 3: Distribution of T_j

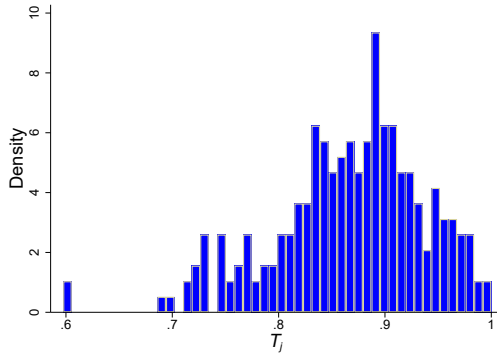
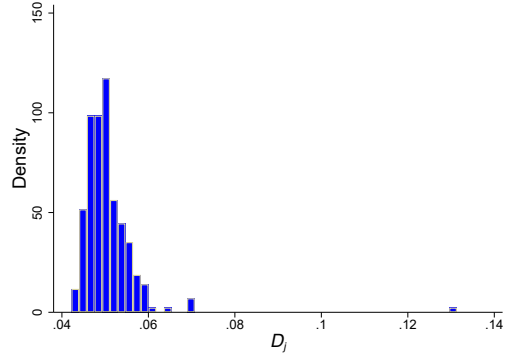


Figure 4: Distribution of D_j



Notes: Figure 3 displays the distribution of T_j across cities, with T_j calculated as in equation 14. Figure 4 uses the same data and displays M as calculated in equation 13. See the caption of Figure 1 for details on sample selection.

these plots suggest that both the level and the dispersion of τ_i may be creating significant inefficiencies.

Discussion of building technology γ . Although the value of γ may be slightly underestimated, it is still very close to 1 and thus suggests that the building production function is nearly linear in improvements. This is similar to findings in other studies: [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 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.¹³ [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. [Murphy \(2018\)](#) also finds evidence that any nonlinearity in the cost of construction must be very small. Moreover, a near-linear production function is intuitively reasonable: roughly speaking, it suggests that a developer can double the number of floors on a building for only slightly more than double the cost. We provide additional discussion of the level of γ and its relation to building supply

¹³Both 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.

elasticities in Appendix H.¹⁴

We next address the possible impact of differences in the type of economic activity on construction techniques and building composition (e.g. building a manufacturing plant versus building an office complex) as generating possible dispersion in γ . We therefore repeat our baseline estimation of $\gamma \cdot T_j$ at the MSA-level by the type of economic activity conducted: commercial, industrial, agricultural, and all other types. For each land use type, we report the inferred γ by treating the city with the highest value of $\gamma \cdot T_j$ as the deregulated benchmark, as we do in our benchmark specification. Since some of these types have a small number of observations at the MSA-level, we omit those with less than 1000 observations from the estimation.

Table 1 reports the estimates by these four types of economic activity. We find that the implied values of γ are above 0.92. Crucially, the two largest land use categories – commercial and industrial – yield similar values of γ . These results suggest that possible differences in construction techniques/building type across these categories of economic activity do not have quantitatively important effects, and that our choice of a common γ is supported empirically. In Appendix E, we also show that our results are robust to different measures of improvement and total value.

Table 1: Estimated improvement share, γ , by land use type

Land use	γ	Benchmark City	Share of Total Value
Commercial	0.925	Midland, TX	0.697
Industrial	0.951	Odessa, TX	0.203
Agricultural	0.972	Fort Collins, CO	0.054
Other	0.938	Syracuse, NY	0.046

Notes: In this table, we recalculate equation 18 at the land use-by-MSA level and report the highest value of $T\gamma$ for each land use code along with the corresponding MSA. We only include MSA-by-land use pairs with more than 1000 parcels, and we report the share of total value in each MSA accounted for by that land use. We aggregate non-commercial, non-industrial, and non-agricultural land types into “other.”

¹⁴It 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 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.

Discussion of older buildings and outdated regulations. One possible issue with our approach is that it may overestimate regulatory severity for older buildings.¹⁵ Specifically, if improvement value $MV_{i,t}$ is declining as the building ages, but the option to rebuild becomes more valuable as the economy grows, then older buildings may have a downward-biased τ_i . Additionally, older buildings may have been subject to outdated regulations.

We address these concerns in three ways, and find that potential issues regarding older buildings do not appear to be quantitatively important. First, we recompute distortions using only young buildings, and we denote the corresponding city-level distortion T_j^{young} . We define young buildings to be less than 10 years old.¹⁶ Figure 5 shows that the baseline T_j and young building T_j^{young} are quite similar. There are a handful of outliers, but the majority of observations are clustered near the 45 degree line. We formalize these statements in Appendix C with regression analysis.

Second, in Appendix C, we investigate whether the size of parcel-level distortions are systematically related to age by regressing these distortions on building age together with a number of controls. We find that building age has little explanatory power for the model inferred distortions, with regression R^2 's of only 0.06 or lower.

Third, we conduct our benchmark counterfactual using T_j^{young} in Appendix E. Our deregulation exercises yield output, employment, and welfare effects that are only moderately smaller than our baseline specification.

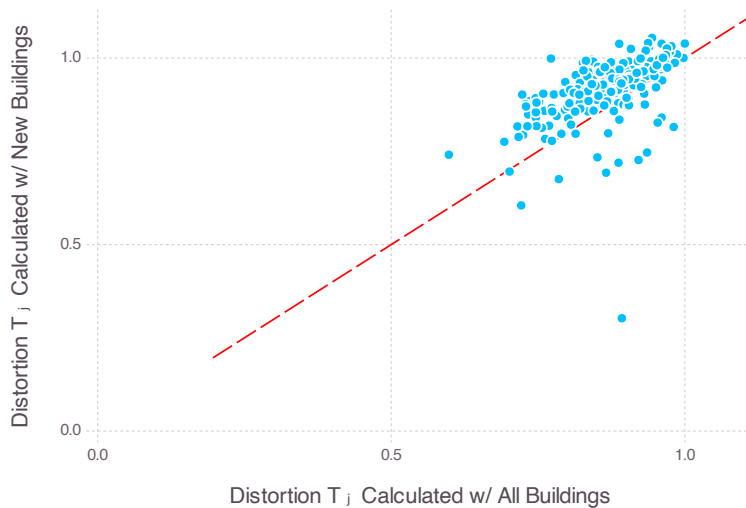
3 Validation

In this section we perform validation analyses to evaluate how the improvement share of total parcel value is informative about the severity of commercial land use regulations. We do this by comparing our measure of regulations to statutory measures of regulations. We also compare our regulatory measures across regions where we expect *a priori* to find systematic differences in regulations. We find that our measures of regulation align well with both of these comparisons.

¹⁵We thank Salim Furth for a very helpful conversation on this topic.

¹⁶As described in Appendix A.1, 57 percent of the buildings in our filtered sample have a recorded age.

Figure 5: T Calculated From New Buildings



Notes: This table compares 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 233 matched MSAs in this sample, as no buildings in 6 MSAs have a recorded age.

3.1 Hand-Collected Zoning Code Features

This section compares our measure of regulatory distortion with two widely-used statutory zoning codes:

1. Floor-area-ratios: restrictions on the ratio of building square footage to land square footage.
2. Height limits: restrictions on the height of buildings.

Since our CoreLogic dataset does not include zoning features (just the alphanumeric codes), we hand-collected floor-area-ratios and height limits from public, city-level zoning code manuals. Two factors limit our analysis. One is that many cities do not provide their zoning code manuals in a format that allows us to easily merge in with CoreLogic's data. Second, our county-level CoreLogic data lacks zoning code information in 39% of cases.

We therefore focus this comparison on New York City (NYC) and Washington, DC, two cities that post their zoning code data online in a particularly user-friendly format. NYC provides their floor-area-ratio restrictions in a usable format,

and they do not impose height limits. DC provides their height restrictions in a usable format, and they do not impose floor-area-ratios.¹⁷ We then hand-match the alphanumeric zoning code in our CoreLogic data (for example “C1”) to the alphanumeric zoning code in [City of New York \(2021\)](#) and then we record the corresponding floor-area-ratio. We repeat the same exercise in DC using [DC Office of Zoning \(2021a\)](#).

Since our regulatory distortions are measured at the parcel-level (τ_i), we first aggregate parcels by zoning code coverage (τ_Z). Denoting $i \in Z$ as the set of parcels subject to zoning code Z , we write:

$$\tau_Z = \frac{\sum_{i \in Z} MV_{i,t}}{\sum_{i \in Z} MV_{i,t} / \tau_i} \quad (20)$$

We plot a binscatter of zoning-code level τ_Z against NYC floor-area-ratios and DC height limits in Figures 6 and 7, respectively. We find a positive but imperfect relationship in both cases.¹⁸ The R^2 in a building-value weighted regression of log distortions on log FARs is 0.089 and on log height limits is 0.22. We expect an imperfect fit because our τ_i are capturing many land use regulations, and because some properties that form this analysis will almost certainly have exemptions or variances to these particular regulations. Our regulatory distortion τ_i takes these factors into account and thus produces a positive, yet imperfect relationship with each of these single, statutory regulations.

Appendix A.3 provides additional validation of our distortions against statutory regulations in San Francisco.

3.2 Cities in California and Texas

Much of the literature on land use regulation has concluded that Texas is lightly regulated and that California is heavily regulated (see for instance [Gyourko, Saiz, and Summers \(2008\)](#), Figure 1). This section shows that our results for Texan and Californian cities are consistent with this view.

Figure 8 plots 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

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

¹⁸To construct the red best-fit line, we weight each zoning code by the sum of building value subject to that code.

Figure 6: FAR in NYC

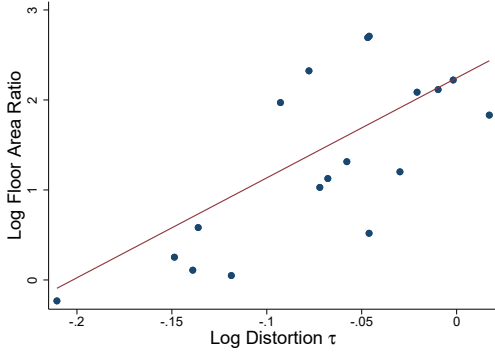
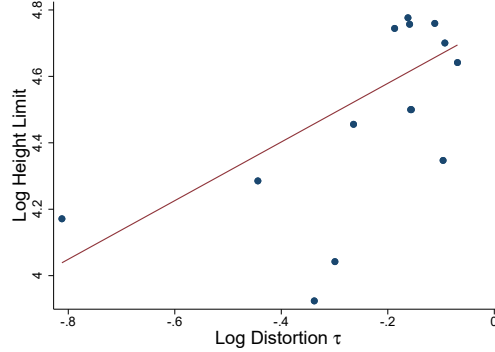


Figure 7: Height Limits in DC



Notes: In Figures 6 and 7, the horizontal axis is the logarithm of the zoning code-level distortion τ_Z , as calculated in equation 20. The vertical axes are the logarithm of the regulation associated with each zoning code, namely floor area ratios in Figure 6 and height limits in 7. 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 6 and 7 are binscatters where the constituent zoning codes of each bin are weighted by the sum of the value of the buildings (see Appendix equation 28) in each code.

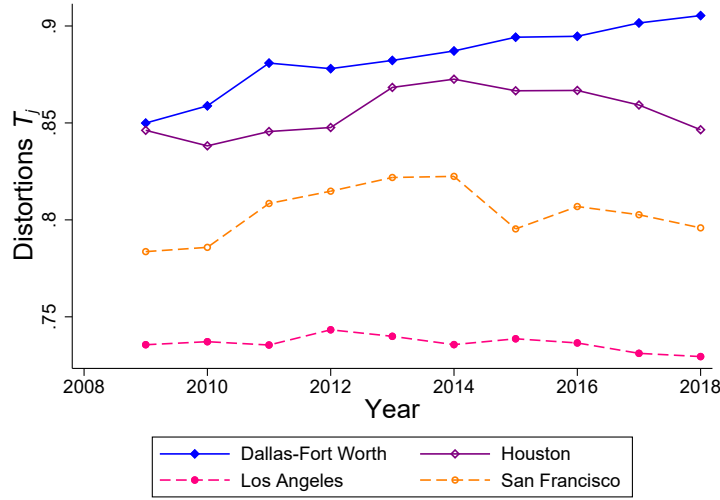
Texas; San Francisco and Los Angeles in California). We find that the major cities in California are more regulated than those in Texas. Indeed, Los Angeles is one of the most heavily regulated major cities. Figure 8 also demonstrates that our measure of regulation is stable across years, which is consistent with the view that land use regulations change slowly over time.

4 General Equilibrium Model

This section presents the general equilibrium model, including the commercial development sector outlined above, to analyze the positive and normative effects of commercial land use regulations. The structure builds on [Herkenhoff, Ohanian, and Prescott \(2018\)](#), and the new model is tailored to incorporate our regulation measure for quantitative analyses.

In what follows, $t \in \{0, 1, \dots, \infty\}$ indexes time and $j \in \{1, 2, \dots, N\}$ 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 by exogenous TFP A_j and endogenous amenities $a_j(\cdot)$. A stand-in household allocates its workers to the j cities, it allocates capital, and it receives profits from developers and final goods producing firms. The final goods firms hire workers and rent capital from the representative household, rent buildings from developers, and combine these production factors to produce a numeraire

Figure 8: 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.

final good. As described above, developers 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 city labor supply $L_{j,t}$. These preferences feature city-specific disutilities of labor.¹⁹ Amenities $a_j(\cdot)$ decrease the marginal disutility of sending workers to a given city. We parameterize amenities as a function of “congestion,” which we define as 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 locations for their workers, but this affects congestion and thus generates an unpriced externality. The household invests i_t in capital and allocates capital $K_{j,t}$ across regions. The wage rate in region j is given by $w_{j,t}$, and

¹⁹Similar to Herkenhoff, Ohanian, and Prescott (2018), these preferences stand-in for idiosyncratic preferences for a given city and other forces that limit interregional mobility. As $\eta \rightarrow 0$, 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.

we assume that capital is perfectly mobile, which gives rise to a national capital market and a single rental rate of capital $r_{k,t}$. The household also receives profits from developers $\pi_{j,b,t}$ and from final goods firms $\pi_{j,f,t}$. The household solves the following optimization problem:

$$\begin{aligned} \max_{c_t, i_t, K_{j,t}, L_{j,t}} \sum_{t=0}^{\infty} \beta^t & \left(\frac{c_t^{1-\sigma}}{1-\sigma} - \frac{1}{1+\frac{1}{\eta}} \sum_{j=1}^N \left(\frac{L_{j,t}}{a_j(L_{j,t}/X_j)} \right)^{1+\frac{1}{\eta}} \right) & (21) \\ \text{subject to: } c_t + i_t &= \sum_{j=1}^N (\pi_{j,b,t} + \pi_{j,f,t} + w_{j,t}L_{j,t} + r_{k,t}K_{j,t}) \\ K_{t+1} &= i_{k,t} + (1 - \delta_k)K_t, \quad \sum_{j=1}^N K_{j,t} = K_t \end{aligned}$$

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.²⁰ We assume they operate constant returns to scale Cobb-Douglas production technologies with city-specific total factor productivity A_j . The building share χ_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:

$$\pi_{j,f,t} = \max_{K_{j,t}, L_{j,t}, B_{j,t}} \underbrace{A_j L_{j,t}^\alpha B_{j,t}^{\chi_j} K_{j,t}^{1-\alpha-\chi_j}}_{Y_{j,t}} - w_{j,t}L_{j,t} - r_{k,t}K_{j,t} - r_{b,j,t}B_{j,t} \quad (22)$$

4.3 Representative Developer

As described in Section 2.2, our model features a representative city-level developer. The developer purchases the final good $m_{j,t}$ and combines it with newly-depreciated land to create new buildings $B_{j,t}^N$, as in equation 11, which we rewrite

²⁰As we will explain in more detail later, $B_{j,t}$ maps into productivity-weighted building square feet supplied by the developers.

below:

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

The price $p_{j,t}$ is given by the net present value of rents, $p_{j,t} = \sum_{s=t}^{\infty} (\beta(1 - \delta_b))^{s-t} r_{b,j,t}$. Lastly, the stock of buildings in each city grows according to a standard law of motion, as in equation 2:

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

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 Calibration

We calibrate an annual version of the model by treating 2018 as the steady state that exists prior to any deregulations that we consider. We therefore drop time subscripts from the variables in this section. We assume an annual discount factor of $\beta = 0.96$ and CRRA utility with curvature of $\sigma = 2$ (Herkenhoff, Ohanian, and Prescott, 2018). We assume a Frisch elasticity of $\eta = 2$ (Keane and Rogerson, 2012), a depreciation rate of $\delta_k = 0.032$ (McGrattan, 2020), and a labor share of $\alpha = 0.594$ based on the Penn World Table (Feenstra, Inklaar, and Timmer, 2015).

The remaining parameters, regional productivities A_j , and regional amenities a_j are obtained via the model and data on output, investment, and employment $\{Y_j, i_k, L_j\}$. We observe regional employment L_j in the 2018 American Community Survey (ACS) (Ruggles, Flood, Goeken, Grover, Meyer, Pacas, and Sobek, 2020) as well as aggregate investment i_k and regional output Y_j from the Bureau of Eco-

Table 2: Parameters

Parameter	Description	Value	Source
β	Discounting	0.96	Herkenhoff, Ohanian, and Prescott (2018)
σ	CRRA	2	Herkenhoff, Ohanian, and Prescott (2018)
η	Labor Curvature	2	Keane and Rogerson (2012)
δ_k	Non-Structures Depreciation	0.032	McGrattan (2020)
α	Labor Share	0.594	Penn World Table, 2018
ρ^L	Remote Labor Supply Share	0.052	American Community Survey, 2018
ρ^W	Remote Wage Bill Share	0.056	American Community Survey, 2018
χ_n	Non-remote Sector Building Share	0.149	Model structure & Bureau of Economic Analysis, 2018
χ_r	Remote Sector Building Share	0	By assumption
δ_b	Depreciation Rate of Buildings	0.02	Section 2.3 & CoreLogic, 2018
γ	Improvement Share of Buildings	0.92	Section 2.3 & CoreLogic, 2018
A_j	Regional TFP		Model structure & data in Table 3
a_j	Regional Amenity		Model structure & data in Table 3

Notes: This Table reports the calibrated parameters. We obtain metro-level employment and wage-bill shares 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.

Table 3: Data Sources

Variable	Description	Source
Y_j	MSA GDP	US Bureau of Economic Analysis (2021a) , 2018
i_k	Equipment+IP Investment	US Bureau of Economic Analysis (2021b) , 2018
L_j	MSA Labor Supply	American Community Survey, 2018

Notes: This Table reports key sources of data (other than CoreLogic). We obtain data on national output, metro-level output, and investment from the Bureau of Economic Analysis; and we obtain metro-level labor supplies from the American Community Survey.

conomic Analysis (BEA).²¹ The parameters are summarized in Table 2 and the data sources are summarized in Table 3.

Remote work. We use the ACS to compute regional labor supply L_j , the remote work share of labor supply ρ^L , and the remote work share of wages ρ^W . 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 find that about 5.2% of the workforce was

²¹Note that we model a rest-of-the-country region in which output is inferred so that the sum of regional output is equal to national output as reported by the BEA. Similarly, we infer the rest-of-the-country region employment to match aggregate employment in the ACS.

remote in 2018, implying $\rho^L = 0.052$. The remote share of the wages is 5.6%, implying $\rho^W = 0.056$. Labor supply in the remote work region is then given by $L_{\text{remote}} = \frac{\rho^L}{1-\rho^L} \sum_{j \neq \text{remote}} L_j$.

We assume a common labor share in every region, including the remote work region. This means that remote workers' share of GDP will be proportional to their share of the wage bill. We measure Y_j using MSA-level GDP from the BEA which allows us to compute remote sector output $Y_{\text{remote}} = \frac{\rho^W}{1-\rho^W} \sum_{j \neq \text{remote}} Y_j$.

Regional capital. We next turn to non-structures capital. The rate of return r_k is determined by the household's Euler equation, $r_k = \frac{1-\beta(1-\delta_k)}{\beta}$. Using aggregate investment i_k from the BEA in conjunction with the steady state law of motion for capital, we recover aggregate capital $K = i_k / \delta_k$.

We can recover χ_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 . This yields: $\chi_n = \left((1 - \alpha) \sum_j Y_j - r_k \sum_j K_j \right) / \left(\sum_{j \neq r} Y_j \right)$. We recover a non-remote sector building share of $\chi_n = 0.149$. With the factor share in hand, we calculate regional capital stocks as:

$$K_j = (1 - \alpha - \chi_j)Y_j / r_k. \quad (23)$$

Regional buildings and improvements. As described in Section 2.2, we estimate $\delta_b = 0.02$ using building ages in our CoreLogic commercial data. This implies the commercial building rental rate $r_{b,j} = p_j(1 - \beta(1 - \delta_b))$ using equation (3). We estimate the city-level price-per-efficiency weighted building square foot p_j from the subset of buildings j_b with a recorded value for building square footage BSF_i :

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

We then recover regional building stocks B_j and the building supply shifters Ψ_j (as defined in equation (17)) from the region- j final goods firm's first-order condition:

$$B_j = \chi_j Y_j / r_{b,j}, \quad \Psi_j = B_j / p_j^{\frac{\gamma}{1-\gamma}}.$$

We recover the total amount of resources expended on improvements from the first-order condition of the aggregate developer (see equation (11)) and the steady-state condition for the law of motion of buildings, $B_j^N = \delta_b B_j$ (see equation (2)). This yields the demand curve for materials which allows us to recover regional improvements:

$$m_j = \gamma \beta T_j \delta_b p_j B_j. \quad (24)$$

Regional productivity. With data on regional output Y_j , regional employment L_j , and recovered series for regional capital and buildings, we can recover total factor productivity:

$$A_j = \frac{Y_j}{L_j^\alpha B_j^{\chi_j} K_j^{1-\alpha-\chi_j}}.$$

Regional Amenities. We recover amenities and the functional form for congestion in two steps. First, we use the household's labor-leisure condition to infer amenities a_j in steady state. Since congestion is not internalized by the household, our inference of amenities is independent of the functional form for congestion. Second, we use internal instruments to infer the functional form for congestion.

To recover steady-state amenities, we 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 $c = \sum_j (Y_j - \delta_k K_j - m_j)$. We then recover amenities from the household's first order condition for labor, which holds regardless of the function form of amenities:

$$a_j = \exp \left(\frac{\sigma \log c + \frac{1}{\eta} \log L_j - \log w_j}{1 + \frac{1}{\eta}} \right). \quad (25)$$

Next, we identify the relationship between amenities and congestion using internal instruments. In the absence of an instrument, the correlation between congestion and amenities is positive, thus a regression would suffer from endogeneity. To address endogeneity, we use the model itself to generate instrumental variables, in an approach that builds on [Anderson and van Wincoop \(2003\)](#), [Allen, Arkolakis, and Takahashi \(2020\)](#), [Walsh \(2019\)](#), and [Rossi-Hansberg, Sarte, and Schwartzman](#)

(2019). We proceed by re-solving the model in which TFP and amenities in all j are set to their average values, and regulatory distortions are all set to zero. This means that the only reason why populations would differ across regions is the building supply shifter Ψ_j . We denote this counterfactual allocation L'_j/X_j and use it as an instrument for L_j/X_j in equation (26):

$$\text{Second stage:} \quad \log a_j = \mu \log \left(\frac{L_j}{X_j} \right) + e_j, \quad (26)$$

$$\text{First stage:} \quad \log \left(\frac{L_j}{X_j} \right) = \gamma \left(\frac{L'_j}{X_j} \right) + u_j. \quad (27)$$

We find $\mu = -0.542$ with a tightly estimated standard error of 0.073.²² This result implies that a doubling of density (doubling the number of workers per unit of commercial land) reduces amenities by 50 percent.

In Appendix D, we explore several alternative approaches to estimating congestion. Equation (26) yields the largest estimate of the negative effects of congestion, so we use it as our baseline, which yields more conservative results in analyzing the impact of regulatory reform. We additionally analyze the impact of doubling the congestion externality in Section 5.1.5.

5 Counterfactuals

This section presents counterfactual experiments that analyze the positive and normative effects of commercial land-use regulatory changes at the aggregate level and at the local level. Appendix F explains the details of how we compute these counterfactuals, and Appendix F.1 describes how we incorporate endogenous amenities in these experiments. Three of the counterfactuals are designed to evaluate the implications of plausible regulatory changes, and the other two evaluate the sensitivity of the effects to changes in the size of the remote work sector and in the size of the congestion externality.

²²We 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 labor force of each MSA. We also report robust standard errors. The first-stage F-statistic is 191.

5.1 Aggregate Counterfactuals

This subsection shows the results of five aggregate counterfactuals, in which we change regulations in all MSAs. Aggregate output changes significantly across all five experiments, and there are also significant changes in the allocation of economic activity across MSAs.

The first experiment, which we refer to as the baseline counterfactual, evaluates what happens if the average regulatory distortion in every MSA was equal to that of Midland, Texas, which is the least-regulated MSA. We therefore set $T_j = 1$ in each MSA. The dispersion is held fixed in the first experiment.

The second experiment evaluates the impact of making regulations more uniform (reducing dispersion in regulations across commercial parcels) within MSAs, but leaving the average level in each MSA, T_j , fixed. We therefore set D_j for every MSA to the level of the second highest D_j observed in the dataset, which is a value of about .07 in Figure 5, compared to a median value of about .05. We choose the second highest D_j , rather than the highest (Yuma, AZ), since it is an outlier with a value of about 0.13 (see Figure 5).

The third experiment repeats the first experiment, but starting from a new baseline in which 40 percent of jobs are remote. [Gupta, Mittal, and Van Nieuwerburgh \(2022\)](#) argue that remote work has substantially impacted commercial sector valuations and cash flows, and so we use an upper-bound estimate of the remote work share from [Dingel and Neiman \(2020\)](#).

The fourth experiment focuses on neighborhood reforms at the zoning code level within each MSA. We therefore collect all parcel-level distortions, τ_i , within each neighborhood in each MSA, where neighborhoods are defined as the geographic location operating under a specific zoning code. We then aggregate them up to the zoning code level, construct the distribution of those zoning code aggregated distortions, and set all of those that are below the median distortion within that distribution to the median level.

The fifth experiment repeats the first experiment, but doubles the size of the congestion externality, μ in equation (26), to assess the sensitivity of deregulations to stronger congestion effects.

We summarize the counterfactuals in Table 4 and explain them in greater detail in the following sections. In Appendix E, we test how the results of these counterfactuals vary as we change our data sample and parameterization.

Table 4: Aggregate Counterfactuals: Description

Counterfactual	T_j	D_j	Amenities
Baseline	1.0	Unchanged	Unchanged
Less Dispersion	Unchanged	Move up to 2 nd highest sample value	Unchanged
More Remote	1.0	Unchanged	Set so 40% Remote
Local Deregulation	Move up to MSA median	Move up to MSA median	Unchanged
Double Congestion	1.0	Unchanged	$\mu' = 2 \times \mu$

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 how we alter amenities. For the “Less dispersion” counterfactual, one small MSA (Yuma, AZ) is an outlier, and so move up all lower values of D_j to the second-highest value \bar{D}_j in our sample. For the “Local Deregulation” counterfactual, we do not change T_j and D_j directly but rather change zoning code level τ_Z to τ'_Z according to the formula $\tau'_Z = \max[\tau_Z, \min[\tau_Z^{p50}, 2\tau_Z]]$, and then we re-aggregate. We move up all distortions to the median in the FIPS code τ_Z^{p50} , but we cap the change at a doubling of the τ_Z and we cap T_j and D_j at 1.0.

Table 5 summarizes the positive effects of the counterfactuals, including the percent changes in aggregate output Y , in the efficiency-weighted building stock B , in employment L , in the capital stock K , in developer 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 in consumption c .

We also compute the percentage change in consumption from the original steady state needed to make the representative household equally well-off as in the new steady state. We derive this analytically in F.2.

5.1.1 Baseline

The first counterfactual (baseline) exercise sets $T_j = 1$ in all regions and leaves all other parameters unchanged. This is a conservative reform as it leaves the dispersion in τ_i within an MSA (D_j) unchanged. We report the results in the first column of Table 5. Panel A shows that this leads to a 3 percent increase in steady output and a 17.6% increase in the building stock. The wealth effect resulting from this deregulation reduces labor supply by about one percent. Consumption rises by 2.2 percent, and the capital stock other than commercial building increases by 2.6%. In terms of welfare, we find that a 2.9 percent increase in consumption such that the stand-in household is indifferent between the original steady state and the steady state under the counterfactual.

Perhaps the most striking quantitative finding is that lower regulation reduces

Table 5: Aggregate counterfactual results

	Baseline	Less Dispersion	More Remote	Local Deregulation	Double Congestion
Panel A.					
% ΔY	3.0%	6.1%	1.5%	3.1%	3.0%
% ΔB	17.6%	59.9%	19.4%	26.0%	17.8%
% ΔL	-0.8%	-2.8%	-0.8%	-2.3%	-0.7%
% ΔK	2.6%	5.2%	0.4%	2.6%	2.7%
% Δc	2.2%	6.1%	1.0%	4.0%	2.2%
% Δ Cons. Equiv.	2.9%	9.2%	1.3%	6.4%	3.0%
% Δ Developer Profit	-2.8%	7.7%	-1.1%	11.0%	-2.7%
Panel B.					
% ΔY , Fix B at baseline	0.2%	-0.5%	-0.4%	-0.8%	0.3%
% ΔY , Fix K at baseline	2.2%	4.6%	1.3%	2.4%	2.3%
% ΔY , Fix L at baseline	3.4%	7.9%	2.0%	4.5%	3.4%

Notes: This table includes the results of our five counterfactuals detailed in Table 4. % ΔX is the percent change in variable X relative to the baseline, where X stands for output Y , building stock B , aggregate labor supply L , capital K , consumption c , and developer profits. The final row of Panel A 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. Panel B reruns the same counterfactuals holding the allocations of buildings, capital, and labor fixed at their 2018 steady state values, respectively.

developer profits, reflecting a larger quantity of commercial space and a lower price per square foot in the new steady state. This finding suggests that regulations that limit commercial space are not only adopted to address the congestion externality, but also reflect rent-seeking on the part of those who benefit from higher commercial building prices, and who promote regulations that restrict building supply.

Panel B illustrates the importance of the three factors of production by calculating the change in output holding B , K , and L fixed, respectively. The first column of Panel B shows that the commercial construction expansion is by far the most important. Labor and capital account for moderate output gains derived from our baseline deregulation.

Table 6 describes the reallocation of workers that occurs across MSAs. 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.

Table 6: Most and Least Regulated Cities for Baseline Counterfactual

	Distortion T_j	Change in Y_j/L_j	Change in L_j
Midland, TX	1.000	0.1%	-3.2%
Shreveport-Bossier City, LA	0.998	0.1%	-3.2%
Monroe, LA	0.987	0.4%	-3.0%
Tuscaloosa, AL	0.985	0.4%	-3.0%
Baton Rouge, LA	0.983	0.4%	-2.9%
Naples-Marco Island, FL	0.715	7.9%	2.5%
Lebanon, PA	0.701	8.3%	2.8%
Myrtle Beach-Conway-North Myrtle Beach, SC-NC	0.693	8.6%	3.1%
Ocean City, NJ	0.598	12.3%	5.7%
El Centro, CA	0.597	12.3%	5.7%

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.

While row three of Table 5B shows that labor reallocation contributes negligibly to output gains, deregulation generally shifts labor from MSAs in initially less-regulated states like Texas to MSAs on the more-regulated coasts. In Figure 9, we show which states gain and lose labor relative to our baseline counterfactual.²³ The states that gain the largest amount are California (+0.9%) and Florida (+0.5%).

5.1.2 Less Regulatory Dispersion Within MSAs

The second counterfactual reduces regulatory dispersion within each MSA, while holding the *average* level of regulation in each MSA (T_j) fixed. We interpret “reduced dispersion” as each MSA implementing regulations with similar severity but more uniformity. This parallels the reduced misallocation experiments in Hsieh and Klenow (2009).

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 (see Figure 4). 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.

²³But note that we do not include the rest-of-country aggregator or remote work sector in this figure.

office buildings account for less than one-fifth of the value of the buildings in the dataset, which suggests that 40 percent may be an upper bound on remote work.

We first use the counterfactual algorithm detailed in Appendix F to compute a new initial steady state where remote work comprises 40% of the labor force. Our approach in generating a large remote sector is to reduce regional amenities, a_j , in all the in-person work regions by a common factor v so that 40% of jobs are optimally allocated by the household to the remote work sector. We then deregulate this economy as in the first (baseline) counterfactual. The second column of Table 5 shows the results. The gains from deregulation are attenuated, but are still considerable, with a 1.5 % output increase and a 1.3% consumption equivalent welfare gain. The output gains from deregulation scale nearly one-for-one with the fraction of workers who are remote (i.e., a 40% remote work share reduces the gains from deregulation by about 50%). These results suggest that commercial land-use deregulation yields significant positive and normative gains even with 40 percent of work being performed remotely.

5.1.4 The Aggregate Consequences of Local Reforms

We next analyze the national consequences of local deregulation. This counterfactual recognizes that many land-use regulations are adopted at the county or city level. This experiment evaluates the impact of reducing regulations at the MSA level for those properties with τ_Z distortions that are worse than those at the median commercial property in the MSA. The reform moves regulations for all properties worse-than-the median up to the median τ_Z in their respective MSA. Our goal is to understand how reforming the most tightly regulated commercial properties matters when we tailor the size of the reform to be consistent with that of the average within the MSA. This counterfactual also demonstrates how this method can be used to perform detailed, specific policy proposals and inform local policy-makers.

We proceed in three steps: (1) we aggregate distortions at the zoning code level to obtain the pre-reform τ_Z , T_j , and D_j ,²⁴ (2) we change τ_Z to the median τ_Z^{p50} in

²⁴ τ_Z is given by equation (20). We then aggregate τ_Z 's as follows:

$$MV_{Z,t} \equiv \sum_{i \in Z} MV_{i,t}, \quad D_j = \left(\frac{\sum_{Z \in j} MV_{Z,t} / \tau_Z}{\sum_{Z \in j} MV_{Z,t} / \tau_Z^{\frac{1}{1-\gamma}}} \right) / \left(\frac{\sum_{Z \in j} MV_{Z,t}}{\sum_{Z \in j} MV_{Z,t} / \tau_Z^{\frac{1}{1-\gamma}}} \right)^{\gamma}, \quad T_j = \frac{\sum_{Z \in j} MV_{Z,t}}{\sum_{i \in j} MV_{Z,t} / \tau_Z}$$

the county, but we cap the change at a doubling of the τ_Z and we cap T_j and D_j at 1.0; and then (3) we re-aggregate to obtain the counterfactual T'_j and D'_j (where primes denote post-reform values, henceforth).

Column three of Table 5 reports these results. Table 5A shows that this relatively modest reform (reforming only those properties that are more regulated than the median at the MSA level) increases output by roughly 3.1%. Since both T_j and D_j improve, the local deregulation produces a larger output gain than our baseline deregulation in which T_j is set to 1.0 and D_j is held fixed. The first row of Table 5B shows that the 26% increase in the building stock drives the output gains. The consumption equivalent welfare gain from local deregulation is 6.4%.

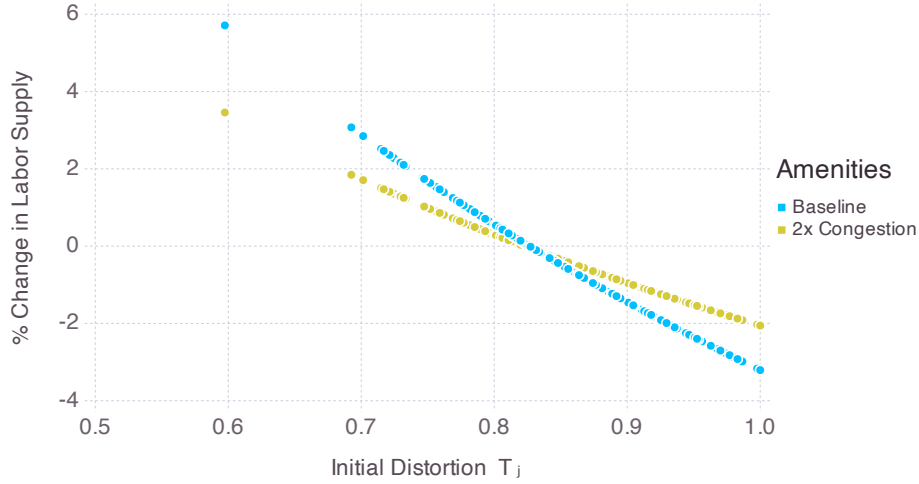
5.1.5 Doubling Congestion

This counterfactual repeats the first (baseline), but with the size of the congestion externality doubled. The fourth column of Table 5 reports the results. Perhaps the most striking finding is that aggregate effects are almost the same as in the baseline counterfactual, despite less worker reallocation to previously highly regulated MSAs when the congestion externality doubles. Figure 10 shows the difference in reallocation between the two cases. One reason why doubling the congestion externality is very similar to the baseline counterfactual is because there is little correlation between amenities and productivity and between TFP and amenities across MSAs. The (unweighted) correlation between MSA TFP and T_j is -0.2, and is -0.12 between MSA TFP and amenities. Figure 11 demonstrates that there is no strong correlation between TFP and the change in population, illustrating more directly that the benefits of deregulation are not driven by reallocation to more productive cities.

5.2 Increasing Floor-Area Ratio Limits in New York City

This section shows how the model can be used to evaluate regulatory reforms at the city level. We conduct a counterfactual that analyzes the impact of relaxing floor-area ratio limits (FAR) within New York City at the level of individual parcels. We report the distribution of FARs in A.2. We focus on New York given the quality and accessibility of its zoning code information and the broad interest within the

Figure 10: Labor reallocation from $T_j = 1$ for baseline congestion v. $2\times$ congestion



Notes: Each point is an MSA. This figure compares the change in labor across MSAs in the baseline counterfactual to doubling the size of the congestion externality. The horizontal axis corresponds to an MSA'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.

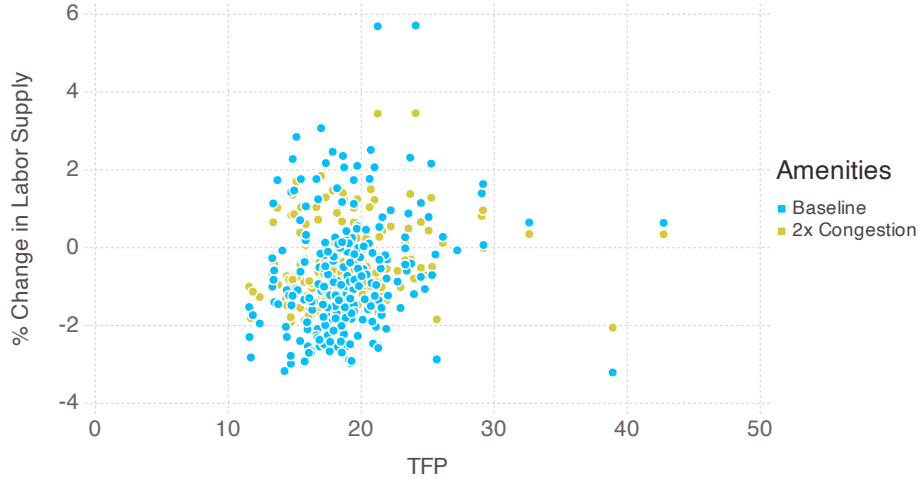
spatial literature regarding New York's land-use regulations. The counterfactual increases the floor-area ratio limit in all commercial buildings in New York to the highest one that we observe in the dataset.

This analysis first requires estimating the contribution of floor-area ratio limits to our overall measure of regulation at the parcel level, and then using that estimate to change each parcel's τ_Z to reflect the change of increasing each parcel's floor-area ratio up to the maximum observed. We therefore begin with our baseline 2018 steady state distortions, and regress τ_Z on FAR_Z at the parcel/zoning code level, weighting zoning codes by their total building value:

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

The regression projects our measure of overall regulatory distortions onto the observed floor-area ratio to capture its individual impact. The regression estimate is then used to construct τ'_Z , which modifies τ_Z (the baseline distortion) based on the difference between its baseline FAR and the highest observed in the dataset,

Figure 11: Labor reallocation from $T_j = 1$ for baseline congestion v. $2\times$ congestion



Notes: Each point is an MSA. This figure compares the change in labor across MSAs in the baseline counterfactual to doubling the size of the congestion externality. The horizontal axis corresponds to an MSA's TFP A_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.

which we denote as FAR_{\max} :²⁵

$$\log \tau'_Z = \alpha \log(FAR_{\max}) + \epsilon_z$$

We then aggregate the τ'_Z to obtain counterfactual T'_j and D'_j .²⁶

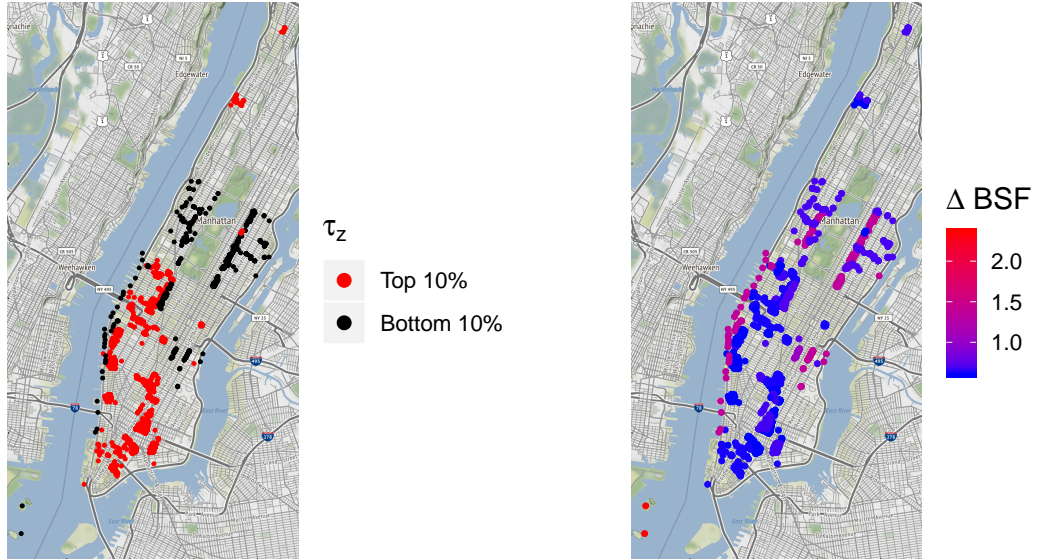
The results are reported in Table 7. To preserve consistency with the rest of our analysis, we report MSA-level counterfactual changes even though the reform is just within New York City. We find that MSA output increases by 1.8%, the MSA building stock increases by 6%, the number of workers in the MSA remains unchanged, and commercial real-estate prices drop by 4% within the MSA.

Figure 12 illustrates the counterfactual changes for Manhattan, the most well-known of New York City's five boroughs. We plot the buildings in the most- and least-regulated deciles of zoning codes in Manhattan, alongside the change in their building square footage in the new steady state following the floor-area ratio reg-

²⁵We "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 τ'_Z would be greater than 1, we set $\tau'_Z = 1$.

²⁶The aggregation is identical to Section 5.1.4. Note, we only use the subsample of buildings where we can find a floor-area ratio for this exercise. See Appendix A.2 for details.

Figure 12: Zoning and counterfactual NYC



Notes: The left panel plots the Manhattan buildings which are subject to the most- and least- regulated ten percent of zoning codes. The right panel plots the change in their square footages in the new steady state after counterfactually moving all FAR up to the highest that we observe.

Table 7: MSA-level gains from maximal floor-area ratios in NYC

Outcome:	Y_{NYC}	B_{NYC}	L_{NYC}	P_{NYC}
Change Rel. to Baseline	+1.8%	+6.0%	+0.7%	-4.0%

ulatory reform. Business activity moves from Midtown, which already has large floor-area ratios, to the Upper East and West sides, which have much lower floor-area ratios and which are known for opposing 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. One is developing a model of the U.S. economy in which commercial real estate is a productive, regulated, and potentially misallocated component of the capital stock. The model yields an intuitive formula for identifying the extent to which commercial real estate investment deci-

sions are distorted by land-use regulations. Second, we apply the theory to the near-universe of commercial property tax records from CoreLogic to estimate a model-consistent index of commercial land-use regulations. Our analysis uses rich, address-level microdata from municipal property tax assessments compiled by CoreLogic.

We validate the index of commercial regulations by hand-collecting 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 conclusion within the literature that metro areas in Texas such as Dallas-Fort Worth and Houston face significantly weaker commercial real estate regulation than metros in California.

Third, we use our distortion measure and model to evaluate the effects of both national and local changes to commercial regulations. In our primary exercise, we raise average city-level regulations up to a deregulated benchmark MSA (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 coastal states.

One benefit of our framework is that it allows for very granular counterfactuals within narrowly defined geographies. Since we recover regulatory distortions at the address-level, we can project our distortions onto specific features of zoning codes such as floor-area ratios. We apply this counterfactual to New York City and find that raising floor-area ratios to the maximum level in the city would reallocate business activity toward the Upper West Side of Manhattan, and yield local output gains of 1.8%.

Our framework opens a number of avenues for future research. The model and empirical analyses can be extended to include residential land-use regulations, heterogeneous workers, 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 regulatory distortions.

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ONLINE APPENDIX

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 and Appendix [A.2](#) describes our hand-collected zoning code data.

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.²⁷ 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 8 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

²⁷To 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.

Table 8: 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
ΣTV	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 ΣTV in the filtered sample; and the average age \bar{a} in the full and filtered sample.

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 9, we further break down the buildings in our filtered sample by CoreLogic's one-digit land use codes. "Commercial"²⁸ 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 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

²⁸The notion of "commercial" buildings in our model encompasses all the categories in this list and is broader than CoreLogic's usage of the term "commercial."

Table 9: Building Types

Code	Type	Share of <i>TV</i>
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.

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, hence we do not use appraised value. CoreLogic also provides a "calculated" value based on which of these three they think is the closest to the true market value. The “valuation approach” used by the assessor to divide the total value of the building into the improvement value and the land value is not recorded in our dataset. However, [Wisconsin \(2021\)](#) provides a useful description the most common land and improvement valuation approaches. To value land, “the sales comparison approach” measures the value of land based on comparable vacant lot sales. The “abstraction approach” measures the total value of the property and then deducts the cost of improvements to arrive at the land value. To value improvements, the sales comparison approach can also be used (in conjunction with a land value) but often times the “cost approach” is adopted. The cost approach values improvements at their replacement cost by using proprietary cost manuals. Total value is then the sum of the land value and improvement value. All of these methods are consistent with our accounting framework in Equation (8), which values improvements at their re- placement cost while treating land as the residual claimant to all remaining profits generated by the property.

We use CoreLogic’s preferred "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 E.

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.1.1 Summary Statistics

In this section we provide some additional descriptive statistics to help understand what drives the variance in building values. We define the net present value of payments to a building as the *building value*, $BV_{i,t}$:

$$BV_{i,t} = \sum_{s=t}^{\infty} (\beta(1 - \delta_b))^{s-t} r_{b,j,t} B_{i,t}. \quad (28)$$

We see that the log of land value per land square foot is more dispersed than the log of building value per building square foot (a measure of revenue per square foot) or the log of improvement value per building square foot (a measure of costs per square foot.)

	Mean	Variance	IQR
$\log(MV_i/TV_i)$	-.796	.817	0.8
$\log(LV_i/TV_i)$	-1.16	.873	3.01
$\log(BV_i/BSF_i)$	4.12	1.33	1.28
$\log(LV_i/x_i)$	-.647	7.60	4.29
$\log(MV_i/BSF_i)$	3.66	1.41	1.27

Notes: In this table we plot the mean, variance, and interquartile range (p75-p25) of several logged ratios of our key variables. *MV* means improvement value, *LV* means land value, *TV* means total value, *BV* is the model-implied building value derived in equation 28, *BSF* is building square footage, and *x* is land square footage.

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 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.

We report some key summary statistics of our measures of regulation in [Table 10](#).

Table 10: Regulation Summary Statistics

Statistic	NYC FAR	DC Height Limit
Mean	4.2	66
Median	2.2	65
Standard Deviation	3.7	25
Min	0.5	20
Max	15.0	130

Notes: This table reports the distribution of floor-area ratios in New York City and height limits (in feet) in Washington, DC.

A.3 Additional validation: San Francisco

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

In Figures 13 and 14, 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 τ_Z and map the top decile (least-regulating, 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.

Figure 13: Model regulatory distortion

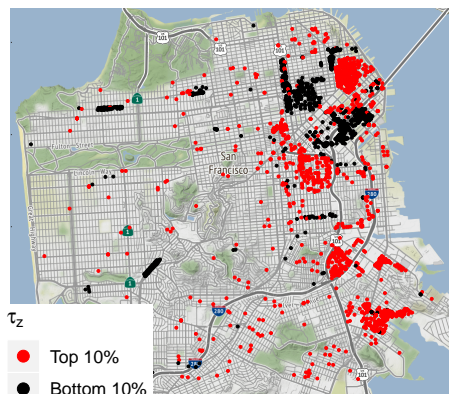
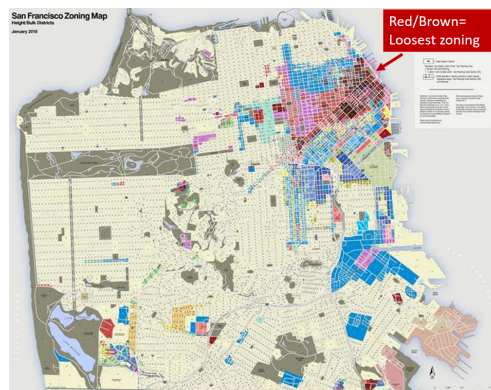


Figure 14: SF Height Limit Zoning Map, 2021



Notes: In Figure 13, we plot zoning code-level distortions τ_Z in San Francisco for the most- and least- distorted zoning codes. We rank zoning codes by their τ_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) τ_Z , and black dots correspond to buildings with the lowest (most regulating) τ_Z . In Figure 13, 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.

B Aggregation Results

B.1 Individual and Aggregate Developers

In this section we establish the connection between the problems of the individual developer and the aggregate developer. In order to do so, we solve equations (5) and (11), 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 (5) 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 developer's building production function in terms of prices and exogenous parameters:

$$B_i^N = (p_j \tau_i \beta \gamma)^{\frac{\gamma}{1-\gamma}} C_i \quad (29)$$

Only a random share δ_b of buildings depreciate and are rebuilt in each period, hence we can recover the sum of individual developers' improvement demand and building supply curves in each period. Given the large number of parcels in each region, we assume the law of large numbers holds and thus $\sum_{i \in j} B_i^N = \delta_b B_j$. Note that the improvement demand curve is in units of the final good.

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

Next we solve equation (11) for both quantity of improvements demanded and quantity of new construction supplied, mirroring the derivation above. Note that the technology that the representative developer 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. We define $\sum_{i \in j} q_i m_i = m_j$.

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

It is straightforward to use equations (12), (13), and (14) 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 developer are identical to the summed-up demand and supply curves of the individual developers.

B.2 Estimating τ_i and T_j

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

We first recover τ_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 δ_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 :

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

And let us again substitute MV :

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

Let us rearrange this expression in order to get γ in terms of TV , MV , and τ :

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

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

This yields equation (19).

We now turn to T_j and reintroduce the parcel-level index i . We can replace τ_i on the left-hand side of equation (16) with equation (19) and recover equation (18):

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

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

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 (18):

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

C Age Regressions

We regress parcel-level τ on age, as well as county fixed effects, for the subset of parcels where we have building age, and report the results in Table 15. We weight parcels by BV . Most notably, the regression R-squared is below 5%, suggesting building age explains very little of our regulatory distortion. We also find that the impact of age on measured τ is surprisingly small—a 50-year-old building would on average have a τ 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 τ seen in Figure 2.²⁹

Figure 15: The role of building vintages: Regression of regulatory distortion (τ) on age

	(1)	(2)	(3)	(4)	(5)	(6)
	τ	τ	$\log \tau$	$\log \tau$	$\log \tau$	$\log \tau$
Age	-0.00189*** (3.44e-06)	-0.00188*** (3.48e-06)	-0.00350*** (6.96e-06)	-0.00350*** (7.20e-06)		
$\log(\text{Age} + 1)$					-0.105*** (0.000225)	-0.0993*** (0.000227)
Constant	0.910*** (0.000162)	0.910*** (0.000158)	-0.116*** (0.000328)	-0.116*** (0.000327)	0.0995*** (0.000765)	0.0820*** (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 τ on age, either in levels or logs, with and without controls for the county in which the parcel is located.

²⁹Admittedly, this may understate the impact of aging on τ 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 16, we report the results of naive regressions of amenities on congestion and labor supply, with and without weighting by the labor supply of each location. Columns (1) and (2) reveal a positive relationship between amenities and labor supply, and columns (3) and (4) reveal a negative relationship between amenities congestion (L/X).

Figure 16: Naive Regressions

	Log Amenities			
	(1)	(2)	(3)	(4)
(Intercept)	10.090*** (0.015)	10.072*** (0.013)	8.534*** (0.395)	6.508*** (0.884)
Log Labor Supply	0.288*** (0.008)	0.265*** (0.007)		
Log Congestion			-0.052** (0.019)	-0.166*** (0.041)
Estimator	OLS	OLS	OLS	OLS
N	239	239	239	239
R^2	0.829	0.884	0.025	0.147

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.

As explained in the text, the relationships in Table 16 are endogenous. We address the endogeneity by using the model itself to generate instrumental variables (e.g. [Anderson and van Wincoop \(2003\)](#), [Allen, Arkolakis, and Takahashi \(2020\)](#), [Walsh \(2019\)](#), and [Rossi-Hansberg, Sarte, and Schwartzman \(2019\)](#)). The first instrument is the model-generated counterfactual congestion L'/X . We re-solve the model setting TFP and amenities to their average value and turning off regulatory distortions, so that populations only differ due to the building supply shifter Ψ_j . This is a measure of the ease of construction in a city—it affects population indirectly by making it cheaper to build, thereby increasing wages and attracting a

larger workforce. The resulting L'/X is the instrument. The second is to directly use the supply shifter in the regional building supply function Ψ , where the assumption is that the ease of building and the availability of commercial land are uncorrelated with exogenous amenities. The third is to directly use the supply of commercial land X . The fourth is the supply shifter per unit of land, a rough measure of how easy it is to build on each unit of land. The fifth is a quadratic in the model-generated counterfactual L'/X .

Table 17 reports the results. Columns (1) and (2) use L'/X as instruments for congestion and they both yield negative point estimates, implying greater congestion causes lower amenities. Column (2) is the most “pessimistic” estimate of all (10) reported columns. To provide the most conservative estimates of the way regulation can affect labor relocation, we adopt this specification in our baseline model. We additionally explore exogenous amenities.

Figure 17: Instrumenting for Congestion L/X

	Log Amenity									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(Intercept)	3.305*** (0.828)	-1.697 (1.573)	3.423*** (0.801)	-1.232 (1.456)	38.350 (93.900)	10.905 (7.140)	6.007*** (1.653)	4.252* (2.061)	72.834*** (18.067)	54.975 (32.063)
Log Congestion	-0.296*** (0.039)	-0.542*** (0.073)	-0.290*** (0.037)	-0.521*** (0.068)	1.340 (4.383)	0.036 (0.328)	-0.169* (0.077)	-0.269** (0.095)	6.352*** (1.752)	4.780 (3.076)
Log Congestion Squared									0.158*** (0.042)	0.125 (0.074)
Weights	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Instrument	L'/X	L'/X	Ψ	Ψ	X	X	Ψ/X	Ψ/X	$L'/X, (L'/X)^2$	$L'/X, (L'/X)^2$
N	239	239	239	239	239	239	239	239	239	239
R^2	-0.540	-0.611	-0.515	-0.528	-18.352	-0.071	-0.107	0.090	-1.757	-1.057
F	58.327	54.807	59.986	59.088	0.094	0.012	4.814	8.110	18.077	30.005
First-stage F statistic	214.130	87.263	243.108	98.712	0.108	6.344	15.482	42.733	14.219	4.556

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.

Lastly, in Table 18, we instrument log labor supply (instead of congestion) with the same five instruments. By and large, these coefficients are smaller than the ones in the naive regression in Table 16. 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; however, as discussed above, we use the most severe estimate of negative congestion externalities on amenities in order to provide the most conservative labor reallocation estimates in our baseline model.

Figure 18: Instrumenting for Labor Supply L

	Log Amenities									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(Intercept)	10.004*** (0.162)	10.124*** (0.154)	10.075*** (0.016)	10.070*** (0.013)	10.045*** (0.156)	10.109*** (0.090)	10.087*** (0.086)	10.056*** (0.028)	9.427*** (2.809)	7.041 (100.114)
Log Labor Supply	0.233* (0.103)	-0.019 (0.736)	0.278*** (0.009)	0.275*** (0.010)	0.259** (0.099)	0.060 (0.413)	0.286*** (0.055)	0.349*** (0.072)	2.132 (9.669)	3.683 (125.712)
Log Labor Supply Squared									0.936 (4.612)	1.349 (43.533)
Instrument Weights	L' No	L' Yes	Ψ No	Ψ Yes	X No	X Yes	Ψ/X No	Ψ/X Yes	$L', (L')^2$ No	$L', (L')^2$ Yes
N	239	239	239	239	239	239	239	239	239	239
R^2	0.799	-0.131	0.828	0.883	0.820	0.353	0.829	0.793	-16.382	-178.020
F	5.152	0.001	1011.586	768.938	6.832	0.021	27.128	23.610	0.040	0.001
First-stage F statistic	1.934	0.146	264.506	355.049	1.994	0.254	5.791	4.168	0.022	0.000

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.

E Robustness Exercises

In this section, we test the robustness of our results to different data filtering choices and calibrations. In particular, we re-estimate 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 Tables 11 and 12.

Table 11: Robustness Exercises: Data Selection

	(1) Baseline	(2) Mkt. Value	(3) Assd. Value	(4) No Agriculture	(5) No Industry	(6) Young Buildings
$\% \Delta Y_j$	3.0%	3.2%	2.9%	2.9%	2.6%	1.4%
$\% \Delta L_j$	-0.8%	-0.8%	-0.8%	-0.8%	-0.5%	-0.4%
$\% \Delta K_j$	2.6%	2.8%	2.6%	2.6%	2.3%	1.3%
$\% \Delta B_j$	17.6%	23.1%	16.6%	16.9%	14.9%	8.4%
$\% \Delta$ Landlord Profits	-2.8%	-3.0%	-2.7%	-2.7%	-3.5%	-1.5%
$\% \Delta c$	2.2%	2.4%	2.2%	2.1%	1.8%	1.0%
$\% \Delta$ Consumption Equiv.	2.9%	3.1%	2.8%	2.8%	2.3%	1.4%

Notes: This table re-runs our baseline counterfactual using several different cuts of the data to test the robustness of our results. The different exercises are described in the text, and the outcome variables are the same as in 5.

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 (columns (2) and (3), respectively). 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 whether agricultural parcels (which arguably use a different technology with a different γ) skew our results in column (4). 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 γ 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.

Column (5) repeats the same exercise except excluding industrial buildings, alleviating concerns that certain structure types have tighter natural height limits. We find that our baseline results are only mildly attenuated, as can be expected given that industrial buildings comprise only one-fifth of the total value of our sample.

Finally, in column (6), 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 8](#). The impact of deregulation falls by roughly half when using this restricted sample.

Table 12: Robustness Exercises: Parameter Values

	(1) $\chi = .13$	(2) $\chi = .10$	(3) $\gamma = .89$	(4) $\gamma = .97$
$\% \Delta Y_j$	2.5%	1.9%	2.3%	4.1%
$\% \Delta L_j$	-0.6%	-0.5%	-0.6%	-1.1%
$\% \Delta K_j$	2.2%	1.8%	2.0%	3.6%
$\% \Delta B_j$	17.1%	16.6%	16.1%	30.7%
$\% \Delta$ Landlord Profits	-3.3%	-4.0%	-2.2%	-3.7%
$\% \Delta c$	1.8%	1.4%	1.7%	3.1%
$\% \Delta$ Consumption Equiv.	2.4%	1.9%	2.2%	4.1%

Notes: This table re-runs our baseline counterfactual under several different parameter values to test the robustness of our results. The different exercises are described in the text, and the outcome variables are the same as in [5](#).

We next test the sensitivity of our results to alternate parameter values in [Table 12](#). Columns (1) and (2) vary χ , the building share of production. A lower building share implies smaller gains from deregulation, as increasing the stock of buildings by a given amount leads to a lower increase in output.

Our baseline model infers $\chi \sim .15$ 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, χ 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 16 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 χY 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, columns (1) and (2) in [Table 12](#) test how our results change at

different values of χ , 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 α so that factor shares sum to 1. Starting from equation (23), 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 χ , but even at $\chi = 0.1$ the gains are significant.

Finally, columns (3) and (4) of Table 12 re-test our results for the highest³⁰ and lowest values of γ (0.97 and 0.89) taken from Table 1. We drop the assumption that no city can have negative regulations and allow $T > 1$ in the case where we set $\gamma = 0.89$. Unsurprisingly, the gains from deregulation increase with γ . Still, they are substantial even at the lowest γ that we consider.

³⁰In the case where we set γ to its highest value of 0.97, we set $p_j = 1$ for all cities for the sake of numerical stability and then allow building supply B_j , shifter Φ_j , and TFP A_j to rescale. Recall that we recover the supply shifter as $B_j/p_j^\gamma 1 - \gamma$, which becomes unstable for very high values of γ . This changes the interpretation of B and A (one square foot of building no longer yields one “efficiency unit” in all cities), but does not otherwise alter our results.

F 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 τ_i terms in equations (13) and (14) and recovering new values for T_j and D_j . When altering zoning codes, we alter τ_z and then re-aggregate following the formulas in the text. Recall the building supply curve from equation (17) and denote Ψ_j^p as the pre-counterfactual Ψ_j . If we increase D_j by some factor Φ_1 and T_j by some factor Φ_2 , we increase Ψ_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_j , D_j , and Ψ_j , 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_j in terms of Y_j, B_j , and K_j :

$$L_j = \left(\frac{Y_j}{A_j K_j^{1-\alpha-\chi_j} B_j^{\chi_j}} \right)^{\frac{1}{\alpha}} \quad (30)$$

We can also use our supply function to recover B_j in terms of Y_j :

$$\begin{aligned} BV_j = p_j B_j &= \frac{\chi_j Y_j}{1 - \beta(1 - \delta_b)} \\ BV_j = p_j B_j &= p_j^{1-\gamma} \Psi_j \\ p_j &= \left(\frac{BV_j}{\Psi_j} \right)^{1-\gamma} \\ B_j = BV_j / p_j &= BV_j^\gamma (\Psi_j)^{1-\gamma} \\ &= \left(\frac{\chi_j Y_j}{1 - \beta(1 - \delta_b)} \right)^\gamma (\Psi_j)^{1-\gamma} \end{aligned}$$

Because we already solved for K_j in terms of Y_j , we can now obtain labor entirely in terms of a guess for Y_j :

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

Now we replace L_j in equation (30) with the above expression to obtain:

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

We rearrange this expression one last time to arrive at the equation upon which our algorithm iterates:

$$Y_j = \left(\left(A_j (K_j)^{1-\alpha-\chi_j} (B_j)^{\chi_j} \right)^{\frac{1}{\eta}+1} \left(Y_j (a_j^{1+\frac{1}{\eta}} \left(\sum_k \theta_k Y_k \right)^{-\sigma} \alpha) \right) \right)^{\frac{\alpha}{\frac{1}{\eta}+1}} \quad (31)$$

We proceed as follows: (1) guess the vector $\{Y_j\}$, (2) this yields the right-hand-side of equation (31), and (3) the left-hand-side of equation (31) yield the update for $\{Y_j\}$. In practice, we use a “damped” algorithm that slowly updates the guesses for $\{Y_j\}$.

F.1 Endogenous Amenities

In this appendix, we detail how we compute counterfactuals 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 (30). Second, we have already computed the relationship between amenities and labor supply in equation (26) and computed the key coefficient μ in the process. We can combine these expressions, along with the original amenity vector a_j and labor supply vector L_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 (32):

$$r_j = \frac{a_j^{cf}}{a_j} = \frac{\exp(\mu \log(L_j^{cf} / X_j))}{\exp(\mu \log(L_j / X_j))} = \left(\frac{L_j^{cf}}{L_j} \right)^\mu \quad (32)$$

We multiply amenities in equation (31) 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.

F.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 λ such that the consumer is indifferent between it and B. Below we show how to use equation (21) to obtain λ . Note that, in the case where amenities depend on congestion, we must combine this with the method described above in Appendix F.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:

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

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 5.

G Planner's Problem

In the presence of congestion externalities, a social planner's solution will generically differ from the undistorted decentralized equilibrium. In this section we therefore compare the current equilibrium and the baseline deregulated equilibrium to the solution of the planner's problem.

To obtain the planner's solution, we use a modified version of the code that calculates decentralized counterfactuals where the planner internalizes congestion effects and where we set $T = 1$ for all cities. As there are no other externalities, this version of the decentralized equilibrium where agents take congestion into account coincides with the planner's problem.

Currently, the disamenity from work in each city is:

$$\frac{1}{1 + \frac{1}{\eta}} \left(\frac{L_j}{a_j} \right)^{1 + \frac{1}{\eta}}$$

Plugging in our specification for endogenous amenities from equation (25), we obtain a new expression:

$$\frac{1}{1 + \frac{1}{\eta}} \left(\frac{L_j}{\exp(e_j)(L_j/X_j)^\mu} \right)^{1 + \frac{1}{\eta}}$$

We want a modified \tilde{a} , $\tilde{\eta}$ that makes the decentralization coincide with the problem of a planner that internalizes congestion:

$$\frac{1}{1 + \frac{1}{\tilde{\eta}}} \left(\frac{L_j}{\tilde{a}_j} \right)^{1 + \frac{1}{\tilde{\eta}}} = \frac{1}{1 + \frac{1}{\eta}} \left(\frac{L_j}{\exp(e_j)(L_j/X_j)^\mu} \right)^{1 + \frac{1}{\eta}}$$

Some algebra yields:

$$\tilde{\eta} = \frac{1}{(1 + \frac{1}{\eta})(1 - \mu) - 1}$$

$$\tilde{a}_j = \left(\frac{1 + \frac{1}{\tilde{\eta}}}{1 + \frac{1}{\eta}} \left(\frac{1}{\exp(e_j)X_j^{-\mu}} \right)^{1 + \frac{1}{\eta}} \right)^{\frac{-1}{1 + \frac{1}{\tilde{\eta}}}}$$

Note that we keep η and a at their original level for remote work.

In Table 13, we compare aggregates in the deregulated economy and the planned economy, as well as in a version of the planned economy where the planner is subject to the same distortions T_j . All variables are expressed as ratios to their

level in the original equilibrium except for the consumption equivalent gain. The deregulated and planned economy look extremely similar to each other. It may seem surprising that the deregulated economy has a higher steady state welfare than the planned economy, but note that the capital stock is much higher. Just as the golden rule capital stock maximizes consumption but is not the steady state of the neoclassical growth model, the planner does not find it optimal to stay at such a high capital stock. The planner allocates more people to remote work, which is unsurprising as remote work does not generate congestion externalities.

Table 13: Planner Problem

	Deregulated	Planner	Constrained Planner
$\% \Delta Y_j$	3.0%	-7.9%	-10.4%
$\% \Delta L_j$	-0.8%	-11.6%	-10.9%
$\% \Delta K_j$	2.6%	-6.3%	-8.3%
$\% \Delta B_j$	17.6%	2.2%	-13.3%
$\% \Delta L_r$	-8.3%	44.0%	56.0%
$\% \Delta$ Consumption Equiv.	2.9%	2.1%	-0.8%

Notes: This table reports the percentage change in outcome variables under three new equilibria. The “Deregulated” equilibrium corresponds to our baseline exercise of setting $T = 1$ for all cities, the “Planner” equilibrium is the steady state of an economy where all variables are set by a social planner, and the “Constrained Planner” equilibrium is similar except the planner faces the same wedges T as developers do in the data. The outcome variables are the same as in Table 5.

Interestingly, the labor forces in each city in the planned economy are exactly 85.6% as large as in the decentralized economy, whereas this ratio varies between 83% and 90% when comparing the planned economy to the original regulated equilibrium. This is a consequence of our constant-elasticity externality: the planner wants to shift labor down uniformly relative to the deregulated benchmark, but the variation in the regulations we see in the data leads workers to be misallocated across cities. Hence, dispersion in the strictness of zoning regulations across cities leads to inefficient misallocation.

H Non-Constant τ and the Elasticity of Building Supply

We have assumed that τ is a fixed parcel-level constant, and that it does not get smaller (more restrictive) as the developer 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.³¹

First, notice that from equation 29, 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 developers 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 τ a decreasing function of the level of construction breaks the link between the improvement share and the price elasticity of building supply. We specify τ as $\tau(m) = \tau_0 m^{-\zeta}$, where $\zeta > 0$. That is, we assume that regulations get more restrictive as the developer tries to increase the quantity of improvements that they put on a parcel. For clarity, we drop subscripts and focus on a parcel where τ_0 , x , and z are equal to 1.³² 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 developer as:

³¹We thank Giacomo Ponzetto and Jacob Adenbaum for their feedback on this topic. We combined their suggestions for how a non-constant τ could work into the example in this Appendix.

³²The 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.

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

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

Now let us return to our original model, where τ 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 τ , 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 τ . 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 τ is a promising direction for future work, but it would likely not change our baseline results.