

# How Do Cities Change When We Work from Home?\*

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## Abstract

How would the shape of our cities change if there were a permanent increase in working from home? We study this question using a quantitative model of the Los Angeles metropolitan area featuring local agglomeration externalities and endogenous traffic congestion. We find three important effects: (1) Jobs move to the core of the city, while residents move to the periphery. (2) Traffic congestion eases and travel times drop. (3) Average real estate prices fall, with declines in core locations and increases in the periphery. Workers who are able to switch to telecommuting enjoy large welfare gains by saving commute time and moving to more affordable neighborhoods. Workers who continue to work on-site enjoy modest welfare gains due to lower commute times, improved access to jobs, and the fall in average real estate prices.

*Keywords:* COVID-19, urban, work at home, commuting, spatial equilibrium.

*JEL codes:* E24, J22, J80, R14, R31, R33, R41.

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# 1 Introduction

The potential savings in overhead costs and commuting time from remote work are significant.<sup>1</sup> Technological conditions have been improving steadily for years, yet the fraction of Americans working from home has remained small. In 2019, just 4.2% of all workers worked from home. In 2020, COVID-19 social distancing requirements forced many companies and organizations to pay a part of the fixed cost of transition to remote work. Abundant survey evidence suggests that many now plan to continue remote work at much higher rates even after the pandemic is over.<sup>2</sup>

A lasting increase in working from home could have far-ranging consequences for the distribution of economic activity inside urban areas.<sup>3</sup> One of the critical factors driving workers' location choices is the need to commute between their job and their residence. Increasing the number of telecommuters makes this trade-off moot for a significant fraction of the workforce. In this paper, we quantify the potential impact of this change using a general equilibrium model of internal city structure. The model features employment, residence, and real estate development choices, as well as local agglomeration and congestion externalities, and endogenous traffic congestion across 3,846 non-rural census tracts of the Los Angeles-Long Beach combined statistical area.

We calibrate our model to match residence and employment patterns prevalent in Los Angeles during the period 2012–2016, with an average of 3.7% of workers working from home. We then conduct a counterfactual exercise in which we gradually increase the fraction of telecommuters all the way to 33%, which according to [Dingel and Neiman \(2020\)](#), corresponds to the share of L.A. metro area workers whose jobs could be performed mostly from home. The effects on city structure over the long run can be broken into three categories.

First, jobs relocate to the core of the urban area, while residents move to the periphery. The largest driver of this effect is workers who previously had to commute and can now work at home. They tend to move farther away from the urban core to locations with more affordable houses. This increases the demand for real estate in peripheral locations and lowers the demand in the core, pushing jobs from the suburbs into more central locations.

Second, average commuting times fall, while commuting distances increase. Since fewer workers commute, traffic congestion eases, which increases average speed of travel. Commuters take advantage of this and also move farther away from their workplaces to live in locations with lower real estate prices.

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<sup>1</sup>[Mas and Pallais \(2020\)](#) provide an overview of the current state of research in telecommuting. [Bloom, Liang, Roberts, and Ying \(2015\)](#) present experimental evidence that telework increases employee work satisfaction without necessarily reducing their productivity.

<sup>2</sup>A May 2020 survey by [Barrero, Bloom, and Davis \(2020\)](#) finds that 16.6% of paid work days will be done from home after the pandemic ends, compared to 5.5% in 2019. Results of a survey by [Bartik, Cullen, Glaeser, Luca, and Stanton \(2020\)](#) also indicate that remote work will be much more common after the pandemic.

<sup>3</sup>A study by Upwork in October 2020 finds that since the beginning of the pandemic 2% of survey participants had already moved residences because of the ability to work at home and another 6% planned to do so ([Ozimek, 2020](#)).

Third, average real estate prices fall. As many workers move into distant suburbs, prices in the periphery increase. However, these price increases are more than offset by the decline of prices in the core. This decline is driven by two factors. The first is the decline in demand for residential real estate in core locations. The second is the reduced demand for on-site office space from workers who now telecommute. In the counterfactual where 33% of workers telecommute, average house prices fall by nearly 6%.

In addition to these three broad trends, our quantitative model predicts considerable heterogeneity in outcomes that is not accounted for by the simple core-periphery continuum. Within the core, locations with high productivity gain jobs while less productive locations lose them. At all distances from the center, locations with better exogenous residential amenities either gain more or lose fewer residents than less attractive equi-distant locations. Overall, the single monocentric dimension of distance from the center only accounts for about half of all variation in predicted outcomes.

The shift to telecommuting implies changes in the income both of workers and the owners of real estate. On the one hand, labor productivity is pushed upward as jobs leave peripheral areas, and employment in the most productive tracts increases. Productivity receives a further boost from the accompanying increase in spatial agglomeration externalities. Simultaneously, labor productivity is pushed downward because more employees work at home and teleworkers do not contribute to agglomeration. In our quantitative exercise, these two effects offset each other almost completely, leading to very small increases in average wages. At the same time, changes in the spatial distribution of real estate demand and the reduced need for office space lead to lower real estate prices and thus a reduction in the income earned by landowners and property developers.

Our results conform fundamentally with previous theoretical findings by, for example, [Safirova \(2003\)](#), [Rhee \(2008\)](#), and [Larson and Zhao \(2017\)](#). Recent work by [Lennox \(2020\)](#) explores the effects of working from home in an Australian context using a quantitative spatial equilibrium model. A related study of ours, [Delventhal and Parkhomenko \(2021\)](#), extends the analysis to the entire U.S. and multiple types of telecommuters. [Behrens, Kichko, and Thisse \(2021\)](#) and [Davis, Ghent, and Gregory \(2021\)](#) develop stylized city models with on-site and remote work in order to study the implications of greater work from home on the demand for floorspace, productivity, income inequality, and city structure. In line with the predictions of our model, [Althoff, Eckert, Ganapati, and Walsh \(2020\)](#) document a relocation of residents from the densest to the least dense locations in the U.S. during the COVID-19 pandemic, while [Gupta, Peeters, Mittal, and Nieuwerburgh \(2021\)](#) and [Liu and Su \(2021\)](#) show that bid-rent gradients in U.S. cities have flattened reflecting higher demand for low density and lower demand for urban amenities.

This paper also follows a number of recent efforts to assess the impact of urban policies and transport infrastructure on city structure, such as those by [Ahlfeldt, Redding, Sturm, and Wolf](#)

(2015), Tsivanidis (2019), Owens, Rossi-Hansberg, and Sarte (2020), Anas (2020), and Severen (2021). Our paper uses a similar framework to assess the impact of a change to the underlying technology of production on urban structure.

The remainder of the paper is organized as follows. Section 2 describes the model. Section 3 provides an overview of how we calibrate the model. Section 4 describes and discusses the counterfactual exercises. Section 5 concludes.

## 2 Model

Consider an urban area that consists of a finite set  $\mathcal{I}$  of discrete locations, each populated by workers, firms, and floorspace developers. Total employment is fixed and normalized to 1.

*Workers* supply their labor to firms and consume residential floor space and a numeraire consumption good. Workers suffer disutility from time spent in commuting between home and work, and this time depends endogenously on aggregate traffic volume. Their choice of residence and employment locations depends on the commuting time, wages at the place of employment, housing costs and amenities at the place of residence, and idiosyncratic location preferences. Residential amenities depend on agglomeration spillovers, which are increasing in the residential density of nearby locations. *Firms* use labor and commercial floorspace to produce the consumption good, which is traded costlessly inside the urban area. Firms’ total factor productivity depends on agglomeration spillovers, which are increasing in the density of employment in nearby locations. *Developers* use land and the numeraire to produce floorspace, which can be put to residential or commercial use. The supply of floor space in each location is restricted by zoning regulations that limit commercial development and overall density.

We introduce work from home by proposing a second type of worker—the telecommuter. Telecommuters only come to their worksite a small fraction of workdays and thus suffer much less disutility from commuting. On the days that they are not in the office, they do not use commercial floorspace and instead produce output using “home office” floorspace in their residence location. Working from home uses floorspace less intensively than on-site work, has a different total factor productivity, and neither contributes to nor benefits from agglomeration spillovers.

This model is similar in many respects to Ahlfeldt, Redding, Sturm, and Wolf (2015). The remainder of the section presents the model and Appendix B provides additional details.

### 2.1 Workers

#### 2.1.1 Commuters and Telecommuters

Before choosing where to work and where to live, workers draw their commuter type. With probability  $\psi \geq 0$ , a worker becomes a “telecommuter.” With probability  $1 - \psi$ , the worker



becomes a “commuter.” The two types differ in the fraction of workdays they commute to work,  $\theta$ . Commuters must come daily and therefore have  $\theta = 1$ , while telecommuters have  $\theta = \theta^T < 1$ .

### 2.1.2 Preferences

A worker  $n$  who resides in location  $i \in \mathcal{I}$ , works in location  $j \in \mathcal{I}$ , and has to commute from  $i$  to  $j$  a fraction  $\theta$  of time, enjoys utility

$$U_{ijn}(\theta, c, h) = \frac{z_{ijn}}{d_{ij}(\theta)} \left( \frac{c}{1 - \gamma} \right)^{1-\gamma} \left( \frac{h}{\gamma} \right)^\gamma, \quad (1)$$

where  $z_{ijn}$  represents an idiosyncratic preference shock for the pair of locations  $i$  and  $j$ , and  $d_{ij}(\theta)$  is the disutility from commuting given by  $d_{ij}(\theta) = (1 - \theta) + \theta e^{\kappa t_{ij}}$ . Individuals consume  $c$  units of the final good and  $h$  units of housing. The share of housing in expenditures is given by  $\gamma$ , and consumption choices are subject to the budget constraint  $(1 + \tau)w_{ij}(\theta) = c + q_i h$ . In this constraint,  $w_{ij}(\theta)$  is the wage earned by a worker who commutes from  $i$  to  $j$  a fraction  $\theta$  of days, and  $q_i$  is the price of residential floorspace in location  $i$ . In addition to wages, workers also earn proportional transfers,  $\tau w_{ij}(\theta)$ , which distribute income from land and the consumption good sold to real estate developers equally among all city workers.

Idiosyncratic shocks  $z_{ijn}$  are drawn from a Frèchet distribution with c.d.f.  $F_z(z) = e^{-z^{-\epsilon}}$ . The indirect utility of worker  $n$  who lives in location  $i$  and works in location  $j$  is given by  $u_{ijn}(\theta) = z_{ijn}v_{ij}(\theta)$ , where

$$v_{ij}(\theta) \equiv \frac{X_i E_j w_{ij}(\theta)}{d_{ij}(\theta) q_i^\gamma} \quad (2)$$

is the utility obtained by a worker, net of the preference shock. In the above formulation,  $X_i$  is the average amenity derived from living in location  $i$ , and  $E_j$  is the amenity derived from working in location  $j$ .

Commuting time is a function of total vehicle miles traveled and road capacity in the entire city:  $t_{ij} = t_{ij}(VMT, Cap)$ . We assume that the capacity is fixed and the elasticity of time on each link  $(i, j)$  with respect to total volume is a constant  $\epsilon_V$ . Appendix E provides more details.

### 2.1.3 Location Choices

Optimal choices imply that the probability that a worker with a given  $\theta$  chooses to live in location  $i$  and work in location  $j$  is

$$\pi_{ij}(\theta) = \frac{(X_i E_j w_{ij}(\theta))^\epsilon (d_{ij}(\theta) q_i^\gamma)^{-\epsilon}}{\sum_{r \in \mathcal{I}} \sum_{s \in \mathcal{I}} (X_r E_s w_{rs}(\theta))^\epsilon (d_{rs}(\theta) q_r^\gamma)^{-\epsilon}}. \quad (3)$$

As a result, the equilibrium residential population of workers with a given  $\theta$  in location  $i$ , and the equilibrium employment in location  $j$  are given by

$$N_{Ri}(\theta) = \sum_{j \in \mathcal{I}} \pi_{ij}(\theta) \quad \text{and} \quad N_{Wj}(\theta) = \sum_{i \in \mathcal{I}} \pi_{ij}(\theta). \quad (4)$$

Finally, total residential population is  $N_{Ri} = (1 - \psi)N_{Ri}(1) + \psi N_{Ri}(\theta^T)$ , and total employment is  $N_{Wj} = (1 - \psi)N_{Wj}(1) + \psi N_{Wj}(\theta^T)$ .

## 2.2 Firms

### 2.2.1 Production

In each location, there is a representative firm that hires both on-site and remote labor and produces a homogeneous consumption good which is traded costlessly across locations. The total output of the firm in location  $j$  is  $Y_j = Y_j^C + Y_j^T$ , where  $Y_j^C$  and  $Y_j^T$  are the amounts produced on-site and remotely, respectively.<sup>4</sup> The on-site production function is given by

$$Y_j^C = A_j (N_{Wj}^C)^\alpha (H_{Wj}^C)^{1-\alpha}, \quad (5)$$

where  $N_{Wj}^C = (1 - \psi)N_{Wj}(1) + \theta^T \psi N_{Wj}(\theta^T)$  is the supply of on-site labor,  $H_{Wj}^C$  is commercial floorspace, and  $\alpha$  is the labor share. The remote production function is also Cobb-Douglas and it combines workers from different locations as follows:

$$Y_j^T = \nu A_j \sum_{i \in \mathcal{I}} (N_{ij}^T)^{\alpha_T} (H_{ij}^T)^{1-\alpha_T}. \quad (6)$$

In this specification,  $N_{ij}^T = (1 - \theta^T) \psi \pi_{ij}(\theta^T)$  is the supply of remote labor of telecommuters who reside in location  $i$  and work for a firm in location  $j$ , whereas  $H_{ij}^T$  is the amount of home office space the firm rents on behalf of these workers in the place of their residence.<sup>5</sup> Parameter  $\nu$  is the productivity gap between on-site and remote work, common to all workers and firms. We let the labor share in remote production,  $\alpha_T$ , to be different from the labor share in on-site production.<sup>6</sup>

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<sup>4</sup>In our model, on-site and remote production are perfectly substitutable. [Davis, Ghent, and Gregory \(2021\)](#) entertain a model with imperfect substitution between on-site and remote work, yet they estimate a high elasticity of substitution.

<sup>5</sup>We assume that the firm rents the floorspace that remote workers need in order to work from home, however this specification is isomorphic to the one in which the firm only pays for labor services of a telecommuter and the telecommuter uses his labor income to rent additional floorspace in his house.

<sup>6</sup>One may expect that  $\alpha < \alpha_T$  because telecommuters tend to work in jobs that require little floorspace. While we do not impose this inequality in our theoretical analysis, it holds in our calibration.

## 2.2.2 Wages

Firms take wages and floorspace prices as given, and choose the amount of on-site labor, telecommuting labor, and floorspace that maximize their profits. Equilibrium payments for on-site work at location  $j$  and remote work for a firm in location  $j$  while living in location  $i$  are, respectively,

$$w_j^C = \alpha A_j^{\frac{1}{\alpha}} \left( \frac{1 - \alpha}{q_j} \right)^{\frac{1-\alpha}{\alpha}} \quad \text{and} \quad w_{ij}^T = \alpha_T (\nu A_j)^{\frac{1}{\alpha_T}} \left( \frac{1 - \alpha_T}{q_i} \right)^{\frac{1-\alpha_T}{\alpha_T}}, \quad (7)$$

where  $q_j$  is the local price of floorspace. The take-home wage of a worker with a given  $\theta$  is the weighted average of payments to his commuting labor and his telecommuting labor:  $w_{ij}(\theta) = \theta w_j^C + (1 - \theta) w_{ij}^T$ .<sup>7</sup>

## 2.3 Developers

There is a large number of perfectly competitive floorspace developers operating in each location. Floorspace is produced using the following technology:

$$H_i = K_i^{1-\eta} (\phi_i(H_i) L_i)^\eta, \quad (8)$$

where  $L_i \leq \Lambda_i$  and  $K_i$  are the amounts of land and the final good used to produce floorspace, and  $\eta$  is the share of land in production.  $\Lambda_i$  is the exogenous supply of buildable land, and in equilibrium it is optimal for developers to use all buildable land, i.e.,  $L_i = \Lambda_i$ . Function  $\phi_i(H_i) \equiv 1 - \frac{H_i}{\bar{H}_i}$  determines the local land-augmenting productivity of floorspace developers.<sup>8</sup> Parameter  $\bar{H}_i$  determines the density limit in tract  $i$ . When  $H_i$  approaches  $\bar{H}_i$ ,  $\phi_i(H_i)$  approaches zero. As a result, it becomes very costly to build due to regulatory or political barriers, such as zoning, floor-to-area ratios, or local opposition to development.

Floorspace has three uses: commercial, residential, and home offices. Commercial floorspace can be purchased at price  $q_{Wj}$  per square foot. Residential and home office floorspace is located in the same structure (e.g., a house) and each can be bought at price  $q_{Ri}$ . Developers sell floorspace at price  $\bar{q}_i \equiv \min \{q_{Ri}, q_{Wi}\}$  to either residential or commercial users. However, the effective price that residents or firms pay for floorspace may differ from  $\bar{q}_i$  due to zoning restrictions. The wedge between prices for residential and commercial floorspace is denoted by parameter  $\xi_i > 0$ . If  $\xi_i > 1$ , regulations increase the relative cost of supplying commercial floorspace. Thus, the relationship

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<sup>7</sup>Note that the wage of a commuter does not depend on her location of residence  $i$ . However, the wage of a telecommuter depends on his location of residence  $i$  because production uses home-office floorspace.

<sup>8</sup>This function was also used in [Favilukis, Mabile, and Van Nieuwerburgh \(2019\)](#) to model density limits.

between residential and commercial floorspace prices is<sup>9</sup>

$$q_{Wi} = \xi_i q_{Ri}. \quad (9)$$

The demand for commercial floorspace ( $H_{Wj}^C$ ) and home office floorspace ( $H_{ij}^T$ ) arises from profit-maximizing choices of firms. The demand for residential floorspace ( $H_{Ri}$ ) comes from utility-maximizing choices of residents. Equilibrium selling price  $\bar{q}_i$  equalizes the demand and the supply of floorspace:

$$H_{Wj}^C + \sum_{i \in \mathcal{I}} H_{ij}^T + H_{Rj} = H_i. \quad (10)$$

Finally, since developers optimally use all land available for development,  $\Lambda_i$ , equilibrium land prices are given by

$$l_i = \frac{\eta}{\Lambda_i} (q_{Ri} (H_{Ri} + H_{Ti}) + q_{Wi} H_{Wi}). \quad (11)$$

Appendix B provides more details.

## 2.4 Externalities

Local total factor productivity and residential amenities depend on density. In particular, the productivity in location  $j$  is determined by an exogenous component,  $a_j$ , and an endogenous component that is increasing in the density of on-site labor in this location, as well as every other location  $s$ , weighted inversely by the travel time from  $j$  to  $s$ :

$$A_j = a_j \left[ \sum_{s=1}^I e^{-\delta t_{js}} \frac{N_{Ws}^C}{\Lambda_s} \right]^\lambda. \quad (12)$$

Parameter  $\lambda > 0$  measures the elasticity of productivity with respect to the density of workers, while parameter  $\delta$  accounts for the decay of spillovers from other locations. Productive externalities may include learning, knowledge spillovers, and networking that occur as a result of face-to-face interactions between workers. Hence, we assume that only commuters and telecommuters who are on-site on a given day contribute to these externalities.

Similarly, the residential amenity in location  $i$  is determined by an exogenous component,  $x_i$ , and an endogenous component that depends on the density of residence in every other location, weighted inversely by the travel time to that location from  $i$ :

$$X_i = x_i \left[ \sum_{s=1}^I e^{-\rho t_{is}} \frac{N_{Rs}}{\Lambda_s} \right]^\chi. \quad (13)$$

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<sup>9</sup>This equality does not need to hold if the supply of commercial or residential floorspace in a given tract is zero. In our quantitative model, however, these corner cases do not occur.

Parameter  $\chi > 0$  measures the elasticity of amenities with respect to the density of residents, and  $\rho$  is the decay of amenity spillovers. The positive relationship between density and amenities represents, in reduced form, the greater propensity for both public amenities, such as parks and schools, and private amenities, such as retail shopping, to locate in proximity to greater concentrations of potential users and customers. All types of workers, commuters and telecommuters, contribute equally to amenity externalities at their location of residence.<sup>10</sup>

## 2.5 Equilibrium

An equilibrium consists of residential and workplace employment of commuters and telecommuters,  $N_{Ri}(\theta)$  and  $N_{Wj}(\theta)$ ; wages of commuters and telecommuters,  $w_j^C$  and  $w_{ij}^T$ ; residential and commercial floorspace prices,  $q_{Ri}$  and  $q_{Wj}$ ; land prices,  $l_i$ ; local productivities,  $A_j$ ; and local amenities,  $X_j$ ; such that equations (4), (7), (9), (10), (11), (12), and (13) are satisfied.

## 3 Data and Calibration

The Los Angeles-Long Beach Combined Statistical Area had a total population of 18.7 million in 2018, distributed across a total land area of 88,000 square kilometers (U.S. Census Bureau, 2020). It comprises five counties (Los Angeles, Orange, Riverside, San Bernardino, and Ventura) and 3,917 census tracts. To omit nearly empty desert and mountain tracts with large land areas, we exclude any tracts that are below the 2.5th percentile of both residential and employment density. This excludes less than 1% of workers and leaves us with 3,846 tracts that constitute the set of locations in the model. We focus on the five years between 2012 and 2016. To construct tract-level data on the residential and workplace employment, we use the LEHD Origin-Destination Employment Statistics (LODES) data for the years 2012 to 2016. Tract-level wages are constructed using the American Community Survey (ACS) and the Census Transportation Planning Products (CTPP). We also use CTPP to estimate bilateral commuting times. Finally, prices of residential and commercial floorspace come from the universe of transactions provided by DataQuick. Refer to Appendix A for more details on the data.

The baseline probability of telecommuting,  $\psi$ , is set to 0.0374. This number corresponds to the fraction of workers who report that they primarily work from home in the 2012–2016 individual-level data from the American Community Survey for the Los Angeles-Long Beach CSA. The fraction of time that telecommuters spend at an on-site workplace,  $\theta$ , is set to 0.114, based on Global Work-from-Home Experience Survey (Global Workplace Analytics, 2020).<sup>11</sup> The elasticity

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<sup>10</sup>It would also be possible that telecommuters, by spending more time in the area of their residence, contribute more to local amenities than commuters.

<sup>11</sup>The survey asked the number of days an employee worked from home per week. We classify workers as telecommuters if they work from home three or more days per week. According to the survey, 9% of workers work from home five days per week, 2% do this four days a week, and 3% work from home three days per week.

of commuting time with respect to total traffic volume in the city,  $\varepsilon_V$ , is set to 0.2, following [Small and Verhoef \(2007\)](#). In Appendix section [E](#) we discuss the robustness of results to different values of  $\varepsilon_V$ .

We calibrate the relative TFP of telecommuters,  $\nu$ , so that the wages of commuters and telecommuters are identical in the benchmark economy.<sup>12</sup> The floorspace share of telecommuters,  $\alpha_T$ , is calibrated so that, on average, the home office of a telecommuter constitutes 20% of her house.<sup>13</sup> The calibrated values of  $\nu$  and  $\alpha_T$  are equal to 0.71 and 0.934, respectively.

We borrow values for the remaining city-wide parameters from previous studies. The share of housing in expenditures,  $\gamma$ , is equal to 0.25, following [Davis and Ortalo-Magné \(2011\)](#). The labor share in production,  $\alpha$ , is 0.8 ([Valentinyi and Herrendorf, 2008](#)), and the land share in construction,  $\eta$ , is 0.25 ([Combes, Duranton, and Gobillon, 2018](#)). Parameters that determine the strength of agglomeration forces and decay speed for productivity and residential amenities are borrowed from [Ahlfeldt, Redding, Sturm, and Wolf \(2015\)](#). In particular, we set  $\lambda = 0.071$ ,  $\delta = 0.3617$ ,  $\chi = 1.0326$ , and  $\rho = 0.7595$ .<sup>14</sup> We also take the variance of the Frèchet shocks and the elasticity of utility with respect to commuting from [Ahlfeldt, Redding, Sturm, and Wolf \(2015\)](#), and set  $\epsilon = 6.6491$  and  $\kappa = 0.0105$ .<sup>15</sup>

Besides city-wide parameters, in order to solve the model, we also need to know vectors of structural residuals:  $E$ ,  $x$ ,  $a$ ,  $\xi$ , and  $\bar{H}$ . The model provides equilibrium relationships that allow us to identify these residuals from observed prices and quantities. Appendix [C](#) provides more details.

## 4 Counterfactuals

The COVID-19 outbreak in early 2020 has forced many individuals to work from home. While before the epidemic around 4% of workers in the Los Angeles metropolitan area worked from

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Based on these numbers, we calculate the fraction of time spent on-site as  $1 - [0.09 \times (5/5) + 0.02 \times (4/5) + 0.03 \times (3/5)] / [0.09 + 0.02 + 0.03] = 0.114$ .

<sup>12</sup>Our empirical analysis finds that wages of telecommuters are higher than those of commuters, however, the wage premium disappears once we control for age, education, industry, and occupation. It is also unclear how the wage gap between the two types will change if many more workers start working remotely.

<sup>13</sup>The average house size was 2,430 square feet in 2010, according to [Muresan \(2016\)](#). Home-based teleworkers have, on average, 500 square feet larger homes than other workers ([Nilles, 2000](#)). Hence, telecommuters' houses are about 20% larger. This gap may reflect differences in income, location within a city, and the need for designated workspace within a house. All of these factors are also present in our model. More recent work by [Stanton and Tiwari \(2021\)](#) estimates a smaller house size difference of about 5–7%.

<sup>14</sup>Note that the parameter  $\chi$  in our model corresponds to the product of the variance of the Frèchet shocks and the elasticity of residential amenities with respect to density in [Ahlfeldt, Redding, Sturm, and Wolf \(2015\)](#).

<sup>15</sup>These two parameters, as well as the four parameters that determine amenity and productivity spillovers, were estimated for the city of Berlin, and we leave the estimation for Los Angeles for future work. Nonetheless, similar structural models with parameters estimated for other cities are characterized by similar magnitudes of productivity agglomeration effects and spatial spillovers. At the same time, the estimates of amenity agglomeration effects and spatial spillovers differ substantially across studies. See [Berkes and Gaetani \(2021\)](#), [Tsivanidis \(2019\)](#), and [Heblich, Redding, and Sturm \(2020\)](#), among others.

home, [Dingel and Neiman \(2020\)](#) estimate that as many as 33% of workers in Los Angeles have jobs that can be done remotely.

In this section, we study how a permanent reallocation from working on-site to working at home would affect the urban economy of Los Angeles. We simulate this increase by permanently raising the probability of telecommuting,  $\psi$ . The maximum permanent increase we consider is all the way to 0.33. We also calculate results for a range of intermediate values.

As the number of teleworkers increases, both firms and workers change their locations within the urban area. In response, the city also experiences endogenous adjustments in the supply of commercial and residential floorspace, as well as commuting speeds. In what follows, we describe the effects on the spatial allocation of workers and firms, floorspace prices, commuting patterns, wages and land prices. Then we discuss the drivers of counterfactual changes, the role of endogenous productivity and amenities, and welfare effects.

## 4.1 Spatial Reallocation

When workers are freed from the need to commute to their workplace, they tend to choose residences farther from the urban core in locations with more affordable housing. As the share of telecommuters rises, this drives a reallocation of residents from the core of the urban area towards the periphery.<sup>16</sup> The top panel of [Figure 1](#) maps the predicted reallocation of residents when the fraction of telecommuters rises to 33%.

As residents decentralize, employment centralizes. There are three main factors driving this reallocation. First, the flipside of a telecommuter being able to access jobs even if they live far away, is that employers can access the labor of telecommuters even if they are located far from where they live. Therefore, employment shifts from locations which are less productive but closer to workers' residences, toward locations closer to the core which have higher estimated exogenous productivity and benefit from greater productivity spillovers. Second, the reallocation of residents increases the demand for floorspace in the periphery and reduces it in the core, creating a cost incentive for jobs to move in the opposite direction. Third, the fact that teleworkers require less on-site office space further improves the cost-efficiency of firms in core locations with high productivity but high real estate prices. The middle panel of [Figure 1](#) maps the predicted reallocation of jobs.<sup>17</sup>

The net effect of these reallocations is to reduce the price of floorspace in core locations and increase it in the periphery.<sup>18</sup> The bottom panel of [Figure 1](#) maps predicted changes in real estate prices when the fraction of telecommuters rises to 33%.

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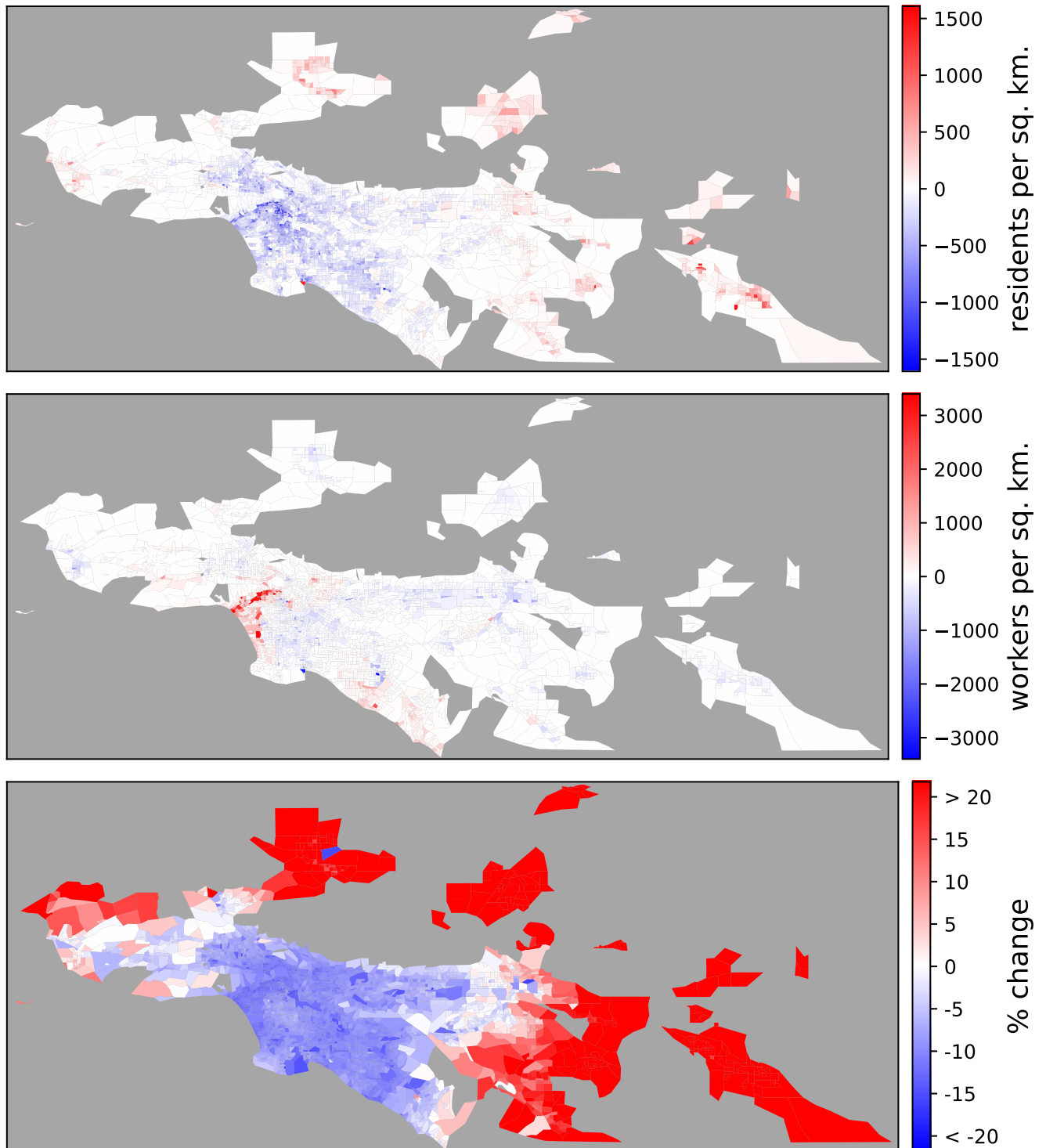
<sup>16</sup>In line with our model's predictions, [Althoff, Eckert, Ganapati, and Walsh \(2020\)](#) document a reallocation of residents from the densest locations to the least dense locations in the U.S. during the COVID-19 pandemic.

<sup>17</sup>For a breakdown of residence and job changes by worker type, see [Appendix D](#).

<sup>18</sup>This prediction is supported by the evidence in [Gupta, Peeters, Mittal, and Nieuwerburgh \(2021\)](#) who document a flattening of bid-rent curves in major U.S. metropolitan areas during the COVID-19 pandemic.



Figure 1: Changes in residence, jobs, and real estate prices

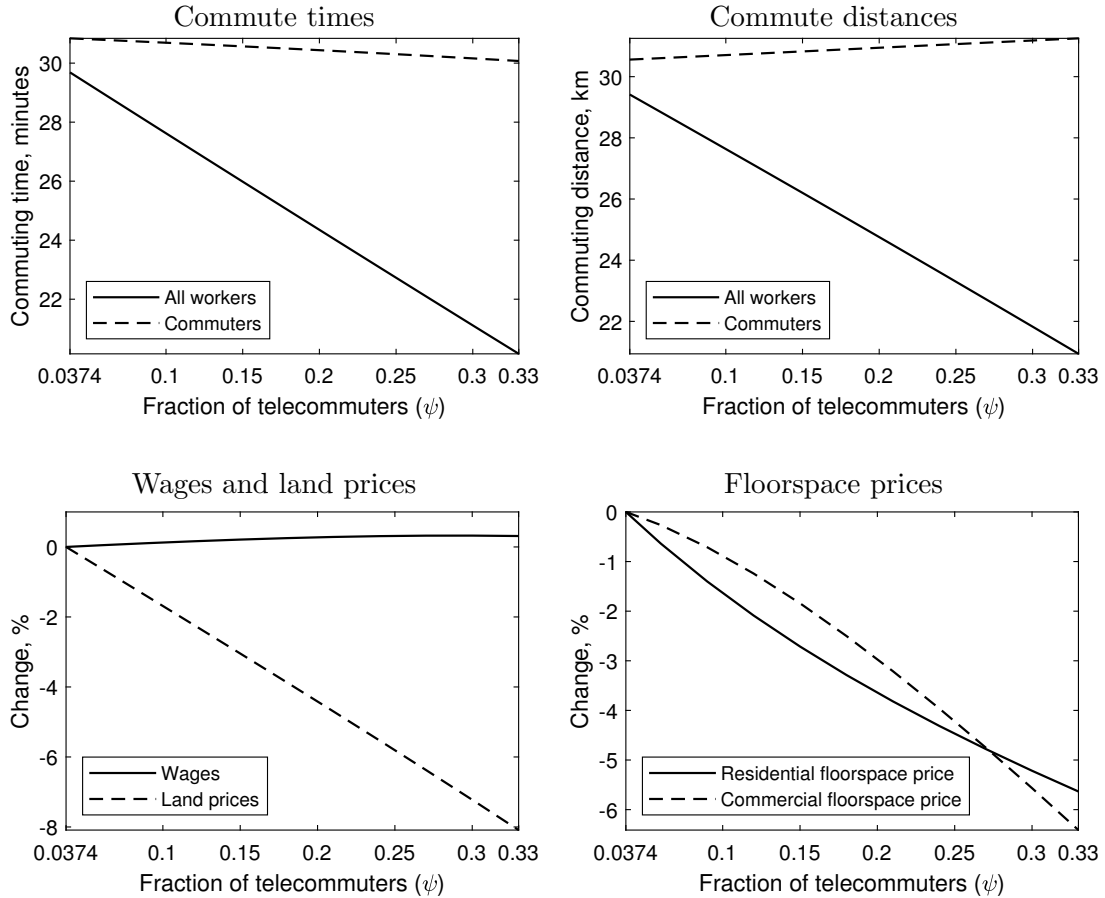


*Note:* Absolute change in residential density (top), job density (middle) and % change in floorspace prices (bottom).

## 4.2 Commuting

A shift to telecommuting brings large benefits to those workers who do not have to come to the office every day anymore and therefore suffer less disutility from commuting. However, those who still have to commute benefit too, as traffic congestion drops and commuting speeds increase. As the upper left panel of Figure 2 shows, with lighter traffic and faster speeds, the average commuting time for those who still commute falls from 31 to 30 minutes. At the same time, the average commute distance for commuters increases by nearly 1 km, as they relocate farther away. This can be seen in the upper right panel. However, the total amount of kilometers traveled falls by 29%, which suggests possible environmental benefits of the increase in telecommuting.<sup>19</sup> The magnitudes of these effects depend importantly on the elasticity of speed with respect to traffic volume,  $\varepsilon_V$ . Simulations for alternative values of  $\varepsilon_V$  can be found in Appendix E.

Figure 2: Commuting, wages, and prices



*Note:* Upper left: average commuting time for all workers and commuters. Upper right: average commuting distance. Lower left: percentage change in average wages and land prices. Lower right: percentage change in floorspace prices. All variables are plotted as a function of the share of teleworkers.

<sup>19</sup>These benefits may be curbed by possible countervailing effects of greater urban sprawl (Kahn, 2000).

### 4.3 Wages and Floorspace Prices

When the share of telecommuters increases, two opposite forces influence average wages. On the one hand, jobs are being reallocated to more productive locations that also benefit from agglomeration externalities. On the other hand, a larger fraction of the workforce does not contribute to these externalities. In our calibration, these two forces almost perfectly balance each other. As can be seen in the lower left panel of Figure 2, a full increase in the fraction of telecommuters to 33% leads to a 0.3% increase in average wages.

As can also be seen in the lower left panel of Figure 2, an increasing share of telecommuters is decisive for the average price of land. Residents reallocate themselves to less expensive locations, and firms with more telecommuters need less office space. If the fraction of telecommuters rose to 33%, the income of landowners would fall by 8%.

The lower right panel of Figure 2 shows that the value of both types of real estate falls by about 6%.<sup>20</sup> The relative decreases in residential and commercial prices depend on the fraction of telecommuters. When the change in the amount of telecommuting is relatively small, the decrease in residential prices is somewhat larger. After the fraction of telecommuters passes 28%, commercial prices are hit harder.

### 4.4 Accounting for Counterfactual Changes

What are the main factors which drive these results? We find that a substantial part of the variation in predicted changes is accounted for by simple measures of centrality such as the distance to the central business district. In this way, there is substantial overlap between our predictions and the predictions that could be obtained from a uni-dimensional “monocentric city” model. We also find that there is significant heterogeneity in predicted outcomes between tracts that are roughly the same distance from downtown L.A. This additional heterogeneity reflects the differences in exogenous local characteristics and transport network connections which our quantitative model allows us to account for.

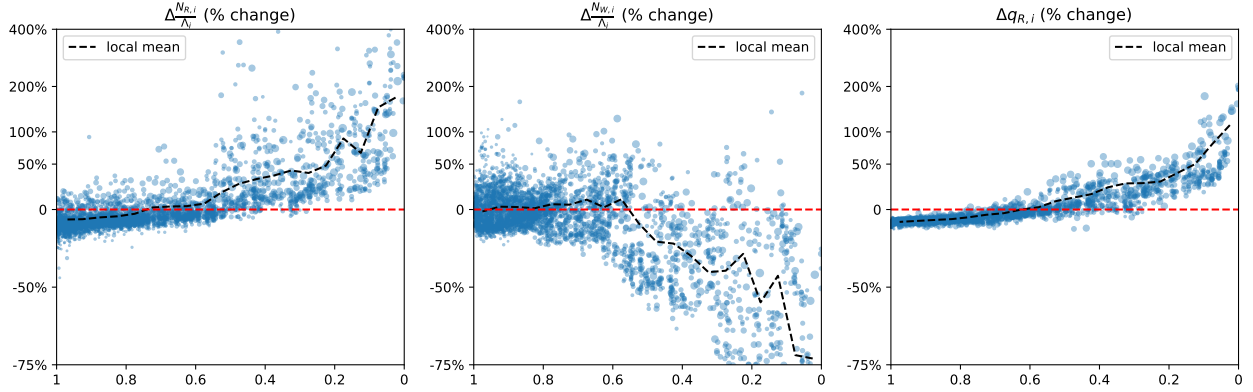
This heterogeneity is highlighted in the three panels of Figure 3. Each panel plots predicted changes on the  $y$ -axis against the land-area weighted centrality rank of a tract on the  $x$ -axis—a centrality rank of 0 represents the most distant tract, a centrality rank of 1 represents the tract closest to the center of the metropolitan area.<sup>21</sup> In the middle panel, we see that while there is an unambiguous prediction of job losses in the periphery, roughly equal numbers of tracts gain and lose jobs from the 60<sup>th</sup> percentile and higher of centrality. In the left panel, we see that

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<sup>20</sup>In this model, residential and commercial prices in a given location move one to one; see equation (9). However, changes in average prices of each type may differ due to changes in the supply of each type of real estate.

<sup>21</sup>We calculate an eigenvector centrality from the  $I \times I$  matrix of inverse commuting disutilities, where  $I$  is the number of model locations. This measure is highly correlated with both straight-line distance from downtown Los Angeles, and travel time from downtown Los Angeles—the correlation is higher than 0.97 in both cases. More details can be found in Appendix F.

Figure 3: Quantiles of Centrality and Counterfactual Reallocations



*Note:* The x-axis is scaled to quantiles of the centrality measure, weighted by land area. The size of each circle is proportional the land area of the tract.

while peripheral tracts are projected to gain residents, predictions are much more ambiguous once the centrality is higher than the 60<sup>th</sup> percentile. In the right panel, we see that real estate price changes fall systematically as we move towards the center of the city. All three panels show substantial disparities in predicted outcomes between tracts of very similar centralities.<sup>22</sup> What can account for this variation?

To help answer this question, we perform a Shapley-style decomposition of the variation in predicted outcomes between centrality, exogenous local productivity and exogenous local employment and residential amenities.<sup>23</sup> We find that distance from the center can account for at most 60% of the variation in changes in floorspace prices, around 40% of the variation in changes in employment, and 50% of the variation in changes in residence across space. Two of the key takeaways from this exercise are that (1) locations with higher exogenous residential amenities have bigger resident gains and smaller resident losses, all else equal; and (2) locations with higher exogenous productivity have larger job gains and smaller job losses, all else equal.<sup>24</sup>

## 4.5 Role of Endogenous Productivities, Amenities, and Congestion

In the baseline counterfactual, we assume that local productivities and amenities are endogenous. We also assume that commuting speeds fall as total vehicle miles traveled goes down, and that these increased speeds also mean that spillovers have a broader reach.

<sup>22</sup>We can also see this variation between equidistant tracts if we return to look at Figure 1. It is perhaps most striking in the middle panel of Figure 1, where we can see that one set of tracts that are close to the downtown experience strong gains in employment, while other tracts, equally close or even closer to downtown, lose jobs. The bottom panel of Figure 1 shows large differences in the size of real estate price reductions between different tracts close to downtown.

<sup>23</sup>Full details of this decomposition are provided in Appendix F.

<sup>24</sup>Maps of structural residuals are shown in Figure 4 in Appendix C.

What is the role of these specification choices in driving our results? We turn each of them off and on in turn, and show the results in Table 1. Column (6), when all margins are turned “on,” corresponds to the benchmark scenario. It turns out that in none of these permutations are our main results significantly altered. Commuting times go down, floorspace prices fall, and overall welfare goes up, all in roughly the same proportions, no matter which set of assumptions is turned on. There are, however, some variations which illustrate the role of different model mechanisms in shaping the results.

Table 1: Breakdown of results

<i>Endogenous productivities:</i>	no	no	yes	yes	yes	yes
<i>Endogenous amenities:</i>	no	yes	no	yes	yes	yes
<i>Endogenous congestion:</i>	no	no	no	no	yes	yes
<i>Spillovers affected by congestion:</i>	n/a	n/a	n/a	n/a	no	yes
	(1)	(2)	(3)	(4)	(5)	(6)
Wages of all workers, % chg	1.77	1.79	-0.39	-0.41	-0.37	0.31
Wages of commuters, % chg	2.66	2.80	0.34	0.45	0.51	1.21
Wages of telecommuters, % chg	-0.13	-0.38	-1.98	-2.26	-2.26	-1.61
Residential floorspace prices, % chg	-4.37	-5.03	-5.75	-6.16	-6.23	-5.63
Commercial floorspace prices, % chg	-6.43	-7.39	-6.14	-6.86	-6.97	-6.41
Time spent commuting, all workers, % chg	-31.42	-30.69	-31.46	-30.80	-32.23	-32.13
Time spent commuting, commuters, % chg	-1.46	-0.43	-1.52	-0.57	-2.63	-2.49
Distance traveled, all workers, % chg	-31.91	-30.69	-31.96	-30.85	-28.96	-28.82
Distance traveled, commuters, % chg	-2.18	-0.42	-2.24	-0.65	2.06	2.27
Welfare by source, % chg						
consumption	2.30	2.52	0.45	0.55	0.64	1.17
goods only	0.84	0.85	-1.26	-1.29	-1.24	-0.57
housing only	4.75	5.70	3.95	4.58	4.73	4.79
+ commuting	11.71	11.54	9.74	9.46	10.02	10.56
+ amenities	11.90	14.38	10.16	12.23	12.80	14.15
+ Fréchet shocks	17.97	19.67	15.28	16.79	17.14	18.91
Welfare by commuter type, % chg						
commuter	1.94	2.06	-0.48	-0.41	0.82	2.24
telecommuter	-3.33	-1.69	-5.52	-4.06	-3.94	-2.47

*Note:* Columns (1)–(6) present results from specifications with different combinations of endogenous productivities, amenities and congestion, and whether spillovers increases when traffic congestion goes down. Each column reports the results of a counterfactual experiment with an increase of the fraction of telecommuters to 0.33.

First, let us compare columns (1) and (2) of Table 1 with columns (3) and (4). If local productivities do not adjust endogenously, wages increase. This is primarily because telecommuters do not contribute to productivity spillovers. If these adjust, the locations which lose in-person workers—nearly every location—see a fall in productivity. As a result, average wages fall.

Second, let us compare columns (1) and (3) with columns (2) and (4). If residential amenities do not adjust, there is a bigger reduction in travel times and distances. This is because allowing

amenities to follow telecommuters out to the periphery increases the attractiveness of peripheral locations for regular commuters, making them willing to put up with longer commutes.

Finally, let us compare columns (5) and (6) with column (4). We see that endogenous congestion leads to larger reductions in time spent commuting. It also flips small reductions in distance traveled into small increases—increased speeds allow workers to travel further while spending less time on the road. Comparing columns (5) and (6), we can see that allowing the reach of spillovers to increase when travel speeds go down gives a small but significant boost to wages.

## 4.6 Welfare

The lower half of Table 1 shows that the increase in telecommuting to 33% of the workforce results in significant welfare gains, which we measure as consumption-equivalent changes in expected utility (see Appendix section B.3 for details). We find that reduced commuting is the single biggest driver of welfare improvements, even when traffic congestion remains fixed at the benchmark level. Focusing on column (6): when commuting is accounted for in addition to the 1.2% gain from consumption, welfare gains rise by over 9 percentage points. After this, improved access to amenities adds another 3.6 percentage points, while workers’ improved ability to fulfill their idiosyncratic preferences contributes less than 5 percentage points.

One important driver of welfare gains for commuters is access to jobs. In large, sprawled and congested cities, such as Los Angeles, good jobs are often inaccessible for households who live on the periphery. To study how a shift to telecommuting impacts job access, we calculate commuter market access for each tract as  $CMA_i = \sum_j (w_j e^{-\kappa t_{ij}})^\epsilon$ . We find that an increase in the fraction of telecommuters improves average job access for those who keep commuting by 16%, largely thanks to lower traffic congestion. We also find that the elasticity of floorspace prices with respect to market access at the tract level falls, meaning that places with better access to jobs command a lower price premium. Further details of these calculations as well as other results can be found in Appendix D.

The utility of the average telecommuter is significantly higher than that of the average commuter, due to reduced disutility from commuting, access to lower-cost housing, and access to better-paying jobs and amenities. As a result, the shift of workers from commuting to telecommuting is an important source of the welfare increases. Workers who remain commuters or telecommuters, see their welfare change only marginally. Commuters who continue to commute benefit from reduced time commuting, access to lower-cost housing, and access to better-paying jobs and amenities, and see their welfare rise by more than 2%. At the same time, telecommuters who were already telecommuting do not benefit from the increase in their mode of work. On the contrary, they need to compete with an increasing fraction of the workforce for residence and job sites that were previously accessible only to them. Their welfare falls by about 2.5%.

## 5 Conclusion

In this paper we used a detailed quantitative model of internal city structure to study what would happen in Los Angeles if telecommuting becomes popular over the long run. We find substantial changes to the city structure, wages and real estate prices, and commuting patterns. We also find that more widespread telecommuting could bring significant welfare benefits.

Our analysis necessarily omits several important channels which could dampen or amplify our findings. First, in our model all workers are ex-ante identical and have the same chances of being able to telecommute. In reality, the ability to telecommute is correlated with occupation, industry and income. Accounting for this would likely have two effects. First, it would center the large shifts in jobs and residence even more on the high-density center-city locations where the share of skilled, telecommute-ready workers is likely to be highest. Second, there would be more downward pressure on the average wage. This is because these center-city locations have higher than average local productivity. If these locations lose proportionally more in-person workers, their reduction in productivity from spillovers will be greater, as will the impact on aggregate average wages. It is also likely that different skill levels of workers differ in their contribution to productivity externalities.<sup>25</sup> If higher-skilled workers are also more likely to telecommute, the effect of this detail would be similar to the previous one: additional downward pressure on wages.

Second, we calibrated the productivity gap between commuters and telecommuters to ensure that their average wages are the same in the benchmark economy, and assume that this parameter remains constant in the counterfactual. We also assume that telecommuters do not contribute at all to productivity spillovers. However, as telecommuting becomes more widespread, technological changes might increase the relative productivity of telecommuters and allow them to contribute more to productivity spillovers even without literal face-to-face interaction. This would put upward pressure on wages, as we find in a related paper of ours, [Delventhal and Parkhomenko \(2021\)](#).

Third, we do not take account of non-commuting travel.<sup>26</sup> If we did, we would probably find an increase in local traffic congestion in the peripheral areas that telecommuters relocate to, alongside the reduction in congestion along the main commuting arteries. This would mitigate gains from moving to the periphery and lead to less decentralization overall. We also do not distinguish between transportation modes in the model. The reduction in congestion brought by more telecommuting could be offset if some transit users start commuting by car.

Finally, we do not allow migration in and out of the city. In practice, as some workers gain the ability to work remotely, they may choose to leave Los Angeles and move to a different city, or even a different country. On the other hand, telecommuters from elsewhere may move into Los

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<sup>25</sup>This is a finding of, e.g., [Rossi-Hansberg, Sarte, and Schwartzman \(2020\)](#).

<sup>26</sup>[Couture, Duranton, and Turner \(2018\)](#) estimate that work-related trips account for only 40% of vehicle miles traveled in the U.S.



Angeles to enjoy local amenities. Indeed, this is what we find in [Delventhal and Parkhomenko \(2021\)](#), which expands the scope of analysis to include the entire U.S.

One more caveat is recommendable in interpreting our predictions for welfare. We model telecommuting as a fact imposed exogenously on workers. They love it because they commute less. Most welfare gains come through this channel. In reality, some workers may dislike remote work. If in our model telecommuting were a choice in which workers balance the benefits against their individual dislike, welfare gains would almost surely be smaller than what we report.

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# A Data Appendix

## A.1 Property Price Data

Our commercial and residential property price data comes from DataQuick, which provides the universe of property transactions and the characteristics of individual properties. The dataset covers 2,354,535 properties over 2007–2016 in the Los Angeles-Long Beach combined statistical area. The data provides information such as sales price, geographical coordinates, transaction date, property use, transaction type, number of rooms, number of baths, square-footage, lot size, year built, etc.

We categorize properties as commercial or residential based on their reported use. Examples of residential use include “condominium”, “single family residence”, and “duplex”. Examples of commercial use include “hotel/motel”, “restaurant”, and “office building”. Table 2 provides descriptive statistics. Table 3 reports the number of observations in each county over the period of 2007–2016. Note that commercial transactions are far less frequent than residential transactions.

We then use the transaction data to estimate hedonic tract-level residential and commercial property indices. For a residential transaction of a property  $p$ , in tract  $j$  in year-month  $t$ , we estimate

$$\ln(P_{pjt}) = \alpha + \beta \mathbf{X}_p + \tau_t + \zeta_j^{res} + \epsilon_{pjt}, \quad (14)$$

where  $P_{pjt}$  is the price per square foot;  $X_p$  contains property characteristics including property use, transaction type, number of rooms, number of baths, lot size, and year built; and  $\tau_t$  is the year-month fixed effect. Then the residential price index in tract  $j$  corresponds to  $\zeta_j^{res}$ , the tract fixed effect.

Because commercial transactions are less numerous and more spatially concentrated, for many Census tracts we only observe very few or no transactions in the period of interest. To overcome this issue, we calculate commercial property indices at the Public Use Microdata Area (PUMA)-level.<sup>27</sup> For a transaction of a commercial property  $p$ , in tract  $j$  of PUMA  $g$  in year-month  $t$ , we estimate

$$\ln(P_{pgjt}) = \alpha + \beta \mathbf{X}_p + \tau_t + \zeta_g^{com} + v_{pgjt}, \quad (15)$$

where  $P_{pgjt}$  is the price per square foot;  $X_p$  is property characteristics including property use; and  $\tau_t$  is the year-month fixed effect. The commercial price index in PUMA  $g$  corresponds to  $\zeta_g^{com}$ , which is the PUMA fixed effect. Then, to obtain tract-level commercial price indices  $\zeta_j^{com}$ , we simply assign the same value of  $\zeta_g^{com}$  to all tracts  $j$  that belong to PUMA  $g$ .

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<sup>27</sup>PUMA is a geographic unit used by the US Census for providing statistical and demographic information. Each PUMA contains between 100,000 and 200,000 inhabitants. There are 123 PUMAs in the Los Angeles-Long Beach combined statistical area.

Table 2: Descriptive Statistics

<b>Panel A. Residential Properties</b>				
County	sqft (mean)	sqft (median)	sales price, \$ (mean)	sales price, \$ (median)
Los Angeles	1752.25	1499	774734.19	389000
Orange	1969.92	1578	714043.38	495000
Riverside	2046.06	1855	489885.35	246649
San Bernardino	1759.41	1584	345662.41	200000
Ventura	1860.88	1626	569042.40	410000

<b>Panel B. Commercial Properties</b>				
County	sqft (mean)	sqft (median)	sales price, \$ (mean)	sales price, \$ (median)
Los Angeles	20687.28	5203	5661399.99	1300000
Orange	16447.48	5329	3879699.73	1260000
Riverside	1329.38	1201	1813988.76	590000
San Bernardino	19486.08	3541	2472923.09	522000
Ventura	12087.09	4565	3513023.97	982500

Table 3: Number of Transactions by County and Property Type

	Los Angeles	Orange	Riverside	San Bernardino	Ventura	Total
Residential	909,954	330,689	557,204	363,173	105,518	2,266,538
Commercial	47,408	12,084	14,045	11,099	3,361	87,997

## A.2 Wage Data

Our sources of wage data are the Census Transportation Planning Products (CTPP) and the American Community Survey (ACS). CTPP data sets produce tabulations of the ACS data, aggregated at the Census tract level. We use the data reported for years 2012 to 2016. We use the variable “earnings in the past 12 months (2016 \$), for the workers 16-year-old and over,” which is based on the respondents’ workplace locations. The variable provides the estimates of the number of people in several earning bins in each workplace tract. Table 4 provides an overview of the number of observations in each bin for the five counties included in our study.

We calculate mean tract-level labor earnings as

$$w_j = \frac{\sum_b nworkers_{b,j} \times meanw_b}{\sum_b nworkers_{b,j}}, \quad (16)$$

where  $nworkers_{b,j}$  is the number of workers in bin  $b$  in tract  $j$ , and  $meanw_b$  is mean earnings in bin  $b$  for the entire Los Angeles-Long Beach combined statistical area, calculated from the ACS microdata.

Next, to control for possible effects of workers’ heterogeneity on tract-level averages, we run the following Mincer regression,

$$w_j = \alpha + \beta_1 age_j + \beta_2 sexratio_j + \sum_r \beta_{2,r} race_{r,j} + \sum_i \beta_{3,i} ind_{i,j} + \sum_o \beta_{4,o} occ_{o,j} + \epsilon_j, \quad (17)$$

Table 4: Number of observations in each earnings bin, by county

Income Bin	Los Angeles	Orange	Riverside	San Bernardino	Ventura
\$1 to \$9,999 or loss	416,469	147,484	86,219	85,854	34,973
\$10,000 to \$14,999	279,132	90,871	51,959	52,605	21,143
\$15,000 to \$24,999	541,649	168,284	97,184	97,059	40,458
\$25,000 to \$34,999	440,298	146,337	79,994	81,911	34,829
\$35,000 to \$49,999	493,434	170,364	77,170	87,969	37,487
\$50,000 to \$64,999	387,533	138,932	57,409	62,487	27,979
\$65,000 to \$74,999	176,079	63,244	24,869	27,687	13,895
\$75,000 to \$99,999	308,994	114,436	39,159	44,409	23,871
\$100,000 or more	486,179	189,108	44,925	43,158	36,346
No earnings	520	134	144	85	55

Earnings in the past 12 months (2016\$) (Workers 16 years and over), based on workplace location, Source: CTPP.

where  $age_j$  is the average age of workers;  $sexratio_j$  is the proportion of males to females in the labor force;  $race_{r,j}$  is the share of race  $r \in \{Asian, Black, Hispanic, White\}$ ;  $ind_{i,j}$  is the share of jobs in industry  $i$ ;  $occ_{o,j}$  is share of jobs in occupation  $o$  in tract  $j$ .<sup>28</sup> Finally, the estimated tract-level wage index corresponds to the sum of the estimated constant and the estimated tract fixed effect,  $\hat{\alpha} + \hat{\epsilon}_j$ . Table 5 presents summary statistics for the estimated tract-level earnings.

Table 5: Descriptive statistics: the estimated tract-level earnings, by county

	Obs	Mean	Std. Dev.	Min	Max
Los Angeles	2,339	61,203.81	13,589.54	21,376.82	170,987.1
Orange	582	63,455.76	11,197.14	24,120.39	113,428.8
Riverside	452	61,477.51	13,606.08	17,286.49	138,802.9
San Bernardino	369	59,823.33	12,741.2	21,101.49	132,544.9
Ventura	172	61,034.83	10,709.51	29,174.4	89,796.23

Earnings in U.S. dollars in the past 12 months (2016\$) (Workers 16 years and over), based on workplace location, Source: CTPP.

<sup>28</sup>We use the following *industry* categories: Agricultural; Armed force; Art, entertainment, recreation, accommodation; Construction; Education, health, and social services; Finance, insurance, real estate; Information; Manufacturing; Other services; Professional scientific management; Public administration, Retail. We use the following *occupation* categories: Architecture and engineering; Armed Forces; Arts, design, entertainment, sports, and media; Building and grounds cleaning and maintenance; Business and financial operations specialists; Community and social service; Computer and mathematical; Construction and extraction; Education, training, and library; Farmers and farm managers; Farming, fishing, and forestry; Food preparation and serving related; Healthcare practitioners and technicians; Healthcare support; Installation, maintenance, and repair; Legal; Life, physical, and social science; Management; Office and administrative support; Personal care and service; Production; Protective service; Sales and related.



### A.3 Commuting Time Data

The CTPP database provides commuting time data for 270,436 origin-destination tract pairs in the Los Angeles-Long Beach Combined Statistical Area for 2012-2016. There are 15,342,889 possible trajectories, and the LODES data for 2012-2016 reports positive commuting flows for 5,647,791 of them. We follow the practice recommended by [Spear \(2011\)](#) and use LODES data as a measure of commuting flows and CTPP data to provide information on commute times.

Table 6: Commuting time coverage, by distance

	N. of trajectories	% covered by time data	% w/ observed positive flows	N. of commuters
< 1 km	10,105	60.8%	96.4%	239,188
< 2 km	36,205	40.5%	93.3%	410,571
< 5 km	188,047	24.4%	86.9%	1,088,797
< 10 km	649,005	15.0%	79.9%	2,248,646
< 20 km	2,099,417	8.2%	69.8%	3,995,134
< 40 km	5,549,775	4.3%	54.4%	5,508,736
< 80 km	10,752,785	2.5%	43.4%	6,515,595
All	15,342,889	1.8%	36.8%	6,935,765

Table 7: Commuting time coverage, by N. of commuters

	N. of trajectories	% covered by time data	N. of commuters
> 100 commuters	1,778	94.4%	259,259
> 50 commuters	8,678	89.9%	723,849
> 25 commuters	27,833	82.2%	1,380,081
> 10 commuters	96,177	63.7%	2,417,561
> 5 commuters	220,555	46.5%	3,289,529
> 1 commuters	1,108,755	17.9%	5,247,370
All > 0	5,647,791	4.8%	6,935,760

Table 6 summarizes CTPP data coverage by trajectory distance. Table 7 summarizes CTPP data coverage by trajectory and the number of commuters observed using that trajectory. These tables show that CTPP has the greatest coverage of high-volume short-distance trajectories, just as [Spear \(2011\)](#) observes and just as would be expected from a dataset based on a partial sample.

The CTPP data places commuting times into 10 bins: less than 5 minutes, 5 to 14 minutes, 15 to 19 minutes, 20 to 29 minutes, 30 to 44 minutes, 45 to 59 minutes, 60 to 74 minutes, 75 to 89 minutes, 90 or more minutes, and work from home. In order to get as accurate commute times as possible for the set of primitive connections of the network, we drop all home-workers, who are irrelevant for transit times. We drop workers in the top time bin, because this bin has no upper bound and so the mean may vary substantially across trajectories. We assign mean commute times to all the remaining bins as the mid-points between the bin bounds. We then drop all observations which report an average commuting speed that is either less than 8 kilometers per hour, a brisk walking pace, or more than 70 miles per hour (112.7 kilometers per hour), the

standard rural freeway speed limit in the United States. Finally, we calculate tract-pair mean commuting times as the average of the mean commuting times in each bin weighted by the share of commuters on that tract-pair reporting times in each bin. Table 8 provides a summary of the overall share of commuters in each bin before and after the cleaning steps described above, and the mean commute time assigned to each bin.

Table 8: Commuting time bins

	share in raw data	share in cleaned data	bin mean time
< 5 min	1.6%	0.9%	5
5-14 min	19.4%	18.9%	10
15-19 min	14.0%	15.7%	17
20-29 min	19.1%	22.5%	25
30-44 min	20.5%	24.4%	37
45-59 min	8.0%	9.6%	52
60-74 min	6.1%	6.9%	67
75-89 min	0.9%	1.0%	82
> 90 min	2.8%	0	??
work from home	7.6%	0	n/a

The previous cleaning steps eliminate observations for 36,279 trajectories, and we are left with commuting time data for 234,157 origin-destination pairs. We then find that there are 211,521 paths for which a commuting time estimate exists for the outbound route but not the reverse. We impute commute times for these missing return journeys, assuming that they can be completed in the same time as the outbound trajectories. This set of connections is then almost enough to connect all tracts—there are only a set of eight tracts that are still detached from the rest of the network. In order to remedy this, we create a connection at the mean travel speed of 31.3 kilometers per hour between these left-out tracts and any tracts within a radius twice as large as the hypothetical radius of the tract if its land area formed a circle.<sup>29</sup>

The final directed network contains 447,277 directed paths. We use the Dijkstra’s algorithm to calculate the fastest path through this network for each origin-destination pair. We assume that these calculated times represent the time required to travel from tract centroid to tract centroid. We then add time to each trajectory to represent the time need to travel from place of residence within tract to residence tract centroid, and from workplace tract centroid to workplace within the tract. Naturally, these times are proportional to tract land area—larger tracts should on average require more internal travel time. Specifically, we assume that the “internal” distance traveled on each end of the trip is equal to the hypothetical average straight-line distance from any point in the tract to the tract centroid, if the tract were a circle.<sup>30</sup> We then assume that each of these distances is traveled at twice the overall average commuting speed in the cleaned data of 31.3 kilometers per hour. For the vast majority of tracts this adds a negligible amount to commuting

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<sup>29</sup> $2 \times \sqrt{\text{landarea}/\pi}$   
<sup>30</sup> $\frac{2}{3} \sqrt{\text{landarea}/\pi}$

time—two minutes or less. For a handful of very large tracts it adds considerable travel time—up to half an hour. We think that this is reasonable given the time that is required to travel within these much larger tracts. These origin-destination distribution effects are also applied to self-commute times, so that a worker that lives and works in the same tract will still have to spend some time traveling to their workplace—more time for larger tracts.

## A.4 Summary

Table 9 gives summary statistics by tract for seven key variables: residential density; employment density; wage by workplace weighted by employees; average constant-quality price of one square foot of residential floorspace; average constant-quality price of one square foot of commercial floorspace; average commute time by residence tract; and average commute distance by residence tract.

Table 9: Data overview

	Mean	Median	St. Dev.	Max.	N. Obs.
Residents/km <sup>2</sup>	1,621.4	1,380.3	1,376.6	15,929.3	3,846
Workers/km <sup>2</sup>	1,285.8	578.7	3,961.0	157,995.7	3,846
Wages (\$\$, weight by employees)	58,874	58,528	7,609	159,059	3,846
Res. price/sq ft (\$\$, weight by residents)	369	331	347	9,349	3,846
Comm. price/sq ft (\$\$, weight by employees)	644	581	324	6,709	3,846
Av. commute time (min, weight by residents)	28.3	26.3	6.8	96.1	3,846
Av. commute distance (km, weight by residents)	26.2	22.8	11.3	131.2	3,846

## B Model Details

### B.1 Floorspace Markets

#### B.1.1 Floorspace Supply

Land-market clearing and profit maximization imply that the equilibrium supply of floorspace is

$$H_i = \phi_i(H_i) ((1 - \eta)\bar{q}_i)^{\frac{1-\eta}{\eta}} L_i. \quad (18)$$

Solving this expression for  $H_i$  and using the definition of construction efficiency  $\phi_i(H_i)$ , yields

$$H_i = \frac{((1 - \eta)\bar{q}_i)^{\frac{1-\eta}{\eta}} L_i}{1 + ((1 - \eta)\bar{q}_i)^{\frac{1-\eta}{\eta}} L_i / \bar{H}_i}. \quad (19)$$

### B.1.2 Floorspace Demand

From equation (3), the probability that an individual who commutes a fraction  $\theta$  of days works in  $j$ , conditional on living in  $i$ , is given by

$$\pi_{ij|i}(\theta) = \frac{E_j w_{ij}(\theta)^\epsilon d_{ij}(\theta)^{-\epsilon}}{\sum_{s=1}^I E_s w_{rs}(\theta)^\epsilon d_{is}(\theta)^{-\epsilon}}. \quad (20)$$

Define  $\tilde{w}_i$  as the average wage earned by residents of location  $i$ . This is given by

$$\tilde{w}_i \equiv \sum_{j \in \mathcal{I}} \left[ w_j^C \frac{\pi_{ij|i}(1) N_{Ri}(1)}{N_{Ri}} + w_{ij}^T \frac{\pi_{ij|i}(\theta^T) N_{Ri}(\theta^T)}{N_{Ri}} \right]. \quad (21)$$

Therefore, the demand for residential and home-office floorspace is given by

$$H_{Ri} = \frac{\gamma(1 + \tau) \tilde{w}_i}{q_{Ri}} N_{Ri}. \quad (22)$$

The demand for home offices is

$$H_{Ti} = \left( \frac{1 - \alpha_T}{q_{Ri}} \right)^{\frac{1}{\alpha_T}} \sum_{j \in \mathcal{I}} (\nu A_j)^{\frac{1}{\alpha_T}} N_{ij}^T. \quad (23)$$

Finally, the demand for commercial floorspace is given by

$$H_{Wj} = \left( \frac{(1 - \alpha) A_j}{q_{Wj}} \right)^{\frac{1}{\alpha}} N_{Wj}^C. \quad (24)$$

## B.2 Factor Incomes and Transfers

The city-wide total land income is

$$\sum_{i \in \mathcal{I}} l_i \Lambda_i. \quad (25)$$

Income generated by land and the consumption good sold for the purposes of real estate development is redistributed to all workers, proportionally to their incomes. The transfers increase labor income by a fraction of  $\tau$  which is equal to

$$\tau = \frac{\sum_{i \in \mathcal{I}} (l_i \Lambda_i + K_i)}{\sum_{i \in \mathcal{I}} \tilde{w}_i N_{Ri} + \sum_{i \in \mathcal{I}} (l_i \Lambda_i + K_i)}. \quad (26)$$

### B.3 Welfare

The expected utility enjoyed by a resident of the city is given by

$$\mathcal{U} \equiv \Gamma\left(\frac{\epsilon-1}{\epsilon}\right) \left[ \sum_{r \in \mathcal{I}} \sum_{s \in \mathcal{I}} X_r E_s \left[ (1-\psi) \left( e^{-\kappa t_{rs}} (1+\tau) w_s^C q_{Rr}^{-\gamma} \right)^\epsilon + \psi \left( (1-\theta + \theta e^{-\kappa t_{rs}}) (1+\tau) w_{rs}^T q_{Rr}^{-\gamma} \right)^\epsilon \right] \right]^{\frac{1}{\epsilon}}, \quad (27)$$

where  $\Gamma(\cdot)$  is the gamma function. Note that the expected utility is defined before the telecommuting lottery and before the location preference shocks realize.

A consumption-equivalent measure of change in welfare is given by  $\Delta$ . This quantity represents the percentage amount by which the composite consumption of goods and housing,  $c^{1-\gamma} h^\gamma$ , must change in order to make the expected utility in the benchmark economy equal to the expected utility in the counterfactual economy. Note that in this model the composite consumption is proportional to wages. Let “ $\tilde{\cdot}$ ” denote variables in the counterfactual economy. Then  $\Delta$  must satisfy

$$\begin{aligned} & \left[ \sum_{r \in \mathcal{I}} \sum_{s \in \mathcal{I}} X_r E_s \left[ (1-\psi) \left( e^{-\kappa t_{rs}} (1+\tau) (1+\Delta) w_s q_{Rr}^{-\gamma} \right)^\epsilon + \psi \left( (1-\theta + \theta e^{-\kappa t_{rs}}) (1+\tau) (1+\Delta) w_{rs}^T q_{Rr}^{-\gamma} \right)^\epsilon \right] \right]^{\frac{1}{\epsilon}} \\ &= \left[ \sum_{r \in \mathcal{I}} \sum_{s \in \mathcal{I}} \tilde{X}_r E_s \left[ (1-\psi) \left( e^{-\kappa \tilde{t}_{rs}} (1+\tilde{\tau}) \tilde{w}_s \tilde{q}_{Rr}^{-\gamma} \right)^\epsilon + \psi \left( (1-\theta + \theta e^{-\kappa \tilde{t}_{rs}}) (1+\tilde{\tau}) \tilde{w}_{rs}^T \tilde{q}_{Rr}^{-\gamma} \right)^\epsilon \right] \right]^{\frac{1}{\epsilon}}. \end{aligned}$$

It follows that the change in welfare  $\Delta$  is a function of the ratio of expected utilities in the counterfactual and the benchmark economies,

$$\Delta = \frac{\tilde{\mathcal{U}}}{\mathcal{U}} - 1. \quad (28)$$

## C Structural Residuals

The amounts of commuting workers and residents are related as

$$N_{Wj}(1) = \sum_{i \in \mathcal{I}} \pi_{ij|i}(1) N_{Ri}(1), \quad (29)$$

Let  $\hat{E}_j \equiv E_j (w_j^C)^\epsilon$ . From equations (20) and (29),  $\hat{E}_j$  can be defined implicitly as:

$$\hat{E}_j = N_{Wj}(1) \left( \sum_{i \in \mathcal{I}} \frac{e^{-\epsilon \kappa t_{ij}}}{\sum_{s \in \mathcal{I}} \hat{E}_s e^{-\epsilon \kappa t_{is}}} N_{Ri}(1) \right)^{-1}, \quad (30)$$

where  $N_{Wj}$  and  $N_{Ri}$  are observed tract-level employment and residential populations, and  $t_{ij}$  are observed average commuting times from tract  $i$  to tract  $j$ . Since we do not observe how many workers telecommute in each tract and since the share of telecommuters in the data is small (3.74% of workforce), we perform this and the following calculations assuming that all workers commute to their jobs. A vector  $\hat{E}$  is solved recursively using equation (30) and then the vector of residuals  $E$  is recovered as  $E_j = \hat{E}_j (w_j^C)^{-\epsilon}$ , using observed tract-level wages.

A similar procedure is applied to solve for vector  $X$ . First, let  $\hat{X}_j \equiv X_j q_{Rj}^{-\gamma\epsilon}$ .  $\hat{X}_j$  can be defined implicitly as:

$$\hat{X}_i = N_{Ri} \left( \sum_{j \in \mathcal{I}} \frac{e^{-\epsilon \kappa t_{ij}}}{\sum_{r \in \mathcal{I}} \hat{X}_r e^{-\epsilon \kappa t_{rj}}} N_{Wj} \right)^{-1}. \quad (31)$$

The vector  $\hat{X}$  is solved recursively using equation (31) and then the vector of residuals  $X$  is recovered as  $X_j = \hat{X}_j q_{Rj}^{\gamma\epsilon}$ , using observed tract-level prices of residential floorspace. Then the exogenous part of local amenities,  $x_j$ , can be recovered using equation (13) and the data on local residential population and land area.

The vector of local productivities  $A$  can be solved for using (7) and the data on wages and commercial floorspace prices as follows:

$$A_j = \left( \frac{w_j^C}{\alpha} \right)^\alpha \left( \frac{q_{Wj}}{1 - \alpha} \right)^{1-\alpha}. \quad (32)$$

Then the exogenous part  $a_j$  can be recovered using equation (12) and the data on local employment and land area.

Since we observe commercial and residential floorspace prices for all Census tracts, we can calculate the zoning parameter  $\xi_i$  as

$$\xi_i = \frac{q_{Wi}}{q_{Ri}}. \quad (33)$$

To calculate  $\xi_i$ , we replace  $q_{Wi}$  and  $q_{Ri}$  with tract-level quality adjusted indexes of commercial and residential prices,  $\zeta_j^{com}$  and  $\zeta_j^{res}$ , respectively, as described in Appendix A.

Finally, in order to recover  $\bar{H}_i$ , we use market clearing conditions for land and floorspace ( $L_i = \Lambda_i$  and equation 19). Combining them, we can recover  $\bar{H}_i$  from the following relationship:

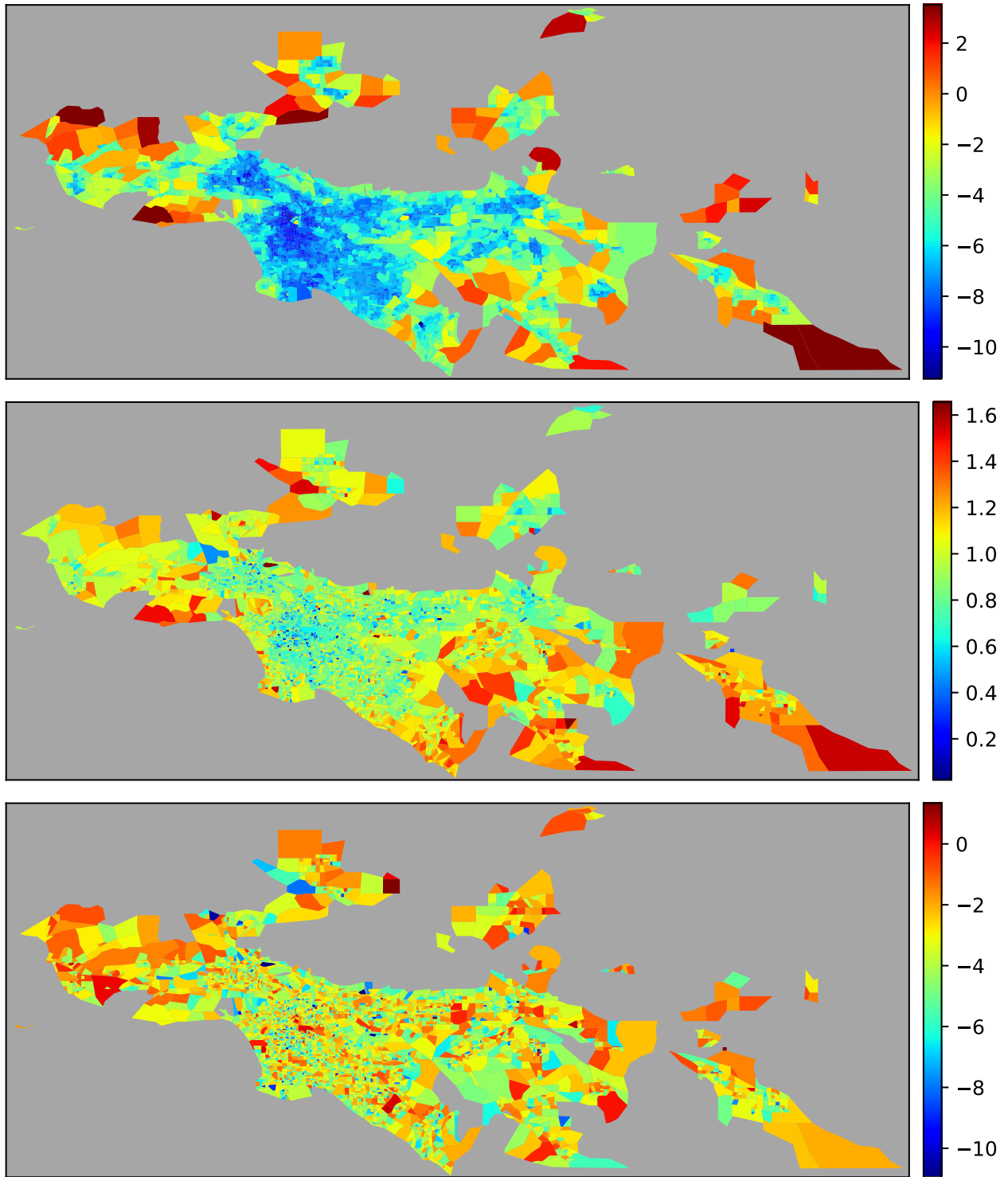
$$\bar{H}_i = \frac{\bar{\phi}((1 - \eta)\bar{q}_i)^{\frac{1-\eta}{\eta}} \Lambda_i}{\bar{\phi}((1 - \eta)\bar{q}_i)^{\frac{1-\eta}{\eta}} \Lambda_i / H_i - 1}, \quad (34)$$

where  $\Lambda_i$  is the observed land area and  $H_i = H_{Ri} + H_{Wi} + H_{Ti}$  is the total demand for floorspace in tract  $i$ .

Figure 4 maps the recovered values for three key structural parameters: the exogenous component of residential amenities,  $x_i$ , the exogenous component of productivity,  $a_i$ , and exogenous

employment amenities,  $E_i$ .

Figure 4: Structural residuals



*Note:* Exogenous residential amenities (top figure), exogenous productivities (middle figure) and exogenous employment amenities (bottom figure).

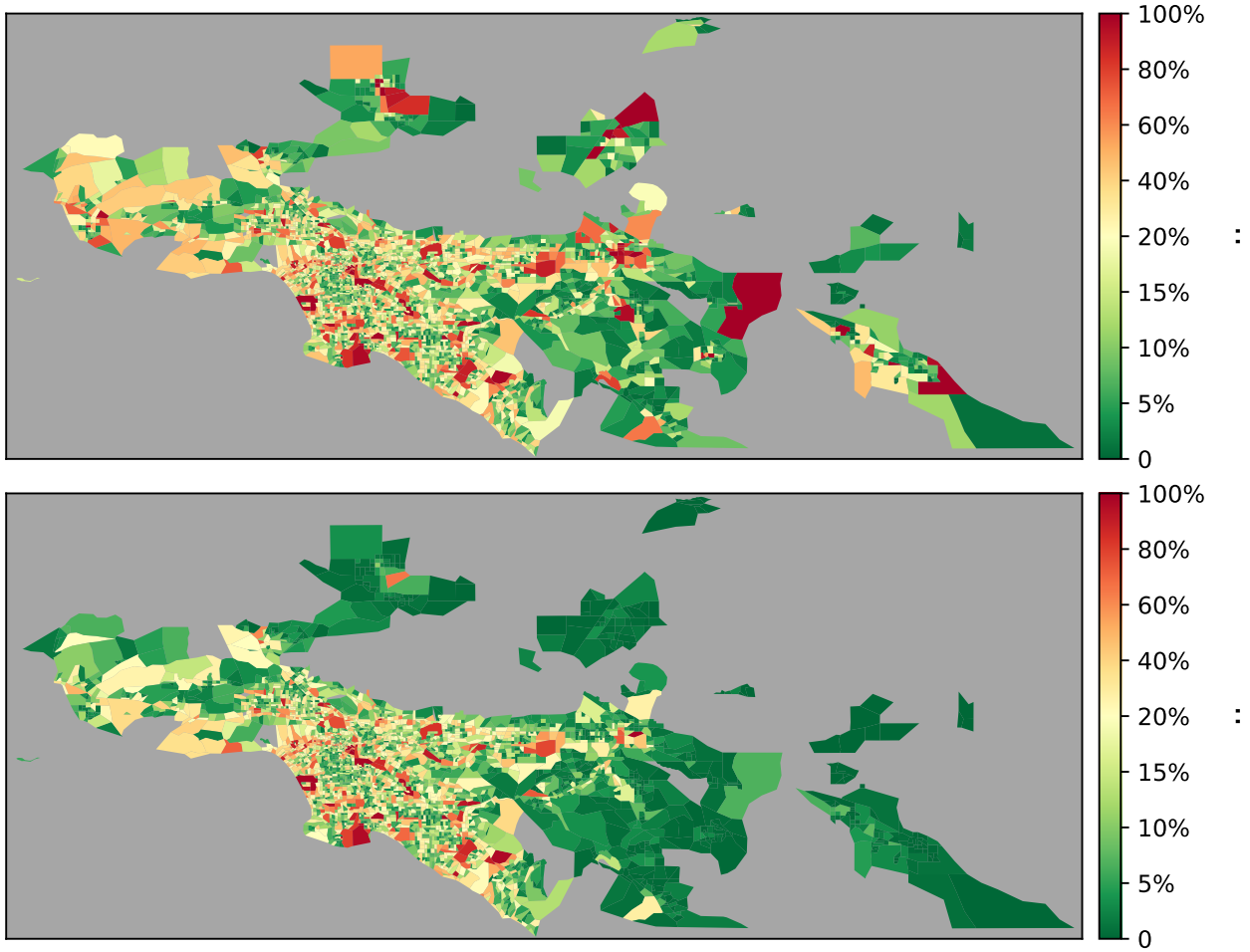


## D Additional Results of Counterfactual Experiments

### D.1 Land Use

When the fraction of telecommuters rises, land use becomes more specialized. Figure 5 shows that in the economy with more widespread telework, commercial development becomes relatively more prevalent in core areas and less prevalent in the periphery. In addition, both types of development become more concentrated in space. As a consequence, the numbers of primarily residential and primarily commercial tracts increase, while the number of mixed tracts goes down (right panel of Figure 6).<sup>31</sup>

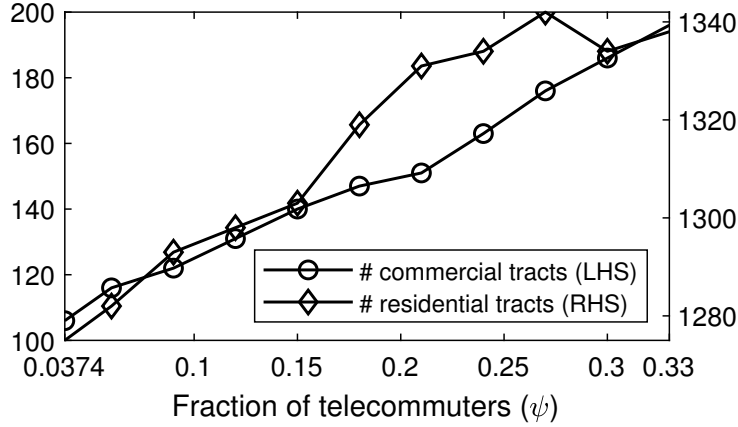
Figure 5: Land Use



*Note:* Benchmark (upper figure) and the  $\psi = 0.33$  counterfactual (lower figure). Maps show the fraction of commercial floorspace in each tract, varying from 0 (green) to 1 (brown). See main text for details.

<sup>31</sup>We label a tract as *commercial* if the share of commercial floorspace in the tract is more than 3 times the share of the average tract. Similarly, we label a tract as *residential* if the share of commercial floorspace in the tract is less than 1/3 of the share of the average tract. All other tracts are labeled *mixed*.

Figure 6: Land Use Specialization

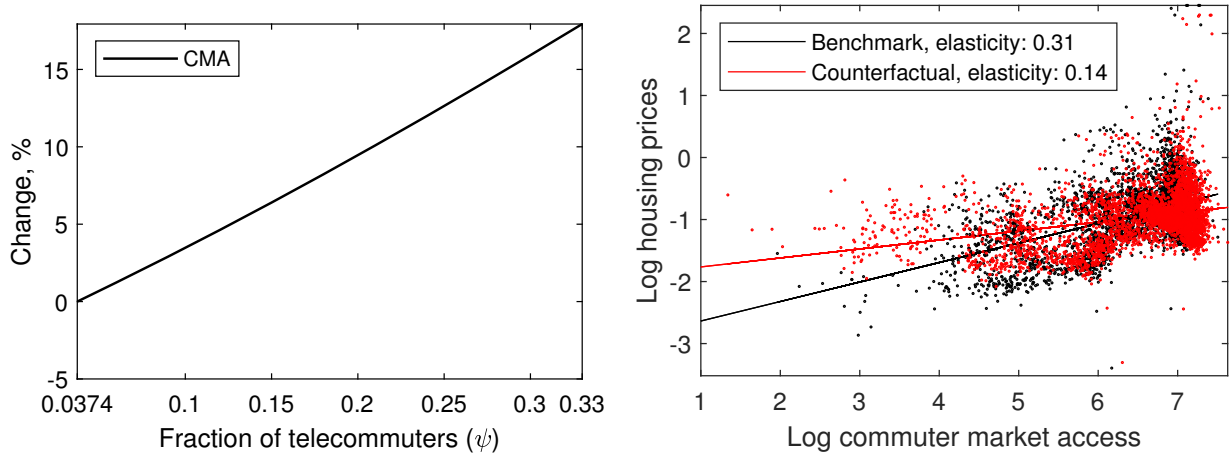


*Note:* The figure shows the number of commercial and residential tracts, as a function of the share of teleworkers. See main text for details.

## D.2 Job access

In large, sprawled and congested cities, such as Los Angeles, good jobs are often inaccessible for households who live on the periphery. To study how a shift to telecommuting impacts job access, we calculate commuter market access for each tract as  $CMA_i = \sum_{j \in \mathcal{I}} (w_j e^{-\kappa t_{ij}})^\epsilon$ . We find that, as the number of teleworkers grows, the average job access increases for those who keep commuting (left panel of Figure 7). Moreover, in the counterfactual economy the elasticity of housing prices with respect to the market access halves, meaning that places with better access to jobs command a lower price premium (right panel of Figure 7).

Figure 7: Access to jobs

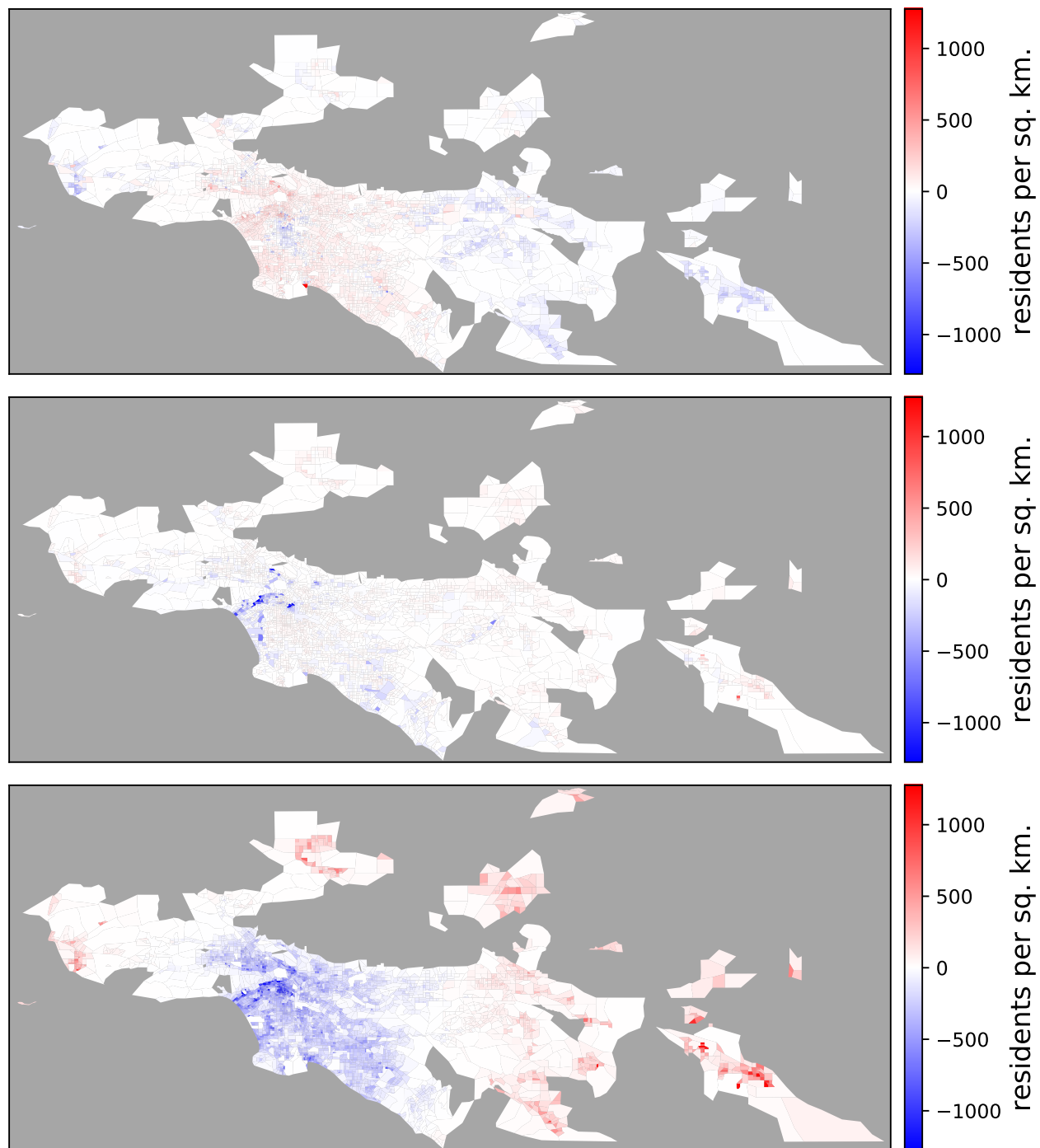


*Note:* Left panel shows the weighted-average commuter market access for each level of  $\psi$ . Right panel shows the relationship between  $CMA_i$  and housing prices  $q_{Ri}$  in the benchmark economy and the counterfactual economy with  $\psi = 0.33$ .

### D.3 Breakdown of residential and job changes by worker type

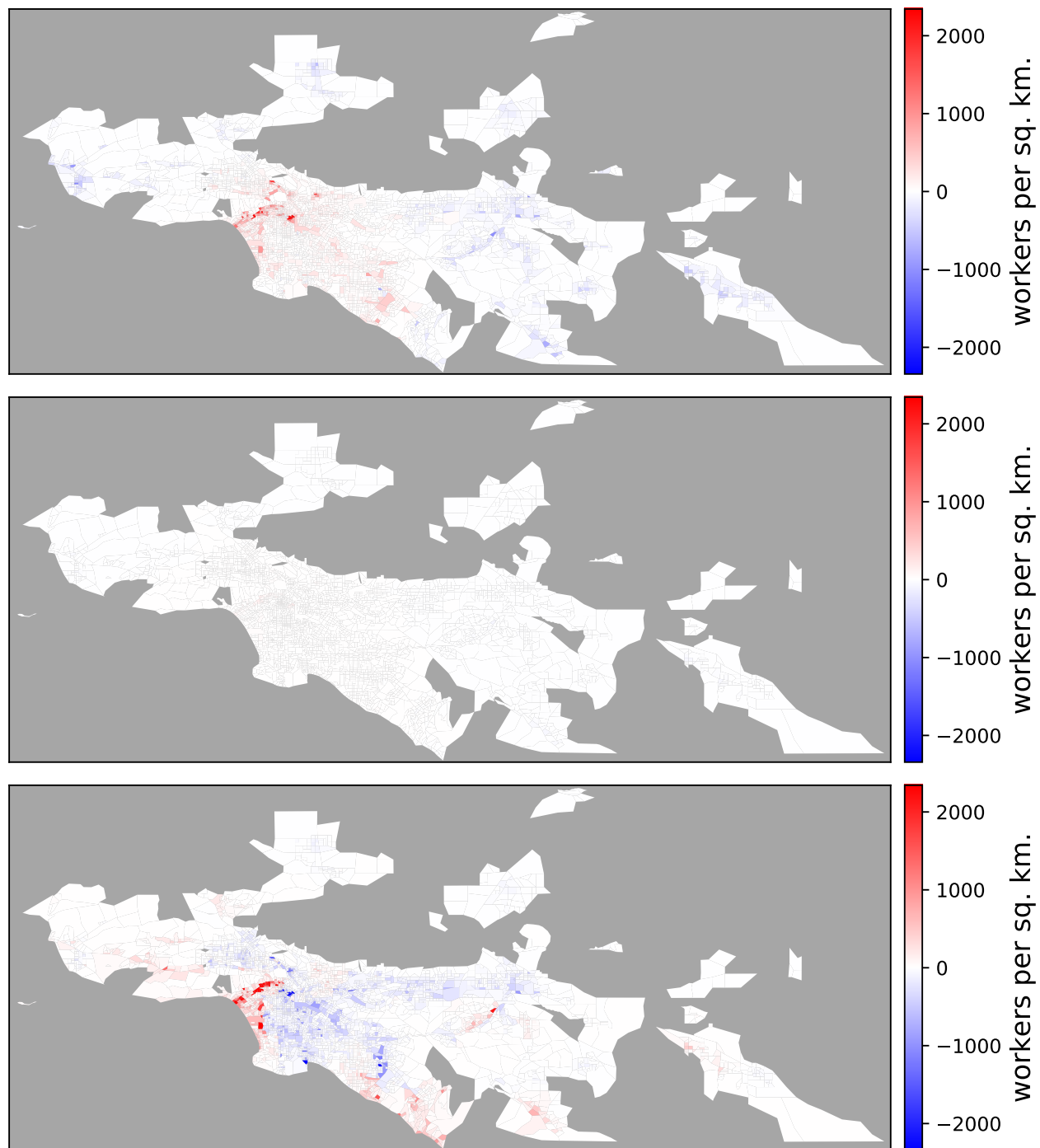
In the context of the counterfactual exercise, there are three types of workers: continuing commuters, old telecommuters, and new telecommuters. In Figures 8 and 9, we show changes in residence and jobs for each category separately.

Figure 8: Residence changes for continuing commuters, old telecommuters, and new telecommuters



*Note:* Absolute change in residential density for continuing commuters (top figure), old telecommuters (middle figure) and new telecommuters (bottom figure). Relative to benchmark economy in counterfactual with  $\psi = 0.33$ .

Figure 9: Job changes for continuing commuters, old telecommuters, and new telecommuters



*Note:* Absolute change in job density for continuing commuters (top figure), old telecommuters (middle figure) and new telecommuters (bottom figure). Relative to benchmark economy in counterfactual with  $\psi = 0.33$ .

## E Elasticity of Speed to Traffic Volume

We set the elasticity of commuting speed with respect to traffic volume is  $\varepsilon_V = 0.2$ , following [Small and Verhoef \(2007\)](#). In the counterfactual economy, we calculate changes in commuting speeds as

$$\frac{speed_{ij}^{CF} - speed_{ij}^{BM}}{speed_{ij}^{BM}} = -\varepsilon_V \frac{VMT^{CF} - VMT^{BM}}{VMT^{BM}},$$

assuming that the road capacity remains unchanged and only taking into account the change in total vehicle miles traveled ( $VMT$ ) in the metropolitan area.<sup>32</sup> Then we recover commuting times as  $t_{ij}^{CF} = distance_{ij} / \max\{speed_{ij}^{CF}, 65\text{mph}\}$ . The maximum operator caps speeds at 65 mph which is the speed limit on most highways in California. Since  $t_{ij}$  and  $VMT$  endogenously depend on each other, when solving for an equilibrium in a counterfactual economy, we iterate the model until  $VMT$  converges.

**Robustness.** Since the results of the counterfactual experiments described in Section 3 crucially depend on changes in commuting speeds, we investigate whether our results are robust to the value of  $\varepsilon_V$ . While 0.2 is a standard value in the traffic modeling literature, other studies used higher values.<sup>33</sup> At the same time, a low value of  $\varepsilon_V$  ensures that many of our counterfactual results are conservative.

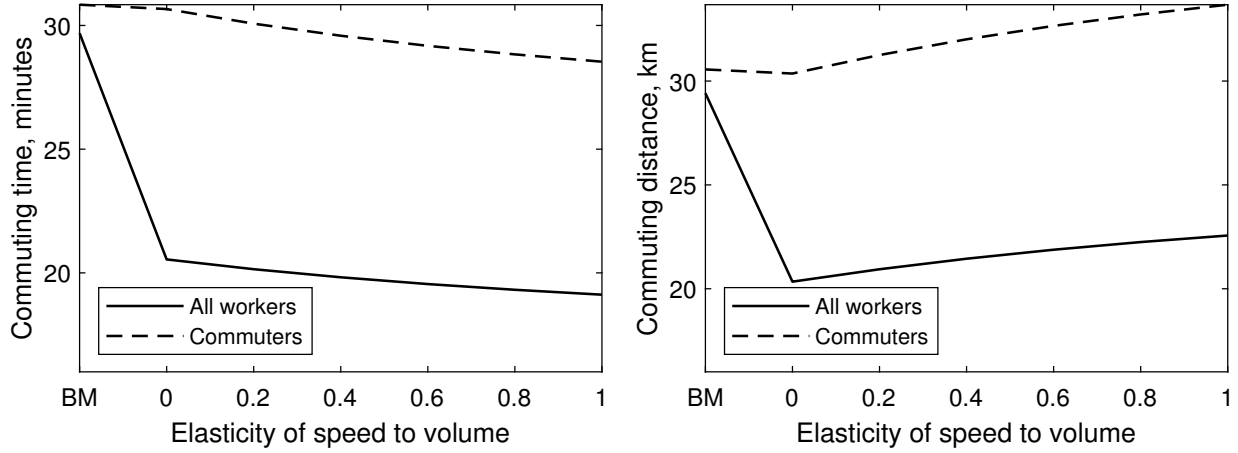
To understand how sensitive our results are to the value of  $\varepsilon_V$ , we compute the counterfactual economy with fraction  $\psi = 0.33$  telecommuters at different levels of  $\varepsilon_V$  ranging from 0 to 1. Our three main sets of results remain robust to the value of  $\varepsilon_V$ . First, regardless of the value of  $\varepsilon_V$ , the economy exhibits the decentralization of residents and centralization of jobs. Second, commuters' trips are characterized by shorter times and longer distances (Figure 10). Third, residential and commercial floorspace prices fall for all values of  $\varepsilon_V$  (Figure 11).

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<sup>32</sup>Note that our methodology does not allow for the differential impact of changes in traffic on individual routes.

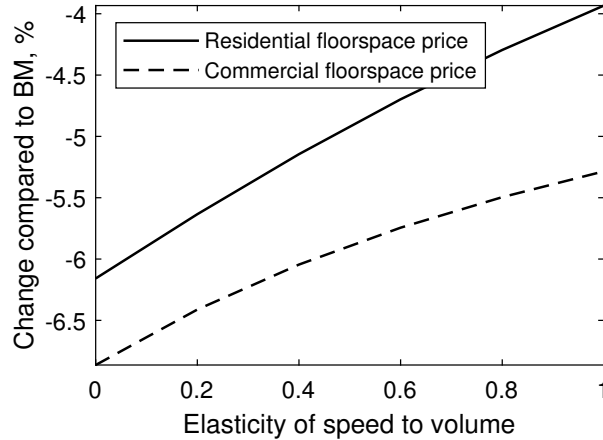
<sup>33</sup>For example, [Akbar, Couture, Duranton, and Storeygard \(2018\)](#) used values of 0.2 and 0.3. [Bento, Hall, and Heilmann \(2020\)](#) estimate a value of about 0.9 for peak-hour commuting in Los Angeles.

Figure 10: Commuting time and distance



*Note:* Left panel displays the average commuting time for all workers and commuters in the benchmark and the counterfactual economies at different levels of the elasticity of commuting speed with respect to traffic volume. Right panel shows the average commuting distance.

Figure 11: House prices

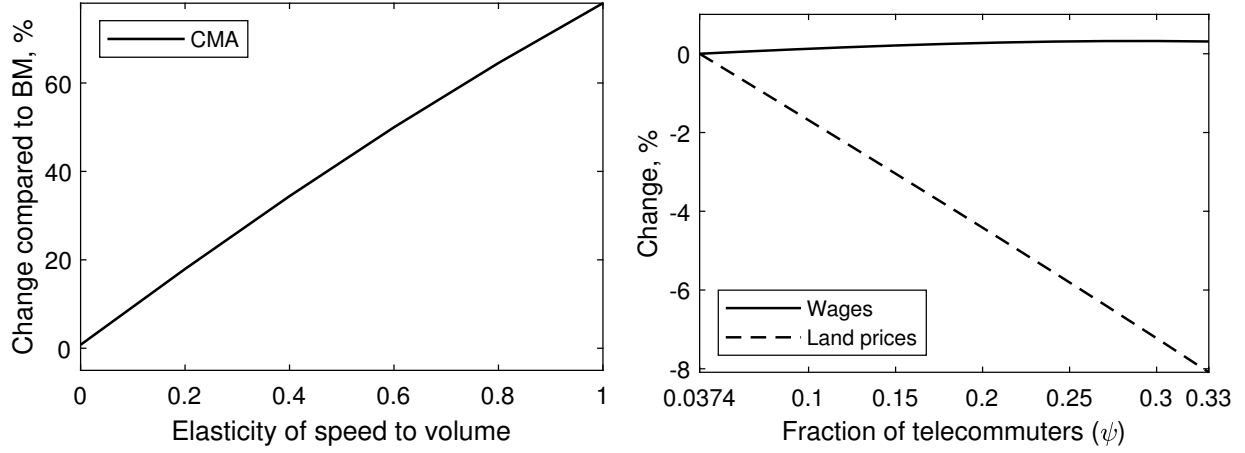


*Note:* The figure displays the counterfactual change in average residential and commercial floorspace prices, as a function of the elasticity of commuting speed with respect to traffic volume.

At the same time, quantitative implications of more telecommuting for wages and welfare are sensitive to the value of  $\varepsilon_V$ . In our main counterfactual with  $\varepsilon_V = 0.2$ , the average commuter market access (*CMA*) increases by about 17%. However, as  $\varepsilon_V$  approaches 1, commutes become speedier and the average *CMA* increases by nearly 80% (left panel of Figure 12). In addition, the higher the elasticity of speed, the stronger will be spatial productivity spillovers. Hence, when  $\varepsilon_V$  goes to 1, wage gains for commuters are much larger and wage losses for telecommuters turn into

small gains, resulting in larger average wage increases (right panel of Figure 12).

Figure 12: Commuter market access, wages, and land prices

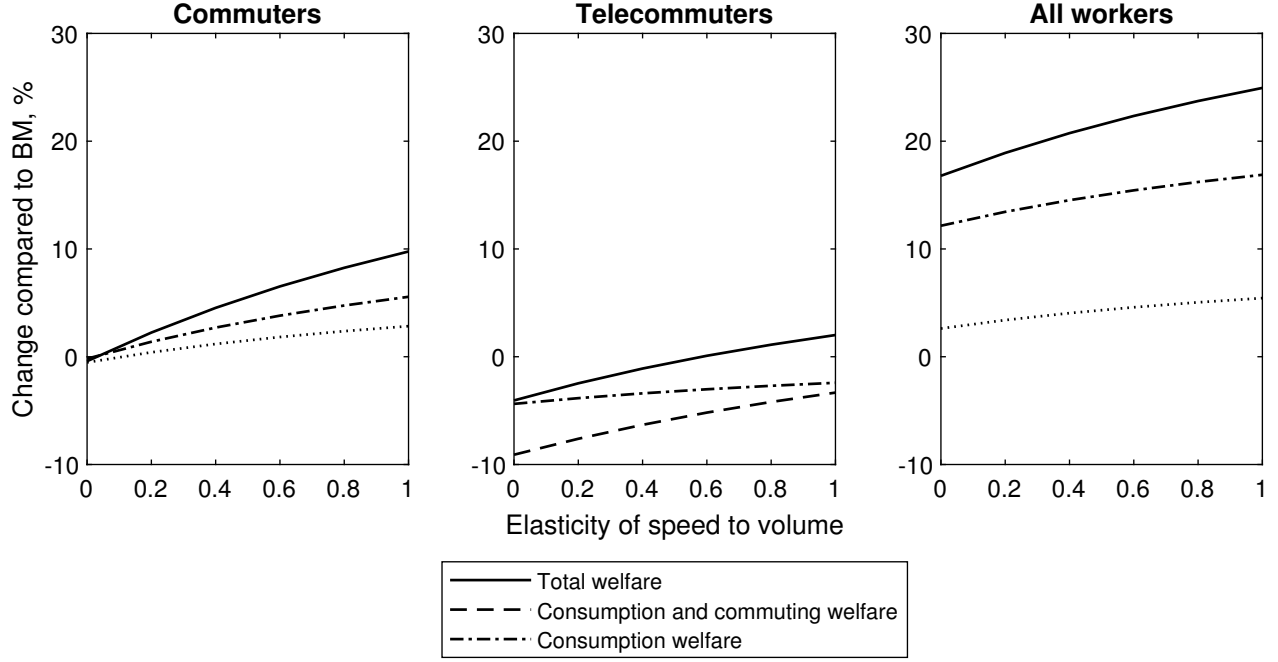


*Note:* Left panel displays the average commuter market access for commuters, as a function of the elasticity of commuting speed with respect to traffic volume. Right panel shows average wages and land prices.

As a result, with higher values of  $\varepsilon_V$ , welfare gains are larger (Figure 13). In particular, as  $\varepsilon_V$  goes to 1, commuters see their welfare increase by almost 10% (compared to 2.2% at  $\varepsilon_V = 0.2$ ), telecommuters experience a 2% increase (compared to a 2.5% loss), and overall welfare increases by nearly 25% (compared to 18.9%).



Figure 13: Welfare



*Note:* Left panel shows the change in total expected welfare of commuters (“total welfare”), welfare net of preference shocks and amenities (“consumption and commuting welfare”), and welfare net of shocks, amenities, and commuting costs (“consumption welfare”). Central and right panels report changes in welfare for telecommuters and all workers, respectively.

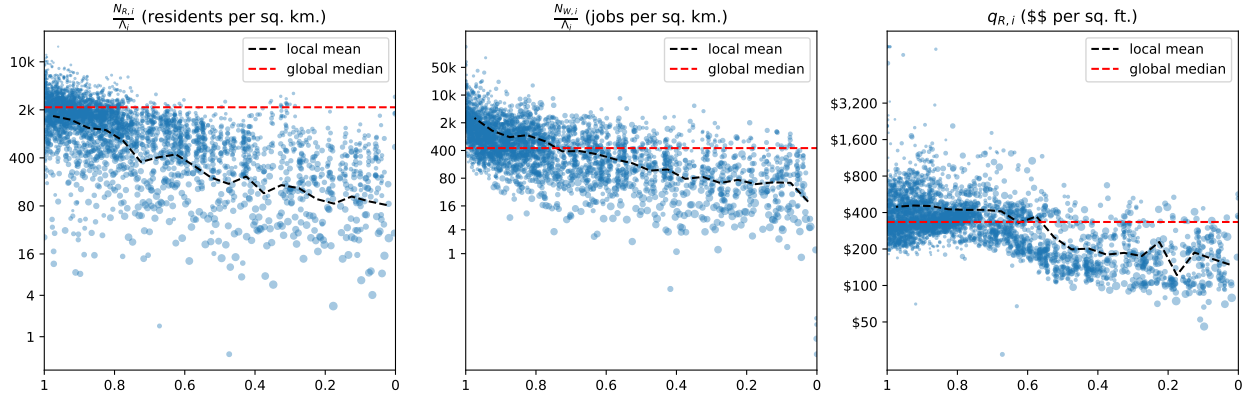
## F Accounting for Spatial Variation in Outcomes

**Centrality.** Distance from the center is a key driver of outcomes in most theoretical models of the city. When dealing with data on real cities, it has been customary to measure this factor simply as the straight-line distance from a “central business district” whose location is determined by convention. Our alternative, which uses information on the city’s transportation network, is the eigenvector centrality of each tract. We calculate it by finding the eigenvector associated with the largest eigenvalue of the  $I \times I$  matrix whose  $ij^{\text{th}}$  element is given by  $\exp\{-\kappa\epsilon\tau_{ij}\}$  and where  $I$  is the number of model locations. This measure reflects the total strength of a given tract’s connections, taking into account not only its direct connections, but also the connections of its connections (second order), and their (third order) connections, and so on ad infinitum.

Interestingly, this measure picks out downtown LA as the most central location on the map. It also turns out to be highly correlated with both straight line distance and travel time to downtown LA (Pearson’s correlation coefficient 0.97 for each). Figure 14 shows the evolution of some key variables along the centrality gradient.<sup>34</sup> Real estate prices, the density of employment, and the

<sup>34</sup>The x-axis is scaled to quantiles of the centrality measure, weighted by land area. In other words, 0.5 on the

Figure 14: Quantiles of Centrality and Initial Allocations



**Note:** The x-axis is scaled to quantiles of the centrality measure, weighted by land area.

density of residence all increase on average the closer one gets to the center. The time required to reach downtown LA is also, naturally, lower near the center.

In Figure 3, we plot the changes that take place in the counterfactual exercise in the same manner as in Figure 14. Here again we see that on average jobs move towards the center and residents move away from it, and that there are big property price increases in the periphery. We can also see that there is a great deal of variation that is unexplained.

**Accounting for counterfactual changes.** In order to have a more complete idea of what is driving the variation in counterfactual outcomes, we expand our view to consider not only a location's initial centrality, but also the change in centrality between the baseline and counterfactual due to changes in average speed, and the exogenous local characteristics  $a_i$ ,  $E_i$  and  $x_i$ . We run a multivariate regression at the tract level, weighted by land area, of these five variables on the log differences between counterfactual and baseline floorspace prices, employment density, and residential density. From the estimated coefficients of these regressions we can infer the sign of each relationship. We then use the Shapley method to decompose the coefficient of determination ( $R^2$ ) for each regression.<sup>35</sup> The share assigned to each explanatory variable is a measure of its importance in accounting for the variation across space in each counterfactual outcome.

Table 10 shows the results of this exercise for the change in floorspace prices. The negative estimated coefficient on centrality confirms the core-periphery gradient of price changes, with prices falling in the core and rising in the periphery. Once this is accounted for, locations whose centrality increases due to change in speed in the counterfactual also see a more positive overall change in prices. The negative coefficients on  $a_i$  indicates that the relative value of real estate in locations with high productivity falls, which is to be expected as workers on average need much

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x-axis represents the single square meter of land area such that 50% of the land area in the metro area is less central (and 50% is more central).

<sup>35</sup>See, e.g., [Shorrocks \(2013\)](#).

Table 10: Accounting for counterfactual floorspace price changes

	Coeff.	Var. expl.
constant	0.274 (0.063)	
centrality	0.022 (0.015)	32.0%
$\Delta$ centrality	3.918 (0.389)	32.1%
$a_i$	-0.270 (0.012)	3.4%
$E_i$	-0.018 (0.001)	1.8%
$x_i$	0.024 (0.001)	15.0%
Total		84.33%

less worksite floorspace than before. The positive coefficient on  $x_i$  indicates that the premium for locations with good natural amenities has increased in the counterfactual, driven by telecommuters who can now choose their residence location more freely. We see that position relative to the core drives the lion's share of the action here: centrality and  $\Delta$  centrality together account for 64.1% of the variation in outcomes. Overall, the factors we consider here account for about 84% of the total variation.

Table 11: Accounting for counterfactual employment changes

	<b>Always commuter</b> Coeff. Var. expl.	<b>New telecommute</b> Coeff. Var. expl.	<b>Always telecommute</b> Coeff. Var. expl.	<b>All</b> Coeff. Var. expl.
constant	-1.292 (0.199)	-7.139 (0.362)	-0.924 (0.119)	-3.835 (0.251)
centrality	-0.138 (0.049)	-1.384 (0.089)	-0.149 (0.029)	-0.684 (0.062)
$\Delta$ centrality	-15.619 (1.237)	-40.542 (2.253)	-10.146 (0.737)	-25.506 (1.561)
$a_i$	1.012 (0.039)	2.508 (0.070)	0.534 (0.023)	1.596 (0.049)
$E_i$	0.057 (0.004)	0.189 (0.008)	0.022 (0.003)	0.107 (0.006)
$x_i$	-0.041 (0.003)	-0.015 (0.005)	-0.010 (0.002)	-0.030 (0.003)
Total	84.36%	39.04%	78.95%	56.78%

For employment density and residential density, we further break the overall changes down into changes in the average choices made by three groups of workers. These groups are: those that commute both in the baseline and the counterfactual (67% of all workers), those that switch from commuting to telecommuting (29.3%), and those that telecommute both in the baseline and the counterfactual (3.7%). Table 11 shows the results for changes in employment density and Table 12 shows the same for changes in resident density. Workers who continue commuting take jobs closer to the urban core and also choose residences that are, on average, closer to the core.

Table 12: Accounting for counterfactual residence changes

	<b>Always commuter</b>		<b>New telecommute</b>		<b>Always telecommute</b>		<b>All</b>	
	Coeff.	Var. expl.	Coeff.	Var. expl.	Coeff.	Var. expl.	Coeff.	Var. expl.
constant	0.840 (0.119)		-0.078 (0.225)		9.789 (0.502)		-0.148 (0.141)	
centrality	0.153 (0.029)	29.5%	0.026 (0.055)	35.6%	1.038 (0.123)	12.4%	-0.045 (0.035)	24.9%
$\Delta$ centrality	-1.282 (0.737)	29.5%	15.681 (1.400)	36.0%	44.651 (3.122)	13.1%	3.514 (0.879)	24.9%
$a_i$	0.171 (0.023)	3.1%	-0.240 (0.044)	2.8%	-8.139 (0.097)	17.2%	0.009 (0.027)	1.9%
$E_i$	0.050 (0.003)	2.4%	0.036 (0.005)	2.6%	-1.051 (0.011)	27.8%	0.046 (0.003)	5.5%
$x_i$	0.004 (0.002)	5.8%	0.010 (0.003)	10.2%	0.338 (0.007)	7.6%	-0.001 (0.002)	7.8%
Total		70.33%		87.19%		78.08%		65.01%

New telecommuters, with the new-found freedom, do the opposite: they choose jobs and residence that are, on average, farther from the core than before. Continuing telecommuters make smaller shifts overall, taking jobs a bit closer to the core and moving their residences a bit farther from it. Across all categories of workers there is a strong shift from commercial to residential use of land in locations where there is a larger increase in centrality due to commuting speed changes.

There is also some heterogeneity in the way that location-specific characteristics correlate with changes in choices for the three groups. For example, those who telecommute both in the baseline and the counterfactual move their residences out of high- $a_i$  and high- $E_i$  tracts, presumably to make room for the overall shift of employment into those tracts, while this pattern isn't seen for the other two groups.

As with changes in land prices, initial centrality and changes in centrality together account for the lion's share of the explained variation: 42.6% out of 56.78% total for employment changes, and 49.8% out of 65.01% total for residence changes. The positive coefficient on  $a_i$  for employment changes, and its 8.3% share in the variation in outcomes, is consistent with an improvement in the allocation of workers to high-productivity locations in the counterfactual. Overall, the included factors account for less of the variation than in the case of floorspace prices. This is partly due to opposing tendencies in the three different types of workers canceling each other out.