

Spatial Implications of Telecommuting*

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Abstract

If the 2020 surge in working from home became permanent, how would the distribution of jobs and residents within and across U.S. cities change? To study this question, we build a quantitative spatial equilibrium model of job and residence choice with commuting frictions between 4,502 sub-metropolitan locations in the contiguous U.S. A novel feature of our model is the heterogeneity of workers in the fraction of time they work on-site: some workers commute daily, some always work at home, while others alternate between working on-site and remotely. In a counterfactual where remote work becomes more common, residents move from central to peripheral areas within cities, and from large coastal to small interior cities, on average. The reallocation of jobs is less monotonic, with increases both in peripheral locations and in the highest-productivity metropolises. Agglomeration externalities from in-person interactions are crucial for welfare effects. If telecommuters keep contributing to productivity as if they worked on-site, better job market access drives considerable welfare gains, even for those who continue to commute. But if productivity declines in response to the reduction in face-to-face interactions, wages fall and most workers are worse off.

Key Words: urban, work at home, commuting, spatial equilibrium

JEL Codes: E24, J81, R31, R33, R41

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1 Introduction

Perhaps no event in recent history has as much potential to utterly transform the urban landscape as the surge in working from home that has occurred in 2020 following the Covid-19 pandemic. Years of steady technical progress have increased the feasibility of remote arrangements.¹ Now, in one fell swoop, one-third of the workforce has made a forced investment in the skills and equipment needed to work out of their homes.² Survey after survey of managers and the workers themselves indicate the likelihood that some of the increase in remote work will become permanent and will have sizable effects on location choices of workers.³

How would the internal structure of American cities change if the tether of commuting is cut loose for a large section of the work force? Will downtown districts be left empty, as telecommuting office workers decamp for the suburbs? And what shifts might occur across cities? Is the era of the big cities over?

In this paper we build a quantitative model of job and residence choice to address these questions. Workers compare wages, property prices, local amenities, and commuting times between 4,502 urban, suburban and rural locations in the contiguous United States. They choose one place to live and one place to work. In addition to on-site workers there are telecommuters, who are also divided into groups. Some visit the office four times a week, others three times, and still others two times, or one time, or never. The less they need to visit the office, the less constrained they are in their choice of the house-job pair. Zero-time-a-weekers are able to live and work on opposite sides of the country.

Recent research by Barrero, Bloom, and Davis (2020) suggests that the fraction of workers who come to work daily will fall from 90% pre-Covid to 73% after the pandemic, while the fraction of those who commute only a few days a week or not at all will grow. Our model generates rich patterns of reallocation both within and across cities in response

¹Mas and Pallais (2020) provides an overview of the current state of research into remote work. Bloom, Liang, Roberts, and Ying (2015) present experimental evidence that telework increases employee work satisfaction without necessarily reducing their productivity, while another experiment by Mas and Pallais (2017) finds that, on average, workers are willing to give up 8% of wages for the option to work from home.

²A survey by Brynjolfsson, Horton, Ozimek, Rock, Sharma, and TuYe (2020) finds that in early May 2020, 35.2% of workers who commuted before Covid-19 were working from home.

³A 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. These projections are supported by the findings of Dingel and Neiman (2020) who estimate that as many as 37% of U.S. jobs can feasibly be done at home. Indeed, some companies (e.g., Facebook and Twitter) announced that many of their employees could keep working from home after Covid-19. Moreover, according to a study by Upwork in October 2020, 2% of survey participants had already moved residences because of the ability to work at home and another 6% planned to do so. Of those who still planned to migrate, 40% would move more than 4 hours away from their current location (Ozimek, 2020).

to this change in commuting frequencies. Residents, led by new telecommuters, move from denser and more central parts of cities to the periphery. They also move from larger to smaller, and from more coastal to more interior cities, on average. These trends have exceptions. Workers actually relocate into a handful of high-amenity locations, and some metro areas, such as Los Angeles and San Diego, grow very slightly.

The trend in job reallocation is not so monotonic. Peripheral areas with low real estate costs and central areas in the most productive cities both add jobs. While the largest percentage increases happen in smaller cities, several large metro areas, including New York and Washington, D.C., see the number of jobs increase. Even in places where jobs increase, however, more of them are held by telecommuters who visit the office less frequently or not at all and often live in different metro areas. This leads to a large decrease in the demand for commercial floorspace and drives a small average decline in real estate prices. New York and Los Angeles see real estate prices fall by about 1%, while San Francisco and San Jose see them decline by about 2%.

We find that welfare effects hinge critically on the extent to which telecommuters contribute to productive externalities. In our baseline scenario the local productivity and amenities of each location do not change in the counterfactual. Improved market access allows wages to go up, and most workers, including full time commuters, experience modest welfare gains. We also compute an alternative scenario in which productivity and amenities are determined endogenously by agglomeration externalities. Our baseline assumption is that productivity externalities arise through face-to-face interactions between workers, so teleworkers do not contribute to them when they are not in the office. In this case, the patterns of reallocation of residence and jobs are nearly the same as before, but the movements are larger due to amplifications via endogenous amenities and productivity. The welfare implications, however, are now different. The reduction in face-to-face interactions lowers overall productivity and drives wages down by over 1%. This makes workers who are still stuck commuting strictly worse off. There are still aggregate welfare gains, but only because there are now more remote workers, who can freely choose locations with better amenities and do not suffer by commuting.

We expand our analysis to explore what would happen if remote workers did make some contribution to workplace spillovers. In the extreme case where they interact in a way that is indistinguishable from on-site workers, all the negative results are reversed. By varying the contribution of telecommuters to spillovers from 0 to 100%, we are able to characterize the level of contribution that would be necessary in order for all classes of workers to be no worse off after the increase in remote work, even if local productivities adjust fully.

This paper builds on previous work by Delventhal, Kwon, and Parkhomenko (2020) in which the authors model the impact of remote work on the allocation of jobs and residence within a single urban area—Los Angeles—modeled as a closed city. Including the entire system of cities changes the prediction for real estate prices—while they fell by nearly 6% in the study of L.A. as a closed city, they fall by only 1% in the current study, as workers from other parts of the country move into the L.A. area attracted by high amenities.

In modeling style our study is related to Monte, Redding, and Rossi-Hansberg (2018), who also analyze the U.S. system of cities using a model in which workers may commute between counties. Our quantitative model contains many small locations within urban counties and thus can study heterogeneous responses of many areas within metro areas. Also related are recent papers which use models of joint job and residence choice at the city level, such as Ahlfeldt, Redding, Sturm, and Wolf (2015) and Heblich, Redding, and Sturm (2020). Our study contributes to this strand of the literature by extending the toolbox to include a full-fledged model of working from home and by exploring what happens when the binding tie of the daily commute is cut for many workers. In addition, we contribute to the theoretical literature that studies telecommuting within the urban environment, e.g., 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.

The remainder of the paper is organized as follows. Section 2 describes the theoretical framework and the methodology of counterfactual experiments. Section 3 discusses the data, as well as estimation and calibration of model parameters. Section 4 reviews the results of counterfactual experiments in which telecommuting becomes more prevalent. Section 5 concludes and outlines possible extensions of our work.

2 Model

Consider a national economy which consists of a set $\mathcal{I} \equiv \{1, \dots, I\}$ of discrete locations and is populated by workers, firms and floorspace developers. Total employment in the economy is fixed and normalized to 1.

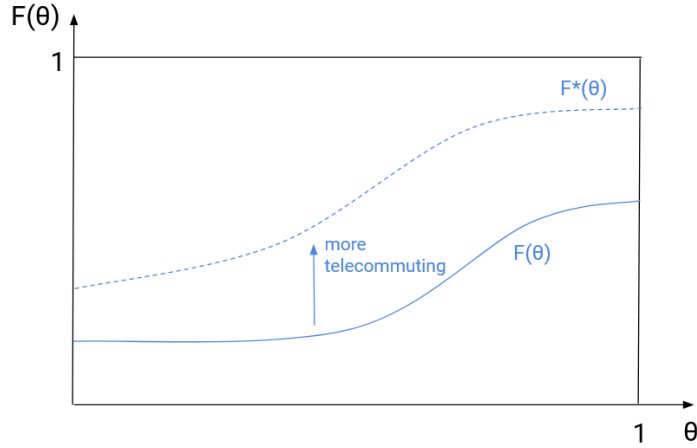
2.1 Workers

2.1.1 Telecommuting

Before choosing where to work and where to live, workers draw their commuter type θ which has a distribution function $F(\theta)$ on support $[0, 1]$. The associated probability

distribution function is $F(\theta)$. Parameter θ is the fraction of work time that an individual has to work on-site. In practice, $F(\theta)$ has a heavy weight on $\theta = 1$ which means that most workers cannot telecommute at all and some weight on $\theta = 0$ which means that there is a non-trivial number of workers who always work remotely. A transition toward more telecommuting corresponds to a shift to $F^*(\theta)$ which is first-order stochastically dominated by $F(\theta)$, as shown in Figure 1.

Figure 1: Distribution of commuter types.



2.1.2 Preferences

A worker n who resides in location $i \in \{1, \dots, I\}$, works in location j , and has to commute there a fraction θ of time, enjoys utility

$$U_{ijn}(\theta) = \frac{z_{ijn}}{d_{ij}(\theta)} \left(\frac{c}{1-\gamma} \right)^{1-\gamma} \left(\frac{h}{\gamma} \right)^{\gamma}, \quad (2.1)$$

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 for type θ given by

$$d_{ij}(\theta) = e^{\theta \kappa t_{ij}}. \quad (2.2)$$

Individuals consume c units of the final good and h units of housing. The share of housing in expenditures is given by γ , and consumption choices are subject to the budget constraint

$$w_{ij}(\theta) = c + q_i h, \quad (2.3)$$

where $w_{ij}(\theta)$ is the wage earned by a type- θ worker who lives in i and works in j , and q_i is the price of residential floorspace in location i .

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

$$v_{ij}(\theta) \equiv \frac{B_{ij}w_{ij}(\theta)}{d_{ij}(\theta)q_i^\gamma} \quad (2.4)$$

is the utility obtained by a type- θ worker, net of the preference shock. In the above formulation, B_{ij} is a location pair-specific shifter defined as

$$B_{ij} \equiv X_i E_j b_{ij}, \quad (2.5)$$

where X_i is the average amenity derived from living in location i , E_j is the average amenity derived from working in location j , and b_{ij} is the pair-specific amenity component.

2.1.3 Location Choices

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

$$\pi_{ij}(\theta) = \frac{(v_{ij}(\theta))^\epsilon}{\sum_{r \in \mathcal{I}} \sum_{s \in \mathcal{I}} (v_{rs}(\theta))^\epsilon} = \frac{(B_{ij}w_{ij}(\theta))^\epsilon (d_{ij}(\theta)q_i^\gamma)^{-\epsilon}}{\sum_{r \in \mathcal{I}} \sum_{s \in \mathcal{I}} (B_{rs}w_{rs}(\theta))^\epsilon (d_{rs}(\theta)q_r^\gamma)^{-\epsilon}}. \quad (2.6)$$

As a result, the equilibrium residential population of type θ in location i is

$$N_{Ri}(\theta) = \sum_{j \in \mathcal{I}} \pi_{ij}(\theta), \quad (2.7)$$

and the equilibrium employment of type θ in location j is

$$N_{Wj}(\theta) = \sum_{i \in \mathcal{I}} \pi_{ij}(\theta). \quad (2.8)$$

The total amount of labor commuting from i to j is given by

$$N_{ij}^C \equiv \int \theta \pi_{ij}(\theta) dF(\theta), \quad (2.9)$$

while the amount of labor telecommuting between i and j is

$$N_{ij}^T \equiv \int (1 - \theta) \pi_{ij}(\theta) dF(\theta). \quad (2.10)$$

Notice that the distinction between on-site and remote labor is not the same as the distinction between commuters and telecommuters, since a worker with $\theta \in (0, 1)$ provides both on-site and remote labor by commuting fraction θ of time and telecommuting the remaining $1 - \theta$. Thus, employment in each location consists of on-site labor

$$N_{Wj}^C = \sum_{i \in I} N_{ij}^C, \quad (2.11)$$

and remote labor

$$N_{Wj}^T = \sum_{i \in I} N_{ij}^T. \quad (2.12)$$

The probability of working in location j , conditional on living in i , is given by

$$\pi_{ij|i}(\theta) = \frac{\left(E_j b_{ij} w_{ij}(\theta)\right)^\epsilon \left(d_{ij}(\theta)\right)^{-\epsilon}}{\sum_{s \in I} \left(E_s b_{is} w_{is}(\theta)\right)^\epsilon \left(d_{is}(\theta)\right)^{-\epsilon}}. \quad (2.13)$$

The probability of living in location i , conditional on working in i , is

$$\pi_{ij|j}(\theta) = \frac{\left(X_i b_{ij} w_{ij}(\theta)\right)^\epsilon \left(d_{ij}(\theta) q_i^\gamma\right)^{-\epsilon}}{\sum_{r \in I} \left(X_r b_{rj} w_{rj}(\theta)\right)^\epsilon \left(d_{rj}(\theta) q_r^\gamma\right)^{-\epsilon}}. \quad (2.14)$$

The following commuter market clearing conditions relate the number of workers in each location to the number of residents in each location:

$$N_{Wj}(\theta) = \sum_{i \in I} \pi_{ij|j}(\theta) N_{Ri}(\theta), \quad (2.15)$$

$$N_{Ri}(\theta) = \sum_{j \in I} \pi_{ij|i}(\theta) N_{Wj}(\theta). \quad (2.16)$$

2.1.4 Welfare

The expected utility of a worker, before she knows her value of θ and before the idiosyncratic preference shocks realize, is

$$V = \varsigma \int \left[\sum_{i \in I} \sum_{j \in I} \left(B_{ij} w_{ij}(\theta) \right)^\epsilon \left(d_{ij}(\theta) q_i^\gamma \right)^{-\epsilon} \right]^{\frac{1}{\epsilon}} dF(\theta), \quad (2.17)$$

where $\varsigma \equiv \Gamma\left(\frac{\epsilon-1}{\epsilon}\right)$ and $\Gamma(\cdot)$ is the Gamma function.

2.2 Firms

2.2.1 Production

In each location, there is a representative firm which 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

$$Y_j = Y_j^C + Y_j^T, \quad (2.18)$$

where Y_j^C and Y_j^T are the amounts produced on-site and remotely, respectively. The on-site production function is given by

$$Y_j^C = A_j \left(N_{Wj}^C\right)^{\alpha_C} \left(H_{Wj}^C\right)^{1-\alpha_C}, \quad (2.19)$$

where N_{Wj}^C is labor, H_{Wj}^C is floorspace, and α_C is the labor share. The remote production function is also Cobb-Douglas and it combines workers from different locations as follows:

$$Y_j^T = \nu A_j \sum_{i \in I} \left(N_{ij}^T\right)^{\alpha_T} \left(H_{ij}^T\right)^{1-\alpha_T}. \quad (2.20)$$

In the previous specification, N_{ij}^T is the number 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.⁴ Parameter ν is the productivity gap between on-site and remote work, common to all workers and firms. We let the floorspace share, $1 - \alpha_m$, differ between the two modes.⁵

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

⁴We 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.

⁵One may expect that $1 - \alpha_C > 1 - \alpha_T$ because telecommuters tend to work in industries and occupations that require little floorspace (e.g., compare software development with manufacturing). While we do not impose this inequality in our theoretical analysis, it holds in our calibration.

for on-site work are

$$w_j^C = \alpha_C A_j^{\frac{1}{\alpha_C}} \left(\frac{1 - \alpha_C}{q_j} \right)^{\frac{1 - \alpha_C}{\alpha_C}}, \quad (2.21)$$

where q_j is the local price of floorspace. The payments for at-home work of an individual who is employed in j and works remotely from i are given by

$$w_{ij}^T = \alpha_T (\nu A_j)^{\frac{1}{\alpha_T}} \left(\frac{1 - \alpha_T}{q_i} \right)^{\frac{1 - \alpha_T}{\alpha_T}}. \quad (2.22)$$

In the previous expression the relevant floorspace price is the price at the location of residence of the worker. The take-home wage of a worker with a given θ is the weighted average of payments to his commuting labor and his telecommuting labor:

$$w_{ij}(\theta) = \theta w_j^C + (1 - \theta) w_{ij}^T. \quad (2.23)$$

Note that the wage of a regular commuter ($\theta = 1$) does not depend on her location of residence i . However, the wage of a worker who works some of the time remotely ($\theta < 1$) depends on his location of residence i because the home-office floorspace is used in production. The average income earned by residents of location i is

$$\tilde{w}_i = \int \sum_{j \in \mathcal{I}} w_{ij}(\theta) \pi_{ij|i}(\theta) dF(\theta). \quad (2.24)$$

2.3 Developers

2.3.1 Supply of floorspace

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

$$H_i = K_i^{1 - \eta_i} (\phi_i L_i)^{\eta_i}, \quad (2.25)$$

where L_i and K_i are the amounts of land and the final good used to produce floorspace, and η_i is the location-specific share of land in the production function. Each location is endowed with Λ_i units of buildable land which is exogenous and serves as the upper bound on the developers' choice of land: $L_i \leq \Lambda_i$. Parameter ϕ_i stands for the local land-

augmenting productivity of floorspace developers.⁶ Let q_i be the equilibrium price of floorspace. Then the equilibrium supply of floorspace in location i is

$$H_i = \phi_i (1 - \eta_i)^{\frac{1-\eta_i}{\eta_i}} q_i^{\frac{1-\eta_i}{\eta_i}} \Lambda_i. \quad (2.26)$$

The price elasticity of floorspace supply is therefore $\frac{1-\eta_i}{\eta_i}$.

2.3.2 Demand for floorspace

Floorspace is used by firms, residents, and telecommuters, and therefore is divided into commercial, residential, and home offices. The demand for commercial floorspace is

$$H_{Wi} = \left(\frac{1 - \alpha_C}{q_j} \right)^{\frac{1}{\alpha_C}} N_{Wj} A_j^{\frac{1}{\alpha_C}}, \quad (2.27)$$

the demand for residential floorspace is

$$H_{Ri} = \frac{\gamma}{q_i} N_{Ri} \tilde{w}_i, \quad (2.28)$$

and the demand for home offices is given by

$$H_{Ti} = \left(\frac{1 - \alpha_T}{q_i} \right)^{\frac{1}{\alpha_T}} N_{Ri} \sum_{j \in \mathcal{I}} \left(v A_j \right)^{\frac{1}{\alpha_T}} \int (1 - \theta) \pi_{ij|i}(\theta) dF(\theta). \quad (2.29)$$

In equilibrium the supply of floorspace must equal to the total demand,

$$H_i = H_{Wi} + H_{Ri} + H_{Ti}. \quad (2.30)$$

2.3.3 Land and floorspace prices

Floorspace demand also determines the demand for land. We follow Monte, Redding, and Rossi-Hansberg (2018) in assuming that land in each location is owned by local immobile landlords who only consume the final good. Thanks to this assumption, we can account for changes in land values when computing welfare effects, while eliminating anticipated income from land ownership as a factor in the location choice problem. In equilibrium, it is optimal for developers to use all buildable land, i.e., $L_i = \Lambda_i$. As a result, the equilibrium

⁶The productivity may depend on terrain, climate, land use regulations, etc.

land price is equal to

$$l_i = \frac{\eta_i}{\Lambda_i} \left[\frac{1 - \alpha_C}{\alpha_C} w_i^C \sum_{j \in \mathcal{I}} N_{ji}^C + \gamma \sum_{j \in \mathcal{I}} w_j^C N_{ij}^C + \left(\gamma + \frac{1 - \alpha_T}{\alpha_T} \right) \sum_{j \in \mathcal{I}} w_{ij}^T N_{ij}^T \right]. \quad (2.31)$$

Finally, equilibrium floorspace prices are given by

$$q_i = \frac{1}{\eta_i^{\eta_i} (1 - \eta_i)^{1 - \eta_i}} \left(\frac{l_i}{\phi_i} \right)^{\eta_i}. \quad (2.32)$$

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:

$$A_j = a_j \left(\frac{N_{wj}^C + \psi N_{wj}^T}{L_j} \right)^{\lambda}. \quad (2.33)$$

Parameter $\lambda > 0$ measures the elasticity of productivity with respect to the local density of workers. Parameter $\psi \in [0, 1]$ is the degree of remote workers' participation in productive externalities. These externalities include learning, knowledge spillovers, and networking that occur as a result of face-to-face interactions between workers. When workers are not on-site, but are working remotely, they may not participate fully in the types of interactions that give rise to these externalities. As we will see, the value of ψ has important consequences for wages and welfare in our counterfactual analysis.

Similarly, the residential amenity in location i is determined by an exogenous component, x_j , and an endogenous component that depends on the density of residents:

$$X_i = x_i \left(\frac{N_{Ri}}{L_i} \right)^{\chi}. \quad (2.34)$$

Parameter $\chi > 0$ measures the elasticity of amenities with respect to the local density of residents.⁷ The positive relationship between residential density and amenities represents

⁷We do not include spatial spillovers of productivity and amenities between adjacent locations. These spillovers are highly localized, as found in Ahlfeldt, Redding, Sturm, and Wolf (2015) and several other studies. Given the size of locations in our quantitative economy, the effect of the spillovers is minimal. For example, the 1st percentile of one-way travel times for location pairs with positive commuting flows is 10.63 minutes (the minimum is 7.68 and the median is 26.56). With spillover decay parameters from Ahlfeldt, Redding, Sturm, and Wolf (2015), $\delta = 0.36$ and $\rho = 0.76$, only a fraction $e^{-\delta t_{ij}} = e^{-0.36 \times 10.63} = 0.0218$

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.⁸

2.5 Equilibrium

Definition 2.1. A *spatial equilibrium* consists of location choice probabilities, $\pi_{ij}(\theta)$; residential and workplace employment, $N_{Ri}(\theta)$ and $N_{Wj}(\theta)$; wages, w_j^C and w_{ij}^T ; land prices, l_i ; floorspace prices, q_i ; local productivity, A_j ; and local amenities, X_j ; such that equations (2.6), (2.15), (2.16), (2.21), (2.22), (2.31), (2.32), (2.33), and (2.34) are satisfied.

2.6 Counterfactual Equilibrium

In order to compute counterfactual changes in equilibrium variables, we use the “exact-hat algebra” approach pioneered by Dekle, Eaton, and Kortum (2007). For any variable with benchmark value of z and counterfactual value of z^* , define $\hat{z} \equiv z^*/z$. Then the counterfactual changes can be computed by solving the following system of equations:

$$\hat{w}_j^C = \hat{A}_j^{\frac{1}{\alpha_C}} \hat{q}_j^{-\frac{1-\alpha_C}{\alpha_C}}, \quad (2.35)$$

$$\hat{w}_{ij}^T = \left(\hat{v} \hat{A}_j \right)^{\frac{1}{\alpha_T}} \hat{q}_i^{-\frac{1-\alpha_T}{\alpha_T}}, \quad (2.36)$$

$$\hat{w}_{ij}(\theta) w_{ij}(\theta) = \theta \hat{w}_j^C w_j^C + (1 - \theta) \hat{w}_{ij}^T w_{ij}^T, \quad (2.37)$$

$$\hat{q}_i = \left(\frac{\hat{l}_i}{\hat{\phi}_i} \right)^{\eta_i}, \quad (2.38)$$

$$\hat{\pi}_{ij}(\theta) = \frac{\left(\hat{X}_i \hat{E}_j \hat{b}_{ij} \hat{w}_{ij}(\theta) \right)^\epsilon \left(\hat{d}_{ij}(\theta) \hat{q}_i^\gamma \right)^{-\epsilon}}{\sum_{r \in I} \sum_{s \in I} \pi_{rs}(\theta) \left(\hat{X}_r \hat{E}_s \hat{b}_{rs} \hat{w}_{rs}(\theta) \right)^\epsilon \left(\hat{d}_{rs}(\theta) \hat{q}_r^\gamma \right)^{-\epsilon}}, \quad (2.39)$$

$$\hat{N}_{ij}^C N_{ij}^C = \int \theta \hat{\pi}_{ij}(\theta) \pi_{ij}(\theta) dF^*(\theta), \quad (2.40)$$

$$\hat{N}_{ij}^T N_{ij}^T = \int (1 - \theta) \hat{\pi}_{ij}(\theta) \pi_{ij}(\theta) dF^*(\theta), \quad (2.41)$$

of the density in one of these locations would be translated into local productivity of another location and a fraction $e^{-\rho l_{ij}} = e^{-0.76 \times 10.63} = 0.0003$ of the density would be translated into amenities.

⁸It is also possible that remote workers, by spending more time in the area of their residence, contribute more to local amenities than commuters.

$$\hat{l}_i = \frac{\frac{1-\alpha_C}{\alpha_C} \hat{w}_i^C w_i^C \sum_{j \in \mathcal{I}} \hat{N}_{ji}^C N_{ji}^C + \gamma \sum_{j \in \mathcal{I}} \hat{w}_j^C w_j^C \hat{N}_{ij}^C N_{ij}^C + \left(\gamma + \frac{1-\alpha_T}{\alpha_T}\right) \sum_{j \in \mathcal{I}} \hat{w}_{ij}^T w_{ij}^T \hat{N}_{ij}^T N_{ij}^T}{\frac{1-\alpha_C}{\alpha_C} w_i^C \sum_{j \in \mathcal{I}} N_{ji}^C + \gamma \sum_{j \in \mathcal{I}} w_j^C N_{ij}^C + \left(\gamma + \frac{1-\alpha_T}{\alpha_T}\right) \sum_{j \in \mathcal{I}} w_{ij}^T N_{ij}^T}, \quad (2.42)$$

$$\hat{A}_j = \hat{a}_j \left(\frac{\hat{N}_{Wj}^C N_{Wj}^C + \psi \hat{N}_{Wj}^T N_{Wj}^T}{N_{Wj}^C + \psi N_{Wj}^T} \right)^\lambda, \quad (2.43)$$

$$\hat{X}_i = \hat{x}_i \left(\hat{N}_{Ri} \right)^\chi. \quad (2.44)$$

In equations (2.40) and (2.41), $F^*(\theta)$ denotes the counterfactual c.d.f. of θ .⁹ In the last two equations, the changes in relevant workplace and residential employment are given by

$$\hat{N}_{Wj}^m N_{Wj}^m = \sum_{i \in \mathcal{I}} \hat{N}_{ij}^m N_{ij}^m, \quad (2.45)$$

for $m \in \{C, T\}$, and

$$\hat{N}_{Ri} N_{Ri} = \sum_{j \in \mathcal{I}} \left(\hat{N}_{ij}^C N_{ij}^C + \hat{N}_{ij}^T N_{ij}^T \right). \quad (2.46)$$

In order to solve the system (2.35)–(2.44), we must have data on commuting flows, $\pi_{ij}(\theta)$, wages w_i^C and w_{ij}^T , and the distribution of commuter types, $F(\theta)$. Section 3.1 describes how we obtain this data. We must also know the economy-wide elasticities, ϵ , γ , α_C , and α_T , as well as local floorspace supply elasticities η_i . Section 3.2 describes how we calibrate or estimate these parameters. Notably, solving the system (2.35)–(2.44) does not require any knowledge of the levels of exogenous location characteristics a_i , x_i , E_i , b_{ij} , ϕ_i , commuting costs, $d_{ij}(\theta)$, the relative productivity of telecommuters, ν , floorspace prices q_i , and buildable land areas Λ_i . This system can be solved recursively and we follow a procedure similar to the one in Monte, Redding, and Rossi-Hansberg (2018).

Counterfactual Welfare Changes. The counterfactual change in the consumption-equivalent welfare is given by

$$\widehat{V} = \frac{\int \hat{w}_{ij}(\theta) w_{ij}(\theta) \left(\hat{\pi}_{ij}(\theta) \pi_{ij}(\theta) \right)^{-\frac{1}{\epsilon}} \left(\hat{d}_{ij}(\theta) d_{ij}(\theta) \right)^{-1} dF^*(\theta)}{\int w_{ij}(\theta) \pi_{ij}(\theta)^{-\frac{1}{\epsilon}} d_{ij}(\theta)^{-1} dF(\theta)}. \quad (2.47)$$

Note that the previous expression yields the same value of $\widehat{V}$ for any pair (i, j) . While we can compute counterfactual changes in all equilibrium variables without knowing commuting costs, $d_{ij}(\theta)$, we need to know them to compute counterfactual changes in

⁹We do not use the hat-algebra notation for F in order to allow that $F(\theta) = 0$ and $F^*(\theta) > 0$ for some θ .

welfare.¹⁰ Appendix A.1 discusses how counterfactual welfare changes can be calculated for each type θ separately and decomposed into various channels (consumption, amenities, commuting, etc.).

3 Data, Calibration, and Estimation

3.1 Data

3.1.1 Locations

The set of model locations is the intersection of the Census Public Use Microdata Areas (PUMA) and counties. The benefit of using PUMAs is that they are defined based on population and therefore allow for rich variation within large urban areas. However, in rural areas PUMAs may be very large and comprise several counties.¹¹ Using PUMAs, when they are contained within a county, and counties, when they are contained within PUMAs, results in 4,504 locations. Two of these locations do not have wage data.¹² Hence, we exclude them from the analysis and end up with 4,502 model locations.

3.1.2 Employment, commuters and telecommuters

We use the LEHD Origin-Destination Employment Statistics (LODES) data provided by the Census Bureau to construct employment by residence and workplace for each of our model locations. We also use LODES to build the commuting matrix between each pair of locations, as discussed in Section 3.2.3. LODES provides employment and commuting flows at the level of Census blocks, and we aggregate the data to the level of our model locations, i.e., PUMAs and counties. This data, however, does not distinguish workers who commute to work from those who work from home. We use survey evidence from Barrero, Bloom, and Davis (2020) to build the distribution of commuter types $F(\theta)$ before Covid-19 and the predicted distribution after Covid-19, as described in Section 4.1.

3.1.3 Commuting times and distances

The Census Transportation Planning Products (CTPP) reports commuting time data for origin-destination pairs of Census tracts across the contiguous United States for 2012–

¹⁰In many gravity models, exact-hat algebra enables expressions for welfare changes which only depend on changes. Here, however, counterfactual changes are driven by a shift in $F(\theta)$. Hence, welfare gains depend on the change in the number of workers who face commuting costs for a particular θ .

¹¹By construction, PUMAs are between 100,000 and 200,000 residents.

¹²These two locations have a total population of only 8,000.

2016. Travel times are reported for over four million trajectories, which is a small fraction of all possible bilateral trajectories, because most pairs of tracts are far enough apart and do not have any commuters traveling between them. We transform this data into bilateral matrix of travel times in two steps. First, we calculate the average location to location travel times as the average of all tract-level travel times reported in the data where the origin is in one model location and the destination is in the other. This provides us with links for the subset of location pairs that are closest to each other.¹³ Then we use these links as the first-order connections in a transport network, and use the Dijkstra’s algorithm to calculate the quickest path through this network between each pair of model locations. Further details of our methodology are contained in Appendix A.3.

3.1.4 Wages

Our tract-level wage estimates are also taken from the database of Census Transportation Planning Products (CTPP), in combination with the microdata from the American Community Survey (ACS). We use these two datasets from 2012–2016 to calculate the quality-adjusted wage index for each model location. For more details, see Appendix A.2.

Existing empirical evidence finds a wage premium of around 10% for telecommuters over regular commuters (Gariety and Scaffer, 2007). Yet, it is not clear if this premium will persist if many more workers telecommute. In addition, our data does not allow us to observe the location of employer of a telecommuter. To be conservative, in the benchmark economy we set $w_{ij}^T = w_j^C$ for all i , where w_j^C equals the wage index described above.

3.1.5 Floorspace supply elasticities and prices

Location-specific housing supply elasticities, $(1 - \eta_i)/\eta_i$, are taken from Baum-Snow and Han (2020). They estimate elasticities of floorspace supply with respect to prices at the Census tract level for over 300 metropolitan areas. We aggregate their estimates to the level of our model locations using population weights. They do not have estimates for locations outside MSAs and these are predominantly rural locations with population densities lower than in metro areas. Because there is a strong negative relationship between population density and the supply elasticity, we assume that locations with missing estimates have the same elasticity as the location with the highest elasticity. At the level of model locations, elasticities vary from 2.07 to 4.82, and the population-weighted mean is 3.38. This implies

¹³We perform the same calculation for the average distance of each location *from itself*, thereby obtaining data-based estimates of the average internal travel time for each location as well.

that η_i ranges from 0.21 to 0.33, and the mean is 0.24.¹⁴

Note that our method of computing counterfactual changes in equilibrium variables and welfare does not require any information on floorspace prices. Yet, in order to calculate changes in prices at higher levels of geography than our model locations (e.g., metropolitan area or the entire country), we need to know price levels in the benchmark economy. To obtain the prices, we estimate hedonic rent indices for each PUMA using self-reported housing rents from the ACS. We follow the procedure in Eeckhout, Pinheiro, and Schmidheiny (2014) and, as regression controls, we include the age of the building, the number of rooms, and the type of the structure (single-family, multi-family, etc.).

3.2 Estimation and Calibration

3.2.1 Externally calibrated parameters

Using similar gravity models of commuting, Ahlfeldt, Redding, Sturm, and Wolf (2015) estimate that the sensitivity of the disutility of commuting to commuting time, κ , is equal to 0.01, while Tsivanidis (2019) estimates a value of 0.012. We set $\kappa = 0.011$, the average of these two estimates. We borrow the estimates of the elasticities of local productivity and amenities with respect to density from Heblich, Redding, and Sturm (2020), and set $\lambda = 0.086$ and $\chi = 0.172$.¹⁵

The share of housing in expenditures, γ , is equal to 0.24, following Davis and Ortalo-Magné (2011). The labor share of commuters in the production function, α , is set to 0.8, following Valentinyi and Herrendorf (2008). We borrow the value for the labor share of telecommuters, $\alpha_T = 0.934$, from Delventhal, Kwon, and Parkhomenko (2020).¹⁶ Due to the lack of empirical evidence and appropriate calibration targets, we do not take a stance on the relative contribution of remote workers to productive externalities, ψ . Instead, we will consider counterfactual scenarios with $\psi = 0$ and $\psi = 1$.

3.2.2 Estimated parameters

Estimate ϵ . First, we estimate the product $\epsilon\kappa$ following the approach in Heblich, Redding, and Sturm (2020). To do this, we take the log of the gravity equation (2.6)

¹⁴Recall that in our model η_i also corresponds to the land share in the production function for floorspace. Hence, the mean η_i in our model aligns well with existing estimates of the land share. For instance, Albouy and Ehrlich (2018) find that the land share is about 1/3 for the U.S., while Combes, Duranton, and Gobillon (2019) estimate a value of about 0.2 for France.

¹⁵In a future version of this paper we will estimate these two elasticities from our data.

¹⁶Since α_T determines the teleworkers' demand for floorspace, it was calibrated to the observed difference between house sizes of commuters and telecommuters. See Delventhal, Kwon, and Parkhomenko (2020) for details.

evaluated at $\theta = 1$,

$$\ln \pi_{ij} = -\epsilon \kappa t_{ij} + \varphi_i^R + \varphi_j^W + \ln b_{ij}, \quad (3.1)$$

where the location-specific fixed effects φ_i^R and φ_j^W subsume local amenities, wages, and floorspace prices. Before estimating this equation, we set $\pi_{ij} = 0$ for all pairs with commuting times of more than 3 hours one way.¹⁷

We first estimate the previous equation by OLS and obtain $\epsilon \kappa = 0.03199$ (Table 1 reports regression results). However, t_{ij} may be endogenous to π_{ij} due to traffic congestion or because the supply of infrastructure responds to commuting demand.¹⁸ Hence, we instrument for t_{ij} with straight-line distance between i and j , δ_{ij} , and obtain $\epsilon \kappa = 0.03409$. To recover the Fréchet shape parameter ϵ we use the calibrated value $\kappa = 0.011$, as discussed above. Our estimate of ϵ is therefore equal to $3.099 = 0.03409/0.011$.¹⁹

Table 1: Estimation of the gravity equation

	(1) OLS	(2) IV
Second stage		
t_{ij}	-0.03199 (0.000046)	-0.03409 (0.000050)
Residence f.e.	yes	yes
Workplace f.e.	yes	yes
Observations	318,870	318,870
R^2	0.792	–
First stage		
δ_{ij}		0.8970 (0.000018)
Residence f.e.		yes
Workplace f.e.		yes
Observations		318,870
R^2		0.996

Note: This table reports estimates of equation (3.1). Standard errors are in parentheses. See the text for details.

¹⁷Out of around 139 mln commuters that we observe in LODES, 9.8 mln travel between locations that are more than 3 hours apart. We believe that most of these observations are due to errors in assigning locations of work or residence, and therefore drop them from our sample.

¹⁸See Heblich, Redding, and Sturm (2020) for a more detailed discussion.

¹⁹Our value of ϵ is on the lower end of the range of estimates in the literature. Monte, Redding, and Rossi-Hansberg (2018) estimate 3.3, Heblich, Redding, and Sturm (2020) find a value of 5.25, and Ahlfeldt, Redding, Sturm, and Wolf (2015) estimate 6.65.

Estimate b_{ij} . Notice that the location pair-specific shifter, b_{ij} , can be identified from the residual in equation (3.1). However, since the estimation procedure only uses location pairs with positive commuting flows, we cannot infer the value of b_{ij} for pairs with zero flows. In this class of models, it is common to set $b_{ij} = 0$ for zero-flow pairs.²⁰ However, our counterfactual experiments study environments in which many more individuals gain the ability to work remotely and may choose residence-workplace location pairs that have not been chosen in the benchmark economy.

In order to resolve this problem, we specify b_{ij} as a function of straight-line distance between i and j ,

$$\ln b_{ij} = \beta_0 + \beta_1 \ln \delta_{ij}, \quad (3.2)$$

and estimate this relationship on the sample of pairs with positive flows. Our hypothesis is that, even though many location pairs have zero commuters due to the high commuting costs, they would have positive number of commuters if the costs were lower and that the flows between such locations depend on the distance between them. Table 2 reports the regression results. We find that there is a statistically significant negative relationship between b_{ij} and δ_{ij} , albeit the distances do not explain much of the variation in the pair-specific shifter. Table 3 provides summary statistics of the estimated values of b_{ij} for pairs with zero flows in the data and shows that b_{ij} varies from around 0.5 to 1.2.

Table 2: Relationship between the pair-specific shifter, b_{ij} , and distance

Dependent variable:	$\ln b_{ij}$
$\ln \delta_{ij}$	-0.1671 (0.0027)
Observations	318,629
R^2	0.012

Note: This table reports estimates of equation (3.2). Standard errors are in parentheses.

Table 3: Summary statistics of the pair-specific commuting flow shifter, b_{ij}

	Mean	S.d.	Min	Max	Observations
b_{ij}	0.6339	0.0732	0.5109	1.2260	19,949,134

Note: This table reports summary statistics of b_{ij} as predicted by the estimated relationship (3.2).

²⁰As, for example, in Monte, Redding, and Rossi-Hansberg (2018) or Heblich, Redding, and Sturm (2020). Dingel and Tintelnot (2020) show that dropping pairs with zero flows may bias the estimates of the Fréchet shape parameter.

3.2.3 Commuting flow matrix

The benchmark economy consists of both commuters and telecommuters, however we cannot tell them apart in the LODES data. Hence, we resort to our model and use the estimated equation (3.1) in order to construct commuting flow matrices for each θ .²¹ Because the gravity equation was estimated at $\theta = 1$ and because b_{ij} are derived from regression residuals, our model will match the observed bilateral flows of commuters nearly exactly. However, since $b_{ij} > 0$ for all pairs with zero observed flows, our model will have positive, even if negligible, flows between each pair of locations. Figure A.8 shows the relationship between commuting flows in the model and the data for $\theta = 1$. Panel (a) demonstrates that the data and the model match up nearly exactly for pairs with positive flows in the data. Yet, as panel (b) shows, zooming into the lower left corner of the scatter plot, one can see that there are small positive flows in the model between locations with zero flows in the data. These flows are negligible—their total volume corresponds to 0.6% of total employment in the economy, even though they account for 98.4% of all location pairs.

4 Implications of an Increase in Telecommuting

In this section, we study a simulated increase in the number of telecommuters and its effect on the location of residents and jobs, floorspace prices, wages, commuting costs, and welfare.

4.1 The Counterfactual Experiment

The counterfactual experiment consists of changing the distribution of commuter types from $F(\theta)$ to $F^*(\theta)$, as shown in Figure 1, while keeping all other parameters at the benchmark level.²² First, we study a counterfactual economy in which local productivity A_i and amenities X_i are fixed at the benchmark level, by setting $\lambda = \chi = 0$. This allows us to isolate the first-order effects of changing commuting requirements from the amplifications via endogenous productivity and amenities. Then, we turn “on” productive and amenity externalities, one by one, by restoring λ and χ to their calibrated levels and let these externalities affect the counterfactual changes. In all previous experiments, we set

²¹Dingel and Tintelnot (2020) also suggest using a model-based commuting matrix to run counterfactuals in settings when there are many zero-flow location pairs in the data.

²²When we solve the system of counterfactual changes (2.35)–(2.44), $\hat{a}_i$, $\hat{x}_i$, $\hat{E}_i$, $\hat{b}_{ij}$, $\hat{\phi}_i$, $\hat{v}$, and $\hat{d}_{ij}(\theta)$ are all equal to 1 for all locations i and j and types θ .

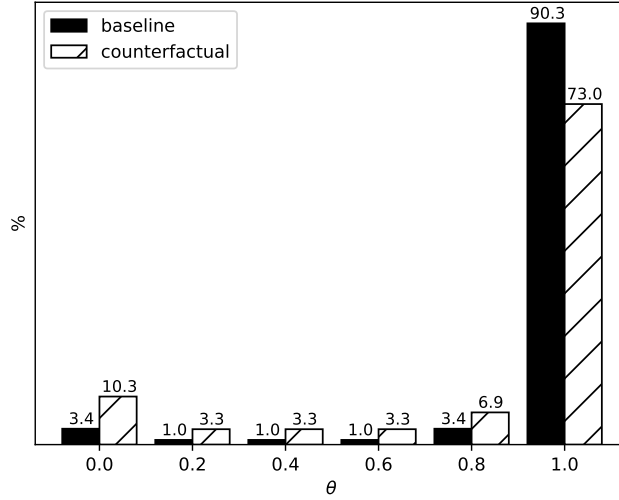
$\psi = 0$ in equation (2.34), i.e., we disallow remote workers to contribute to productive externalities. In the last two experiments, we let remote workers to fully contribute to productive externalities as if they were physically present in the office, by setting $\psi = 1$; we calculate results when amenities are exogenous, and again when they are endogenous.

Distribution of commuter types. We discretize the distribution of commuter types, $F(\theta)$, to six support points, $\theta \in \{0, 0.2, 0.4, 0.6, 0.8, 1\}$. We chose this support so that each value of θ can be interpreted as the number of days per week that an individual commutes to work. For example, a worker with $\theta = 0$ always works at home, a worker with $\theta = 0.2$ commutes one day a week, and a worker with $\theta = 1$ commutes five days a week.

In order to build empirical benchmark and counterfactual distributions of θ we turn to Barrero, Bloom, and Davis (2020). Using evidence from a survey of employers conducted in May 2020, they find that in 2019, 3.4% of employees worked at home 5 or more days a week, 2.9% did so 2–4 days, another 3.4% worked from home one day, and the remaining 90.3% rarely or never worked at home. Thus, in the benchmark economy, the probability distribution of commuter types is $f = (0.034, 0.01, 0.01, 0.01, 0.034, 0.903)$, where we split the 2.9% who worked at home 2–4 days a week equally between 2, 3, and 4 days. The survey also asks about plans of employers after Covid-19 as to how often their employees would work at home and on-site. They find that 10.3% will work at home 5 or more days a week, 9.9% will do so 2–4 days a week, 6.9% will work from home one day a week, and only 73% will rarely or never work at home. Therefore, the counterfactual distribution is $f^* = (0.103, 0.033, 0.033, 0.033, 0.069, 0.73)$. This shift in the distribution implies that in the counterfactual economy 17.6% of work days will be done from home, a more than a threefold increase compared to 5.8% in the benchmark.²³ Figure 2 demonstrates the benchmark and the counterfactual distributions of commuter types.

²³ $\sum_{\theta \in \{0, \dots, 1\}} (1 - \theta) f(\theta) = 0.058$ and $\sum_{\theta \in \{0, \dots, 1\}} (1 - \theta) f^*(\theta) = 0.176$. The latter number is less than half of 0.37 which, according to Dingel and Neiman (2020), is the fraction of jobs in the United States that can be done at home. It is reasonable to expect, however, that employers and employees may prefer to conduct a significant amount of work on-site even when it can feasibly be done from home.

Figure 2: Change in the distribution of commuting frequency



4.2 Results

When more workers gain the ability to commute less frequently or not at all and when there are no agglomeration effects in productivity or amenities, two immediate effects occur. First, the importance of distance between employers and employees weakens, and workers who experience a fall in θ relocate further from their jobs.²⁴ Second, as the supply of on-site labor falls and the supply of remote labor increases, the demand for commercial real estate plummets and the demand for residential real estate goes up. The rest of the section describes how these two basic mechanisms change residential and employment density, floorspace prices, wages, and discusses welfare implications of more widespread telecommuting. We conclude the section by discussing the importance of agglomeration externalities and the relative contribution of teleworkers to productive externalities for our results.

4.2.1 Residential density

More telework leads to the increased sprawl of residents who leave dense and expensive urban cores for less dense distant suburbs and rural areas, as panel (a) in Figure 3 demonstrates. The map in panel (a) of Figure 9 confirms that most locations that gain density are located in suburban and rural areas, while locations that lose density are primarily in

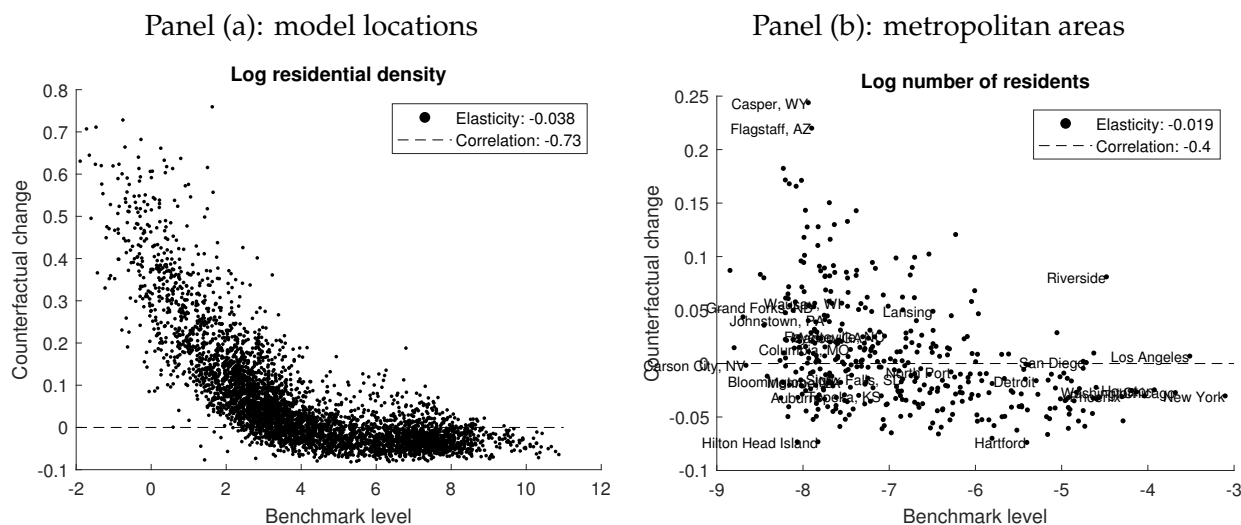
²⁴For example, the benchmark economy has few commuters from San Diego to Los Angeles, CA. These cities are 120 miles apart and a one-way commute takes about 3 hours, either by car or train. In the counterfactual economy, there is a 149% jump in the number of weekly commuter trips from locations in San Diego county to Downtown L.A., largely driven by those who commute once or twice a week.

urban areas.

Does this mean that telecommuting will create a massive exodus from cities to rural areas? Panel (b) of Figure 9 demonstrates that even though many rural and suburban locations experience a large *percentage* increase in residents, in the vast majority of them the *absolute* changes in density are small. We find that most people will keep living in cities—the fraction of workers that reside in the 397 largest MSAs only declines from 85.9% in the benchmark to 84.6% in the counterfactual.²⁵ Moreover, as panel (b) of Figure 3 shows, not all large metro areas shrink: Los Angeles, as well as the neighboring Riverside-San Bernardino and San Diego grow larger.

A closer look at the two largest metro areas, New York and Los Angeles, unveils a rich pattern of reallocations. In Los Angeles (panels (c) and (e) of Figure 9), the crescent between Santa Monica and Downtown loses residents. This area is characterized by proximity to jobs and sky-high real estate prices. As it becomes less important to be close to jobs, people move to more affordable suburbs in San Fernando Valley, San Bernardino County, and Orange County. In contrast, most areas in the New York metro area (panels (d) and (f) of Figure 9) lose residents. The biggest reductions occur in Manhattan and adjacent parts of Brooklyn and Queens, while parts of the Bronx and the Staten Island, as well as some far-flung suburbs attract new residents.

Figure 3: Change in Residents



Note: These scatterplots show the relationship between the benchmark residential density and the counterfactual change in log density. Panel (a) shows this relationship for model locations, panel (b) shows this relationship for metropolitan areas. “Elasticity” is the coefficient of the OLS regression of the counterfactual change on the benchmark level.

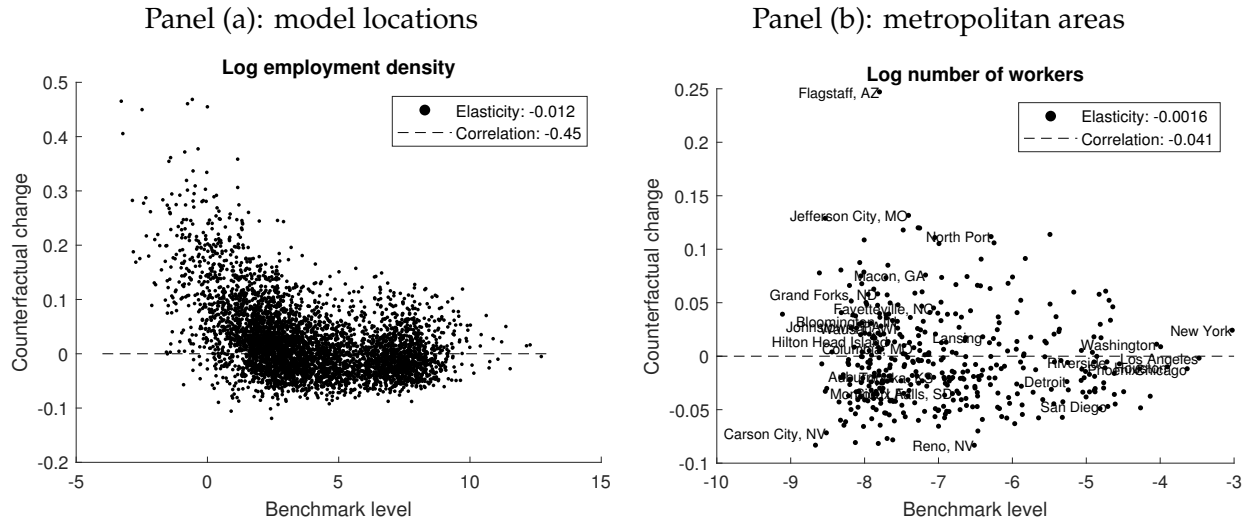
²⁵We use Core-Based Statistical Areas (CBSAs) for our MSA-level results.

4.2.2 Employment density

We find that telecommuting also results in the outflow of employment from high-density to low-density locations, albeit the effect is much weaker than for residents (panel (a) of Figure 4). In fact, as panel (b) in Figure 4 demonstrates, many of these reallocations occur within metropolitan areas, and there is virtually no relationship between the initial size of an MSA and the change in its employment. Indeed, some metro areas, such as New York and Washington, D.C., experience moderate increases in employment. The maps in Figure 10 confirm that in many urban locations employment grows.

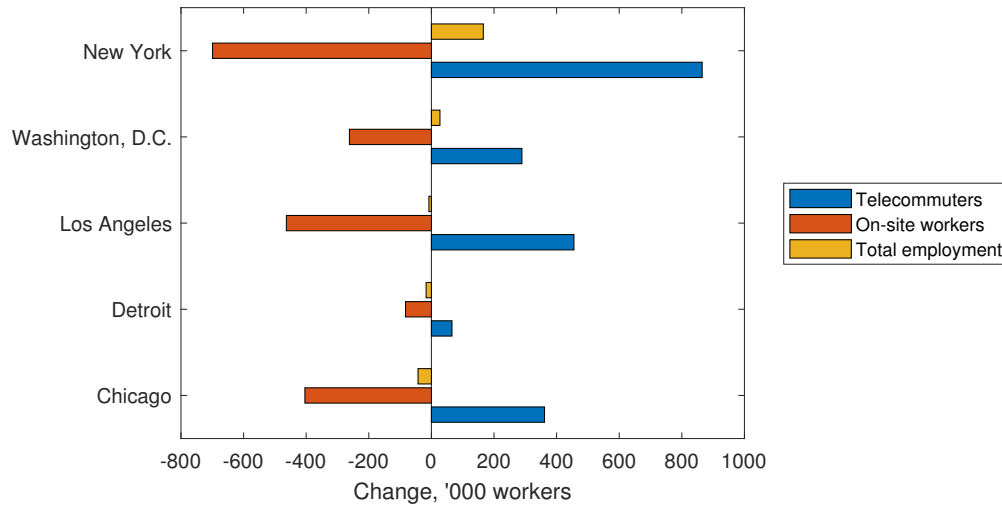
How is it possible that some places lose residents and gain workers at the same time? This happens because a large portion of the increase in employment comes from telecommuters. With less frequent commutes, more workers combine the benefits of working in high-wage cities, such as Washington, D.C., and living in more affordable places nearby, such as Richmond, VA. Similarly, firms located in highly productive metro areas can increase their size by hiring more workers from distant places. Figure 5 focuses on five metropolitan areas and shows that areas which experience employment growth in the counterfactual do so thanks to a jump in the number of telecommuters, while on-site employment falls in all places shown in the figure.

Figure 4: Change in Employment



Note: These scatterplots show the relationship between the benchmark employment density and the counterfactual change in log density. Panel (a) shows this relationship for model locations, panel (b) shows this relationship for metropolitan areas. "Elasticity" is the coefficient of the OLS regression of the counterfactual change on the benchmark level.

Figure 5: Changes in total, on-site, and remote employment in selected metro areas



Note: This figure shows the counterfactual change in total, on-site, and remote work days in several metropolitan areas. The change in work days is converted to a worker equivalent.

4.2.3 Floorspace prices

The rise of telecommuting reallocates the demand for floorspace across uses—commercial and residential—and across locations. In particular, as fewer workers spend time in offices, the stock of commercial real estate declines. At the same time, these workers require more residential floorspace to be able to work at home productively, and therefore the supply of residential real estate goes up. The rise in residential demand is further exacerbated by the migration of residents to suburban and rural areas where housing is cheaper and therefore large houses are more affordable.

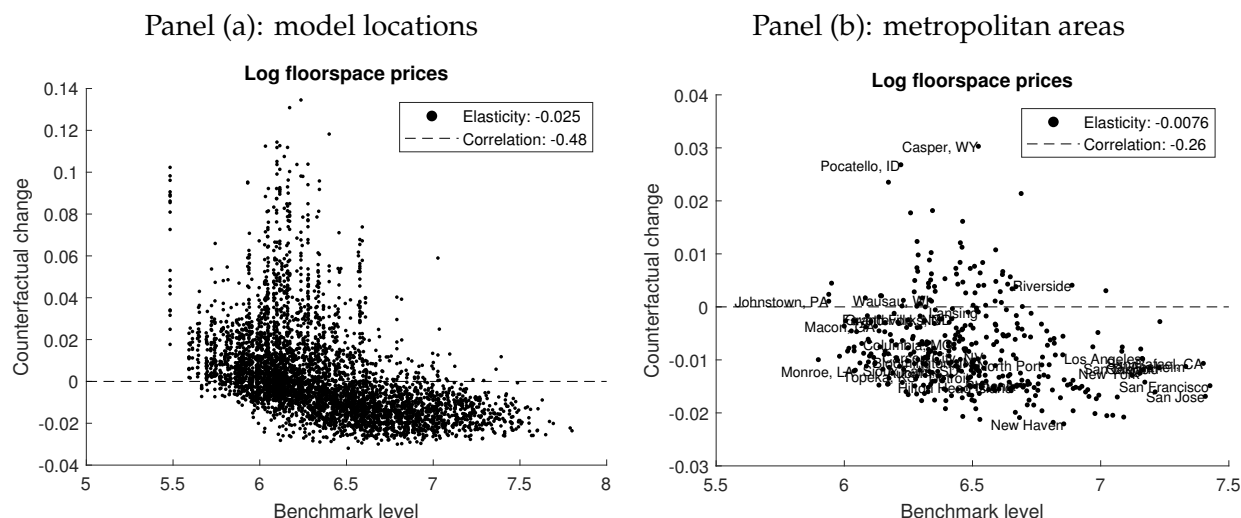
We find that, on average, floorspace prices only fall by 2%. However, there are sizable differences in price changes across locations. As panel (a) in Figure 11 and panel (a) in Figure 6 show, many suburban and rural areas experience large increases in prices. This happens because some residents and employers relocate to these areas. However, as panels (b) and (c) in Figure 11 demonstrate, even within the largest cities, some locations see an increase in prices. While the densest places, such as Manhattan in New York and Downtown Los Angeles, become cheaper, several peripheral areas become more expensive.

The aggregate average fall in floorspace prices is due to the combination of two effects: First, residents move on average to less dense places, where in the benchmark economy prices were lower. Second, residents move on average to places with a higher

elasticity of floorspace supply to price. To assess the importance of the second channel we run an alternative counterfactual exercise in which the elasticity of housing supply is uniform across space and equal to the population-weighted national average. Housing costs only fall by 1.82% in this alternative exercise, indicating that about 7% of the total fall in prices is due to reallocation to more flexible housing markets.

Even when many more workers can telecommute, large metropolitan areas remain attractive places to live and run businesses, and real estate there does not become dramatically cheaper (panel (b) in Figure 6).²⁶ Having said that, while telecommuting is unlikely to improve housing affordability in the “superstar” cities, it offers the opportunity for many workers to move to more affordable places while retaining their jobs in major economic hubs.

Figure 6: Floorspace prices



Note: These scatterplots show the relationship between the benchmark log floorspace prices and the counterfactual change in log floorspace prices. “Elasticity” is the coefficient of the OLS regression of the variable on the vertical axis on the variable on the horizontal axis.

4.2.4 Wages

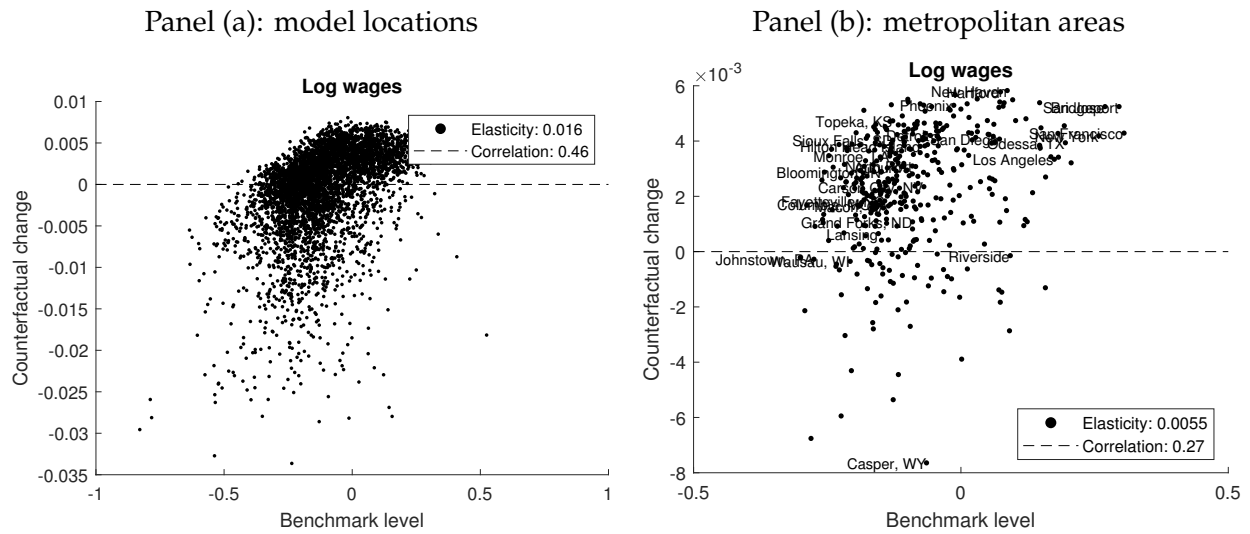
One important effect of the rise in telecommuting is that it increases resident market access for many workers by lowering their commuting frequency. This implies that more

²⁶These results contrast with Delventhal, Kwon, and Parkhomenko (2020) who find that floorspace prices in Los Angeles would fall by nearly 6% with more telecommuting. However, that paper models Los Angeles as a closed city and does not consider the possibility that residents and firms may move in and out of the city. In this paper, we allow such migration and find that, as more widespread telecommuting increases the population and employment in Los Angeles, floorspace prices only fall by 1%.

individuals have access to the most productive locations and many of them switch from less productive jobs they held before. As a result, as Figure 7 demonstrates, telecommuting increases the dispersion of wages across model locations and also across metropolitan areas. In the vast majority of metro areas average wages go up.

These findings suggest that, even though remote work may bring greater employment opportunities to workers who do not currently live in the most successful local labor markets, it is unlikely to make the distribution of income more equal. On the contrary, we find that the variance of log wages at the place of work, $w_{ij}(\theta)$, goes up from 0.022 in the benchmark to 0.023 in the counterfactual. However, since the importance of living close to jobs fades, the competition for expensive real estate in the most successful places becomes less intense and results in greater spatial mixing of people with different income levels. We find that the variance of log wages at the place of residence, $\tilde{w}_i$, goes down from 0.017 in the benchmark to 0.015 in the counterfactual.

Figure 7: Wages



Note: These scatterplots show the relationship between the benchmark log wages of commuters at the place of work, w_j^C , and the counterfactual change in log wages. “Elasticity” is the coefficient of the OLS regression of the variable on the vertical axis on the variable on the horizontal axis.

4.2.5 Aggregate Results and Welfare Effects

We find that, by weakening the link between the place of work and the place of residence, a shift toward more telework results in modest wage gains, especially for telecommuters, and a slight reduction in real estate prices (column (1) in Table 4). Both of these effects result in a 0.8% larger aggregate consumption (column (1) in Table 5). Individuals further

gain by spending less time on commuting (column (1) in Table 4 and column (1) in Table 5). In addition, as many workers commute to work less frequently or not at all, they can pick location pairs with better residential and workplace amenities, X_i and E_j (column (1) in Table 5).

Yet, most of the welfare gains can be attributed to better matches between firms and workers, as measured by the value of the Frèchet preference shock. Because a commuter must reside close to her job and because the distribution of preference shocks is i.i.d. across pairs of locations, it is unlikely that she would be able to choose a pair of locations i and j with a high value of z_{ijn} . A telecommuter places a lesser importance on the disutility of commuting and can therefore choose a pair with a higher value of z_{ijn} . We find that gains from greater consumption, less commuting, and better access to amenities increase aggregate welfare by almost 5%, however, better access to location pairs with higher values of preference shocks further increases aggregate welfare gains to nearly 35%.

These welfare gains took into account those workers who experienced a decrease in θ , i.e., switched from more to less commuting. What are the welfare effects on workers who did not change their commuting frequency in the counterfactual? Column (1) in Table 5 lists welfare gains for workers with each θ and demonstrates that welfare gains are larger for those who commute more frequently. Commuters experience an increase in wages and a fall in housing costs. In addition, as the demand for living close to places with good employment opportunities recedes, commuters gain from being able to pick residence locations with shorter commutes and better amenities. At the same time, full-time remote workers experience a slight reduction in expected utility. The main reason for that is that in the benchmark economy telecommuters tended to live in less dense areas with cheap housing. As the number of telecommuters grows, these areas experience a surge in housing demand and increasing floorspace prices, thereby harming those telecommuters who lived there before.

Table 4: Aggregate results

<i>Productive externalities</i> ($\lambda > 0$):	no	no	yes	yes	yes	yes
<i>Amenity externalities</i> ($\chi > 0$):	no	yes	no	yes	no	yes
<i>Remote labor adds to productive externalities</i> ($\psi = 1$):	no	no	no	no	yes	yes
	(1)	(2)	(3)	(4)	(5)	(6)
Wages, all workers, % chg	0.28	0.17	-0.98	-1.14	0.29	0.11
Wages, on-site labor, % chg	0.47	0.36	-0.82	-0.99	0.45	0.26
Wages, remote labor, % chg	0.09	-0.01	-1.08	-1.21	0.24	0.10
Floorspace prices, % chg	-1.95	-2.69	-2.15	-3.02	-1.96	-2.90
Time spent commuting, all workers, % chg	-7.04	-6.44	-7.00	-6.34	-6.90	-6.20
Time spent commuting, commuters ($\theta = 1$), % chg	-0.13	0.44	-0.09	0.53	0.01	0.67
Distance traveled, all workers, % chg	-6.42	-5.06	-6.49	-4.88	-6.27	-4.57
Distance traveled, commuters ($\theta = 1$), % chg	-0.46	0.92	-0.54	1.12	-0.31	1.43

Note: Columns (1)–(6) present results from models with different combinations of productive and amenity externalities, and whether remote labor contributes to productive externalities, as specified in the header of the table.

Table 5: Welfare Decomposition

<i>Productive externalities</i> ($\lambda > 0$):	no	no	yes	yes	yes	yes
<i>Amenity externalities</i> ($\chi > 0$):	no	yes	no	yes	no	yes
<i>Remote labor adds to productive externalities</i> ($\psi = 1$):	no	no	no	no	yes	yes
	(1)	(2)	(3)	(4)	(5)	(6)
Welfare by commuter type, % chg						
$\theta = 0$	-0.05	1.69	-1.19	0.72	0.20	2.20
$\theta = 0.2$	0.21	0.76	-0.95	-0.31	0.32	1.00
$\theta = 0.4$	0.33	0.56	-0.86	-0.57	0.39	0.69
$\theta = 0.6$	0.43	0.48	-0.80	-0.71	0.44	0.53
$\theta = 0.8$	0.51	0.45	-0.75	-0.79	0.50	0.45
$\theta = 1$	0.57	0.46	-0.72	-0.82	0.55	0.44
Welfare by source, % chg						
consumption only	0.81	0.86	-0.42	-0.38	0.82	0.87
+ commuting	4.01	3.90	2.73	2.59	3.98	3.83
+ amenities	4.90	5.26	3.66	4.09	5.00	5.50
+ Frèchet shocks	34.92	35.84	33.28	34.31	35.05	36.13

Note: Columns (1)–(6) present results from models with different combinations of productive and amenity externalities, and whether remote labor contributes to productive externalities, as specified in the header of the table. Appendix A.1 provides more details on welfare results by type and source.

4.2.6 Role of Agglomeration Externalities

Next, we consider what would happen if local productivity, A_j , and amenities, X_i , adjusted endogenously to changes in employment and residential density (see equations 2.33 and 2.34). In the context of these counterfactual exercises, it is important that workers only contribute to agglomeration externalities when they are on-site ($\psi = 0$): a one-day-per-week commuter only contributes to these externalities one fifth as much, and a full-time telecommuter does not contribute at all. As a result, even if no workers changed their residences or jobs, more telework would result in lower aggregate productivity. Yet, when the productivity in a given location falls, wages fall as well making some workers seek employment elsewhere and therefore amplifying the initial reduction in productivity. Similarly, when some individuals move to suburban or rural areas from dense urban locations, amenities in these places decline and, as a result, even more residents leave. Figures (A.1)–(A.7) in the Appendix repeat Figures (3)–(11) and show that all of the effects described in Sections 4.2.1–4.2.4 are stronger when the agglomeration externalities are present. There is more reallocation of residents and jobs toward less dense places, greater convergence in floorspace prices, and larger divergence in wages.

The changes in density and prices with agglomeration externalities do not bring any real quantitative surprises—almost all the same locations and variables see changes in the same direction as before, the changes are just bigger. In terms of welfare, however, we find that the picture is now completely changed. Tables 4 and 5 show this change in steps. Column (1) of each table corresponds to the baseline counterfactual, when endogeneity for both amenities and productivity is turned “off.” Column (2) shows the effect of turning “on” endogeneity only for amenities. Column (3) shows the effect of turning endogeneity “on” only for productivity. Finally, column (4) shows the effect of turning endogeneity “on” for both at once.

Endogenous amenities. When only amenities are endogenous, the reduction in distance traveled and time spent commuting for commuters, is reversed. This is because telecommuters bring amenities out to the periphery with them when they move, and commuters are thus induced to follow them, and accept longer commutes in exchange for better residential amenities. The small increases in wages for all categories of workers are attenuated because the migration of commuters to higher-productivity tracts is thus less pronounced and because increased demand for floorspace in the periphery induces telecommuters to slightly reduce the sizes of their home offices and, thus, their productivity. In terms of welfare, commuters still experience some gains but the gradient in welfare gains is now reversed—now telecommuters benefit most, because they take the amenities

with them. Overall welfare gains are still positive due to the increase in at-home work days for most workers.

Endogenous amenities also considerably increase the role of the relocation of residents to places with more elastic housing supply in accounting for the reduction in floorspace prices. In an alternative exercise in which only amenities are endogenous but the floorspace supply elasticity takes the average value everywhere, floorspace prices fall by only 2.43%. This indicates that nearly 10% of the total reduction is due to the improvement in the average housing supply elasticity, as compared to 7% in the “basic” counterfactual in column (1).

Endogenous productivity. When only productivity is endogenous, small gains in wages turn into a nearly 1% drop. This is because telecommuters no longer contribute to externalities when working remotely, reducing the productivity especially of those work locations which are most accessible to commuters. The effect on commuting times and distances barely changes compared to the baseline counterfactual. In terms of welfare, each category individually now suffers losses between 0.7% and 1.2%, with reductions larger for telecommuters than commuters. Overall welfare gains are negative when only accounting for consumption, because wages and overall productivity are now lower. Once commuting and amenities are taken into account, the overall welfare effect is positive, due to the reallocation of workers from commuting to telecommuting, which offers reduced time on the road and a freer choice of residence.

Endogenous amenities and productivity. When both amenities and productivity are endogenous, wages fall further and commute times and distances traveled by commuters go up. Average floorspace prices fall by over 3%, more than in the baseline scenario or either of the “piecemeal” scenarios, which helps to offset the consumption cost of lower wages. Everyone now earns less, but they have access to more affordable housing on average. When accounting for consumption, commuting disutility, and amenities together, the overall increase in welfare is now only 4.1%. This increase is due entirely to an improved situation for the lucky commuters who can now work from home. Commuters who are “stuck” working on-site full-time see their welfare fall by 0.8%.

One way to think about the counterfactual results with agglomeration effects, is that they give us a peek at what could happen in the long run. In the short and medium run, the levels of productivity and amenities may not change much even if many more people telecommute. Co-workers can still connect via Zoom, while restaurants or schools may remain open at the same capacity levels. In the long run, however, a permanent reduction

in face-to-face interactions and a fall in the demand for living and working in dense urban places, may result in a permanent blow to productivity and a reallocation of neighborhood amenities.

4.2.7 Telecommuters' contribution to workplace externalities

But what if future advances allow telecommuters to participate in all work-related activities just as efficiently as they would in person? In the preceding discussion, we have only considered scenarios in which remote workers do not contribute at all to productive externalities which, in terms of our model, means setting $\psi = 0$.

One alternative is to make the opposite extreme assumption, and set $\psi = 1$. Column (5) in Tables 4 and 5 shows the results when $\psi = 1$ and only productivity externalities are turned "on." Column (6) in each table shows the results when amenity externalities are "on" also. The contrast between columns (4) and (6) is striking. Allowing telecommuters to contribute to local productivity externalities reverses most of the negative effects of the increase in telecommuting which showed up in columns (3) and (4) when we turned endogenous productivity "on." Instead of falling, wages now rise modestly. Instead of disadvantaging left-behind commuters, this group now benefits considerably, their expected utility increasing by 0.44%. The reduction in real estate prices, combined with the rise in wages allows a larger gain in average consumption welfare than in any of the other scenarios.

In other ways, the results for columns (4) and (6) are similar. Just as was the case when telecommuters did not contribute to externalities, full commuters end up travelling farther and spending more time on the road. The motivations are the same: an increase in the relative wage advantage of jobs in the city centers, and an increase in the amenities of farther-flung suburbs. When telecommuters improve productivity, too, the city center wage advantage is made bigger, hence larger changes in average commute time and distance.²⁷

As ψ changes from 0 to 1, all of the aggregate results shown in Tables 4 and 5

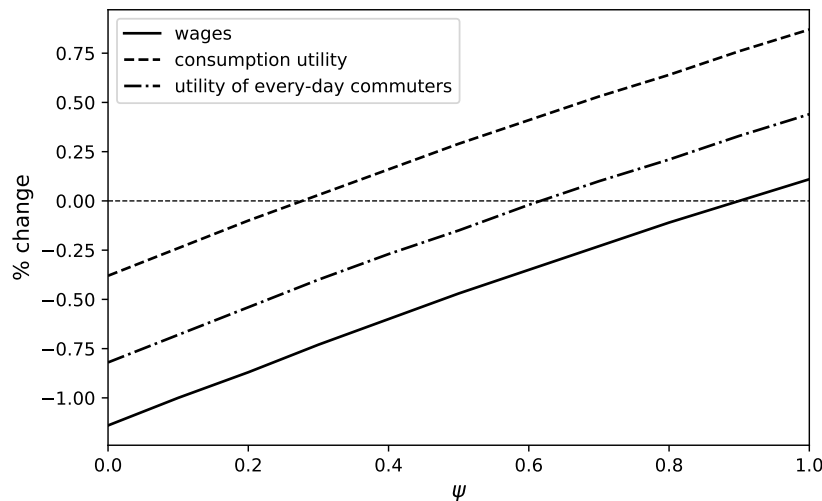
²⁷The direction and size of the change in aggregate commuting is almost exactly the same if we compare columns (3) and (5), when endogenous amenities are absent. Therefore, the difference between (3) and (5), or (4) and (6), give an estimate of the importance of telecommuters' productivity contribution in drawing workers into city centers. In contrast, the change in commuting variables between columns (5) and (6) highlights the considerably larger role of endogenous amenities in the suburbs of promoting long commutes. The fact that the change from (3) to (4) is also nearly the same as the change from (5) to (6) indicates that the two influences on commuting—that of endogenous amenities and that of improved center-city productivity—operate independently of one another, without amplifying or canceling each other out in a major way.

transition smoothly from column (4) to column (6).²⁸ Figure 8 shows this transition for average wages, for consumption utility, and for the utility of left-behind commuters. These are three aggregate outcomes for which, if telecommuters make no contribution to production externalities, the effect of increased telecommuting is negative. Varying ψ between 0 and 1 suggests another way to think about its importance: What would the contribution of telecommuters to externalities have to be in order to turn these negative results positive?

Average consumption utility is the first to turn positive as ψ increases: if remote workers contribute 30% as much to workplace spillovers as on-site workers, that is enough for the utility derived from consumption of goods and housing, averaged across all types of workers in the economy, to increase. The next to turn is overall utility for left-behind full-time commuters. If telecommuters contribute to workplace spillovers 60% as much as their on-site colleagues, this is enough to erase the losses suffered by every-day commuters. The hardest nut to crack, so to speak, is the average wage. For the counterfactual increase in telecommuting we consider, the average wage will go down unless remote labor contributes fully 90% as much as local labor to productive externalities.

Is it likely that the “true” value of ψ could be as high as 0.3, or 0.6, or 0.9? There is little information available to form the basis of an objective answer to this question. Any assessment, therefore, will depend heavily on the priors held by the individual observer.

Figure 8: Remote workers’ workplace externalities: wages and welfare



²⁸The transition from column (3) to column (5) is also smooth.

5 Conclusions and Further Work

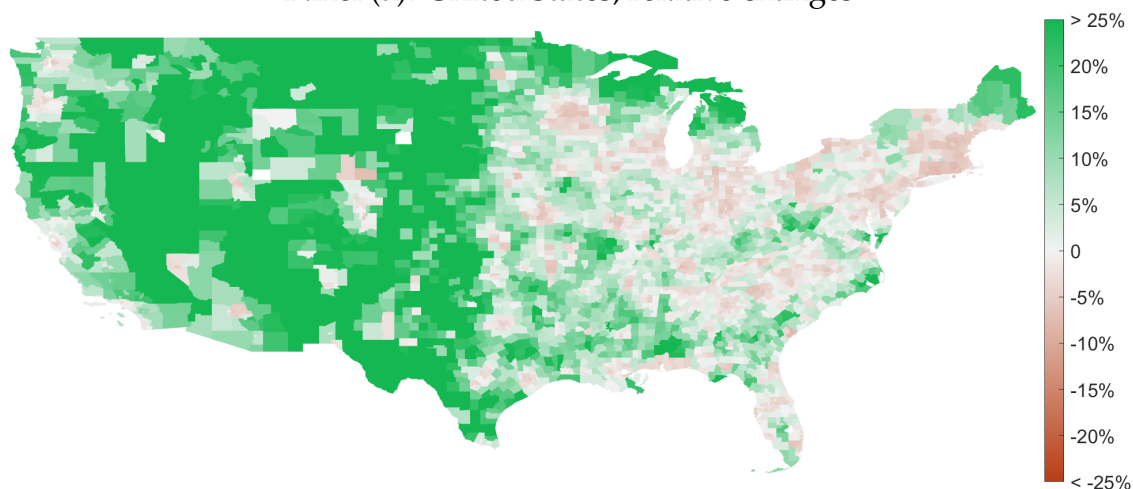
In this paper we have built a quantitative general equilibrium model of employment and residence choice in which a portion of workers work from home either some or all of the time. In a counterfactual experiment, we increased the share of telecommuters, and saw that the model predicted rich patterns of reallocation both within and across metropolitan areas. In particular, there is a mostly monotonic shift of residents from central locations to the periphery, while jobs go up both in very small and very big cities. The question of how a decrease in face-to-face interaction will affect productivity in the long run is the key to predicting the overall welfare impact of such a change.

Our analysis has a number of limitations which open opportunities for extensions. First, our model does not consider trade between locations and its impact on wages and prices. Costly trade would probably act as a centripetal force, increase the cost of living in remote areas that otherwise might receive more migration from new telecommuters. Second, it might be useful to introduce multiple occupations to our analysis. Considering local differences in industrial and occupational structure could be central to understand quantitative implications of telecommuting, since the ability to work remotely varies across industries and occupations. Considering trade costs could tone down our findings, since some of the firms, especially those that produce non-traded goods, and therefore some of their workers, would have to remain in dense urban areas because this is where most of their customers are. Third, our model does not distinguish between transportation modes and our counterfactual scenarios assume that commuting costs do not change. With fewer commuters traffic congestion may become less severe, though after Covid-19 many workers may switch from public transit to private cars.

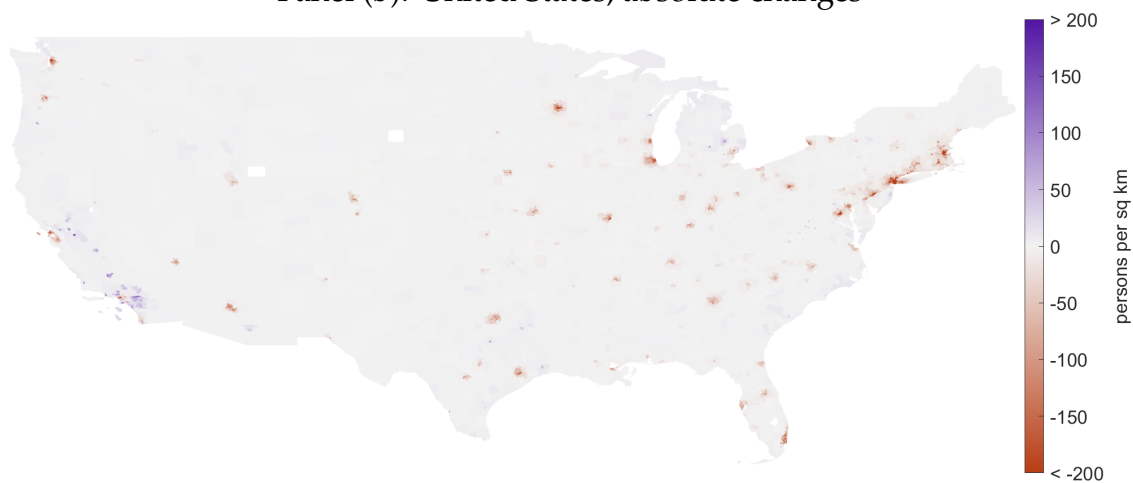
Figure 9: Density of residents

Maps

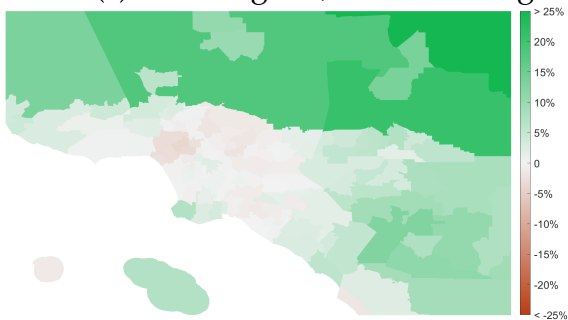
Panel (a): United States, relative changes



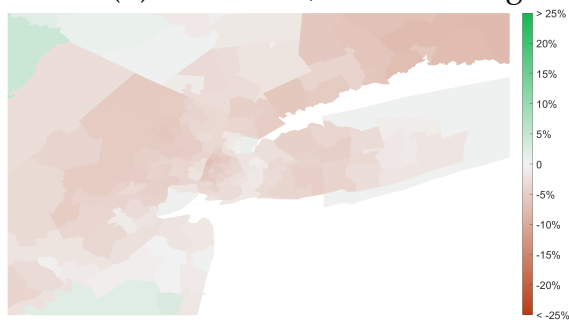
Panel (b): United States, absolute changes



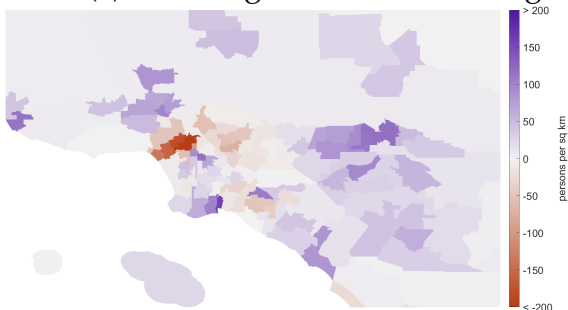
Panel (c): Los Angeles, relative changes



Panel (d): New York, relative changes



Panel (e): Los Angeles, absolute changes



Panel (f): New York, absolute changes

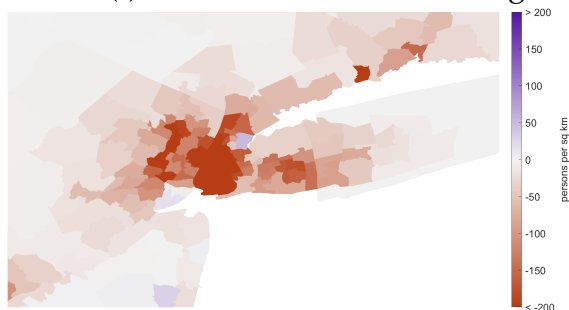
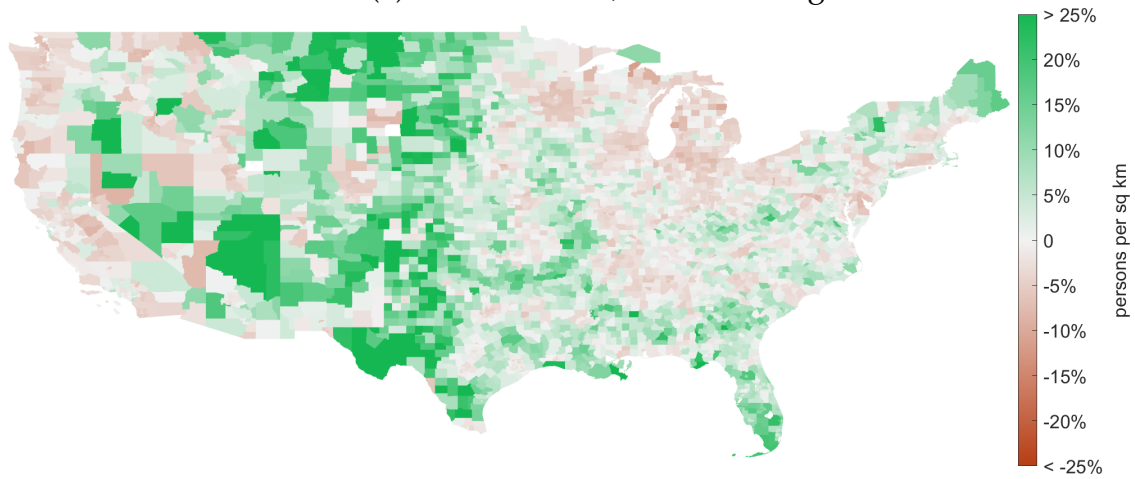
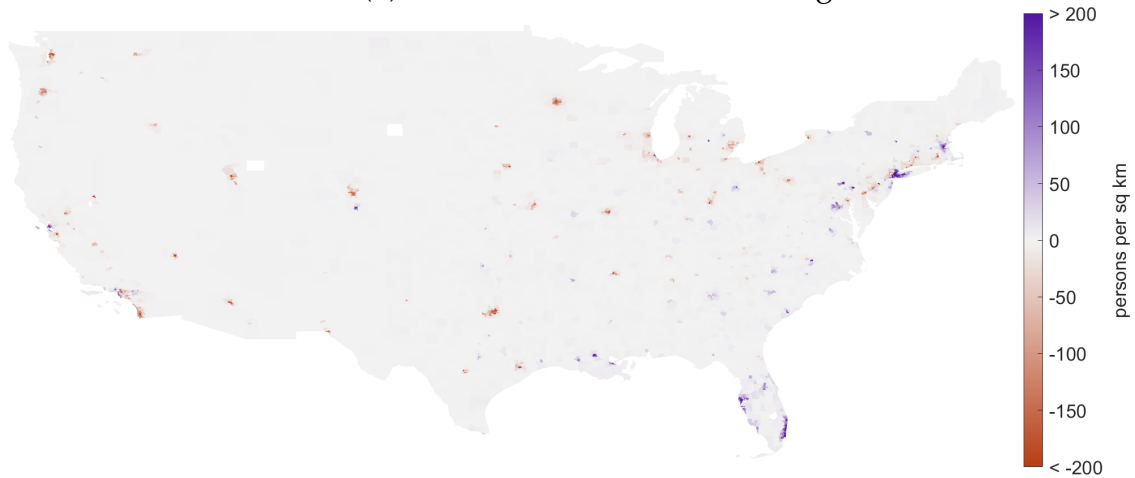


Figure 10: Density of workers

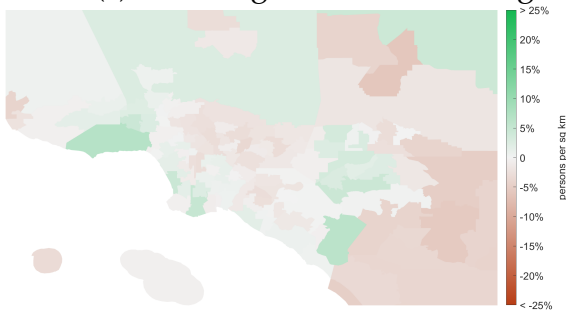
Panel (a): United States, relative changes



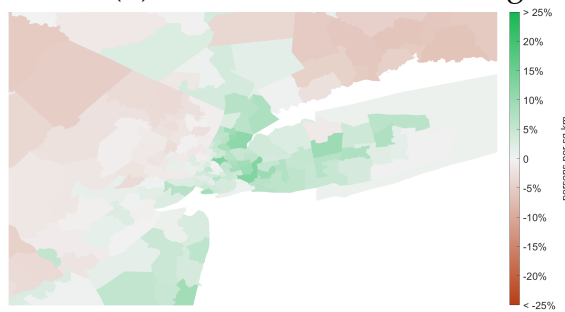
Panel (b): United States, absolute changes



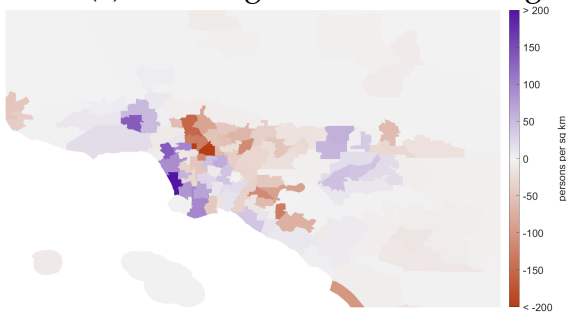
Panel (c): Los Angeles, relative changes



Panel (d): New York, relative changes



Panel (e): Los Angeles, absolute changes



Panel (f): New York, absolute changes

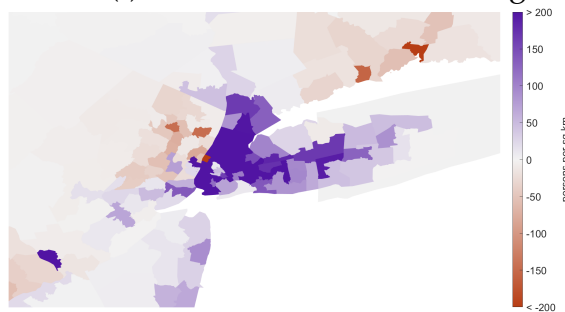
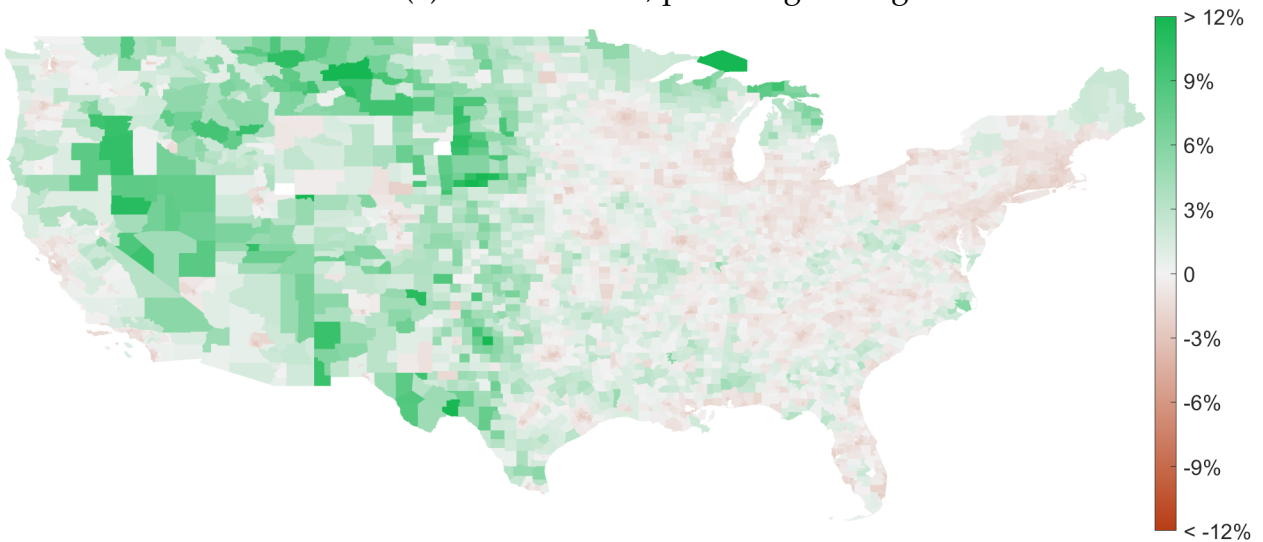
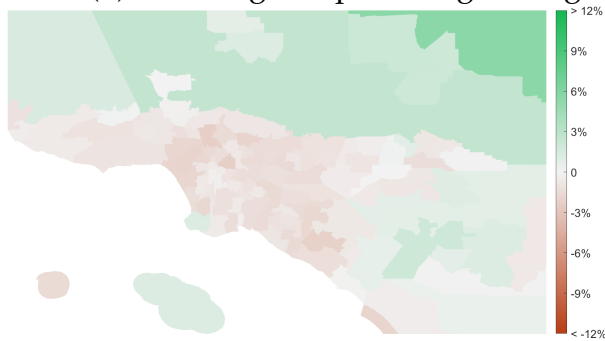


Figure 11: Floorspace Prices

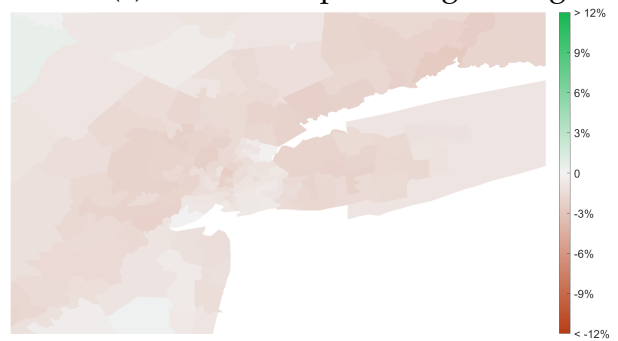
Panel (a): United States, percentage changes



Panel (b): Los Angeles, percentage changes



Panel (c): New York, percentage changes



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A Appendix

A.1 Welfare Decomposition

Welfare by type. The expected utility of a worker after he learns his type θ but before location preference shocks are realized, is given by

$$V(\theta) = \varsigma \pi_{ij}(\theta)^{-\frac{1}{\epsilon}} \frac{X_i E_j b_{ij} w_{ij}(\theta)}{d_{ij}(\theta) q_i^\gamma}. \quad (\text{A.1})$$

Hence, we compute counterfactual changes in welfare for each worker who did not switch his commuter type θ as

$$\widehat{V}(\theta) = \hat{\pi}_{ij}(\theta)^{-\frac{1}{\epsilon}} \frac{\hat{X}_i \hat{E}_j \hat{b}_{ij} \hat{w}_{ij}(\theta)}{\hat{d}_{ij}(\theta) \hat{q}_i^\gamma}. \quad (\text{A.2})$$

Note that the previous expression yields the same value of $\widehat{V}(\theta)$ for any pair (i, j) .

Welfare by source. Aggregate composite consumption (i.e., $c^{1-\gamma} h^\gamma$) is given by

$$\int \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{I}} w_{ij}(\theta) q_i^{-\gamma} \pi_{ij}(\theta) dF(\theta). \quad (\text{A.3})$$

Therefore welfare gains resulting from changes in *consumption* are calculated as the ratio of aggregate counterfactual and benchmark consumption levels:

$$\widehat{V}_C = \frac{\int \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{I}} \hat{w}_{ij}(\theta) w_{ij}(\theta) (\hat{q}_i q_i)^{-\gamma} \hat{\pi}_{ij}(\theta) \pi_{ij}(\theta) dF^*(\theta)}{\int \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{I}} w_{ij}(\theta) q_i^{-\gamma} \pi_{ij}(\theta) dF(\theta)}. \quad (\text{A.4})$$

Similarly, we calculate welfare gains resulting from changes in *consumption and commuting* by adjusting the previous expression by the commuting cost of traveling from i to j :

$$\widehat{V}_{C,C} = \frac{\int \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{I}} \hat{w}_{ij}(\theta) w_{ij}(\theta) (\hat{q}_i q_i)^{-\gamma} \hat{\pi}_{ij}(\theta) \pi_{ij}(\theta) \hat{d}_{ij}(\theta) d_{ij}(\theta) dF^*(\theta)}{\int \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{I}} w_{ij}(\theta) q_i^{-\gamma} \pi_{ij}(\theta) d_{ij}(\theta) dF(\theta)}. \quad (\text{A.5})$$

Then, we calculate welfare gains resulting from changes in *consumption, commuting, and amenities* by adding relevant residential, workplace, and bilateral amenity levels to the previous expression:

$$\widehat{V}_{C,C,A} = \frac{\int \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{I}} \hat{X}_i X_i \hat{E}_j E_j \hat{b}_{ij} b_{ij} \hat{w}_{ij}(\theta) w_{ij}(\theta) (\hat{q}_i q_i)^{-\gamma} \hat{\pi}_{ij}(\theta) \pi_{ij}(\theta) \hat{d}_{ij}(\theta) d_{ij}(\theta) dF^*(\theta)}{\int \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{I}} X_i E_j b_{ij} w_{ij}(\theta) q_i^{-\gamma} \pi_{ij}(\theta) d_{ij}(\theta) dF(\theta)}. \quad (\text{A.6})$$

Finally, welfare gains resulting from changes in *consumption, commuting, amenities, and Fréchet shocks* correspond to total welfare gains and are given by equation (2.47).

A.2 Local Wage Indices

Our source of wage data is the Census Transportation Planning Products (CTPP). CTPP data sets produce tabulations of the American Community Survey (ACS) data, aggregated at the Census tract level. We use the data reported for the five-year period from 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 each of the several earning bins in each workplace tract.²⁹

We calculate mean tract-level labor earnings as

$$\hat{w}_j = \frac{\sum_b nworkers_{b,j} \times meanw_b}{\sum_b nworkers_{b,j}}, \quad (A.7)$$

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 each PUMA, calculated from the ACS microdata.

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

$$\hat{w}_j = \alpha + \beta_1 age_j + \beta_2 sexratio_j + \sum_r \beta_{2,r} race_{r,j} + \sum_i \beta_{3,i} ind_{i,j} + \sum_o \beta_{4,o} occ_{o,j} + \epsilon_j, \quad (A.8)$$

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 .³⁰ The estimated tract-level wage index corresponds to the sum of the constant and the tract fixed effect, $\hat{\alpha} + \hat{\epsilon}_j$. Finally, we aggregate the tract-level wage indices to the level of our model locations using employment weights.

A.3 Estimation of Travel Times

In constructing a matrix of location to location travel times, we follow the practice recommended by Spear (2011) and use LODES data as a measure of commuting flows and Census Transportation Planning Products (CTPP) data to provide information on commute times. The CTPP database reports commuting time data for origin-destination pairs of Census tracts across the contiguous United States for 2012–2016, and is tabulated using

²⁹The bins are $\leq \$9,999$; $\$10,000$ – $\$14,999$; $\$15,000$ – $\$24,999$; $\$25,000$ – $\$34,999$; $\$35,000$ – $\$49,999$; $\$50,000$ – $\$64,999$; $\$65,000$ – $\$74,999$; $\$75,000$ – $\$99,999$; and $\geq \$100,000$.

³⁰We 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.

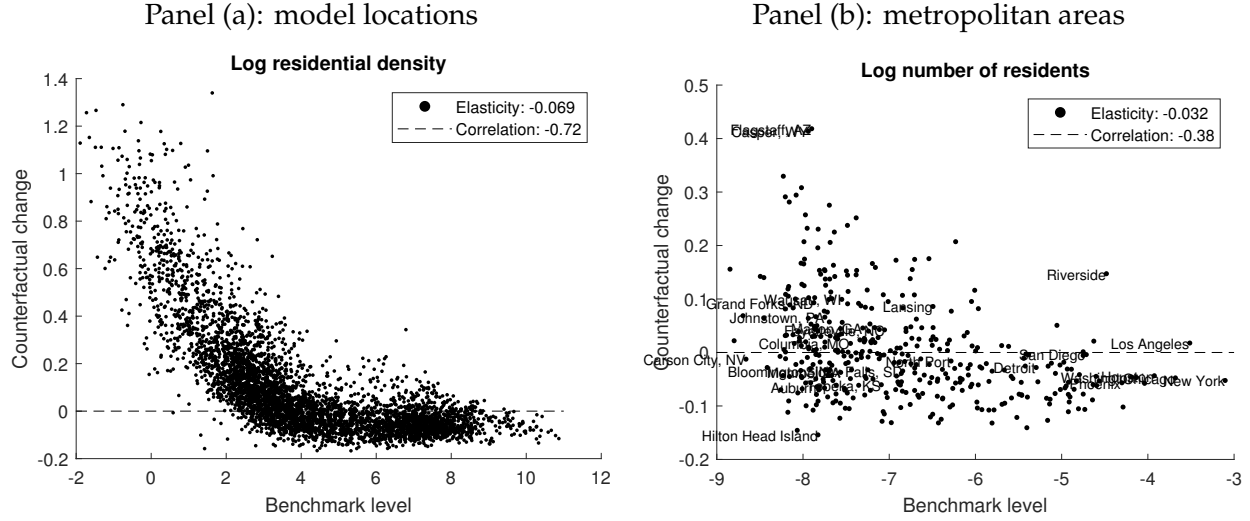
American Community Survey (ACS) data.³¹ Travel times are reported for a little over four million trajectories, which is a small fraction of all possible bilateral trajectories, because most pairs of tracts are far enough apart that the ACS survey does not observe anyone commuting between those two points. We process this data in the following three steps:

1. We calculate the average travel time between each pair of locations as the average of all reported tract-to-tract travel times with an origin inside one location and a destination in the other. To minimize the influence of outliers on these estimates, we throw out the calculation for any pair of locations for which less than 10% of all possible tract-to-tract travel times is reported by CTPP. We also exclude average travel times that imply a travel speed of more than 100 kilometers per hour or less than 5 kilometers per hour. We perform this same calculation for the average distance of each location *from itself*, thereby obtaining data-based estimates of the average internal travel time for each location as well.
2. To prevent “breaks” in the network, we check to see if any location does not have an estimated travel time to its 5 nearest neighbors. If travel times are missing for any of these location-to-location trajectories, we project a travel time using the estimated coefficients of a regression of average location-to-location travel times on average great circle distance and an indicator variable that takes the value one if the origin is the same as the destination. This procedure adds about 10,000 additional links, out of 20,268,004 possible location-to-location trajectories.
3. We take the approximately 34,000 primitive connections, the travel times for which we have calculated as detailed above, as the first-order connections in a transport network. We use Dijkstra’s algorithm to find the least possible travel times through this network between each pair of model locations.

³¹The CTPP data divides 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.

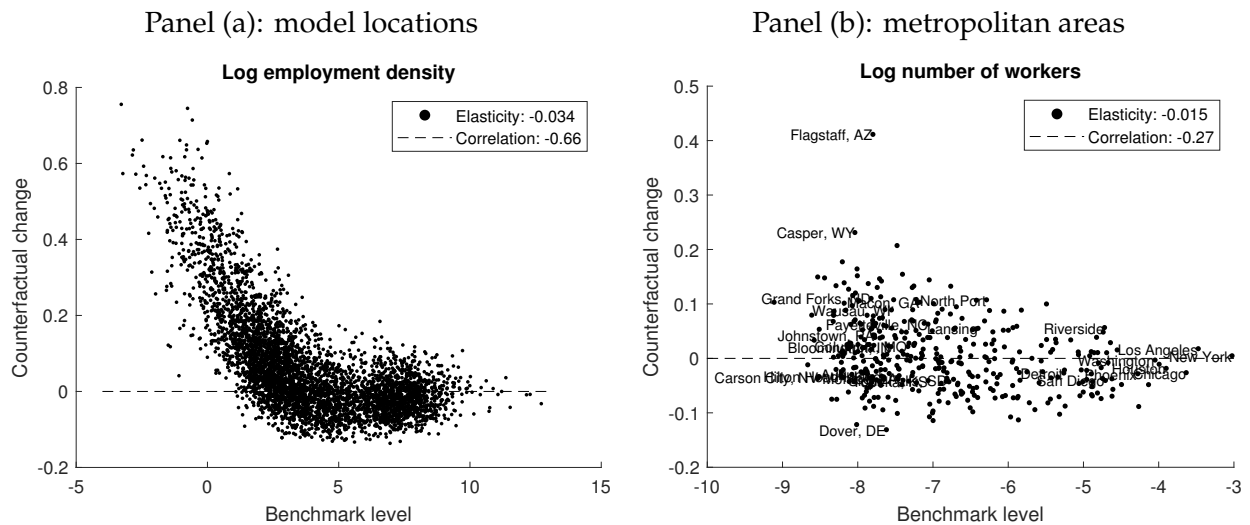
A.4 Counterfactual Results with Agglomeration Effects

Figure A.1: Change in Residents



Note: These scatterplots show the relationship between the benchmark residential density and the counterfactual change in log density. Panel (a) shows this relationship for model locations, panel (b) shows this relationship for metropolitan areas. "Elasticity" is the coefficient of the OLS regression of the counterfactual change on the benchmark level.

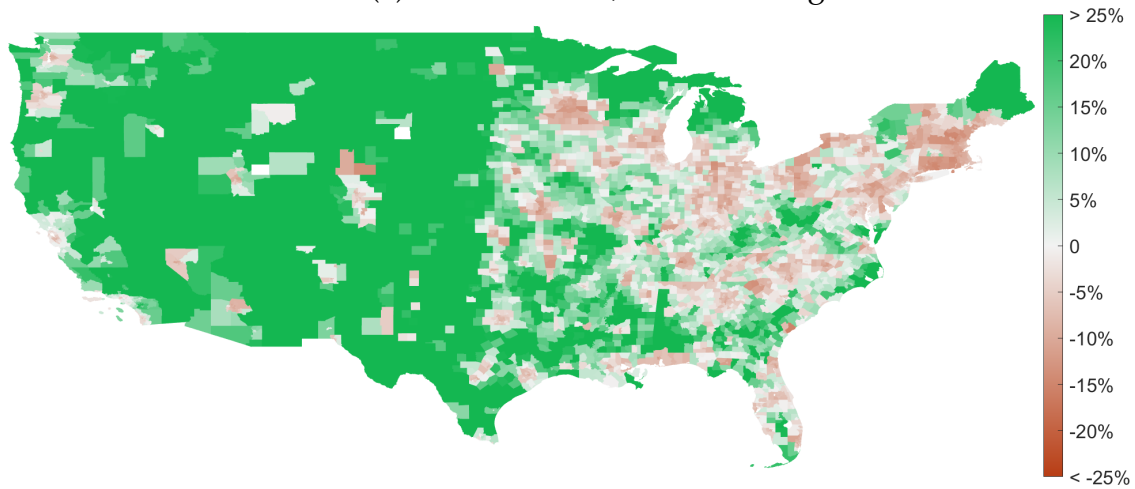
Figure A.2: Change in Employment



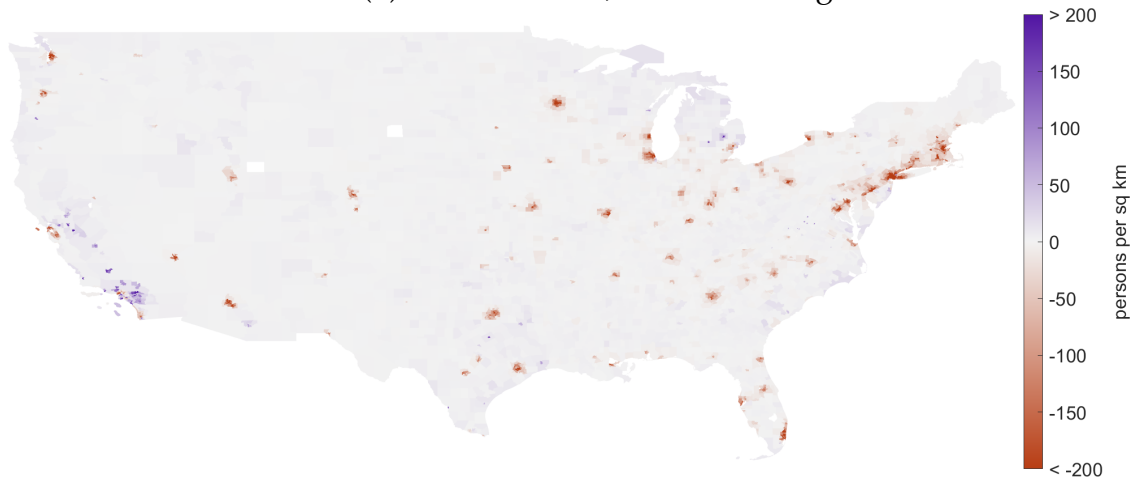
Note: These scatterplots show the relationship between the benchmark employment density and the counterfactual change in log density. Panel (a) shows this relationship for model locations, panel (b) shows this relationship for metropolitan areas. "Elasticity" is the coefficient of the OLS regression of the counterfactual change on the benchmark level.

Figure A.3: Density of residents

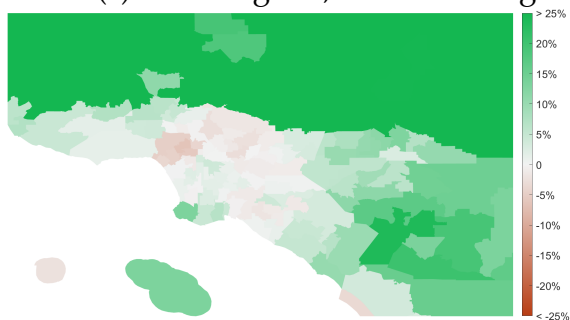
Panel (a): United States, relative changes



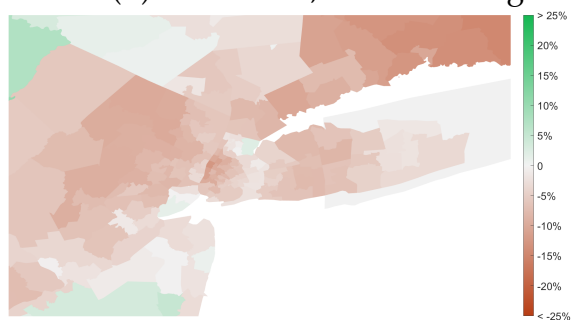
Panel (b): United States, absolute changes



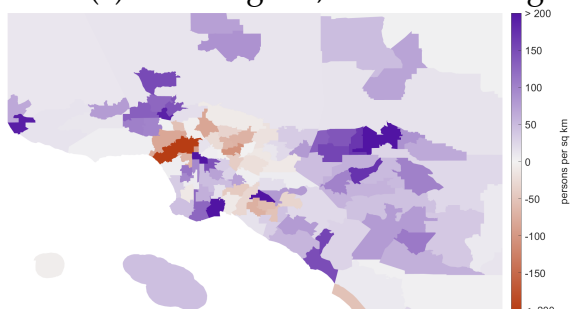
Panel (c): Los Angeles, relative changes



Panel (d): New York, relative changes



Panel (e): Los Angeles, absolute changes



Panel (f): New York, absolute changes

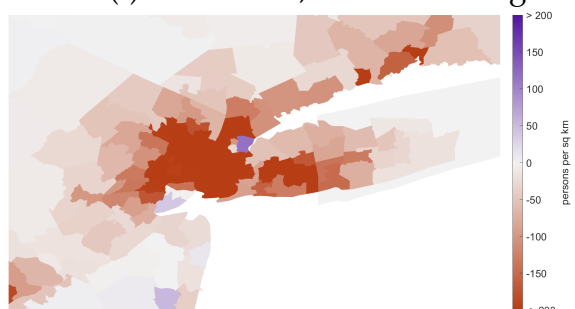
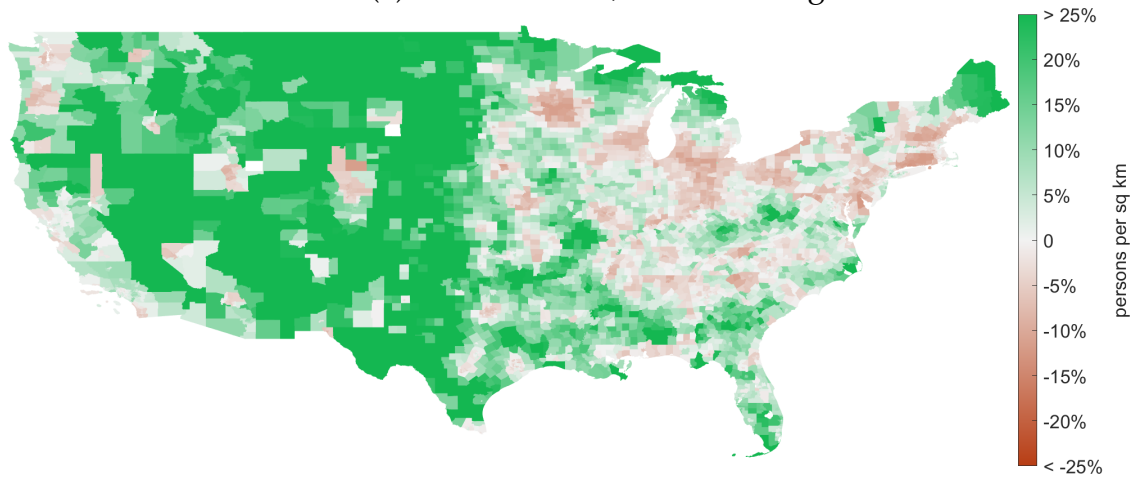
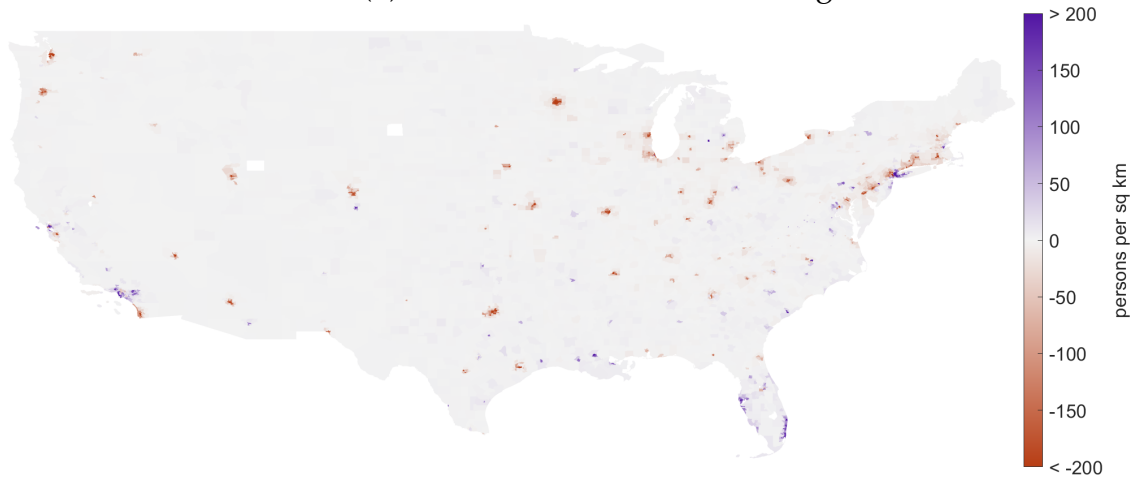


Figure A.4: Density of workers

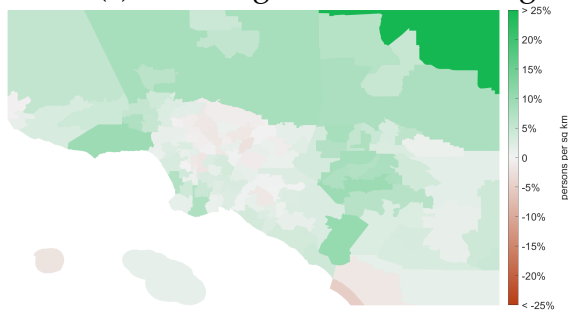
Panel (a): United States, relative changes



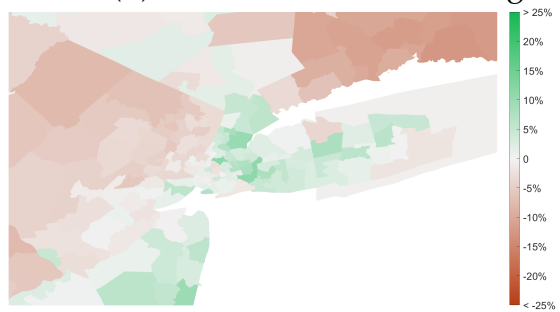
Panel (b): United States, absolute changes



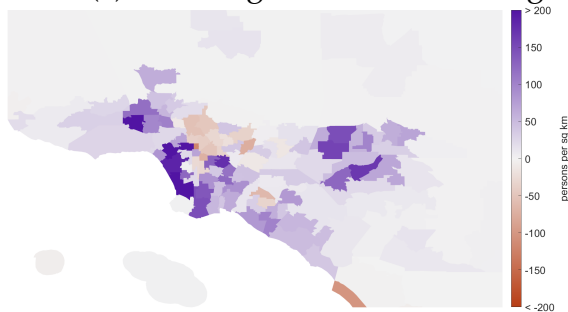
Panel (c): Los Angeles, relative changes



Panel (d): New York, relative changes



Panel (e): Los Angeles, absolute changes



Panel (f): New York, absolute changes

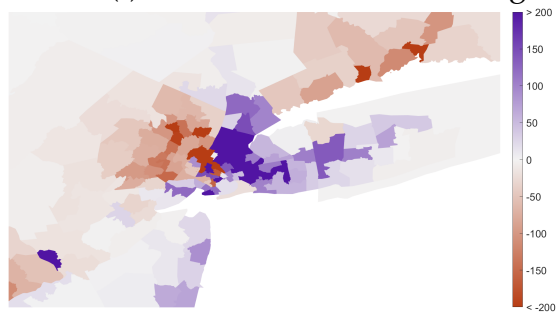
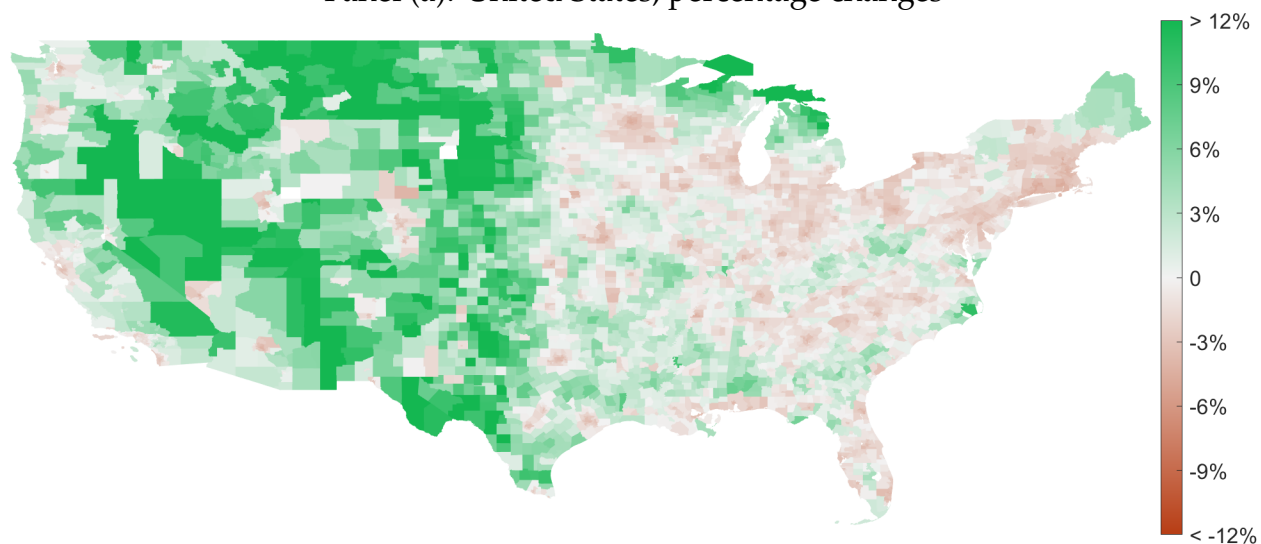
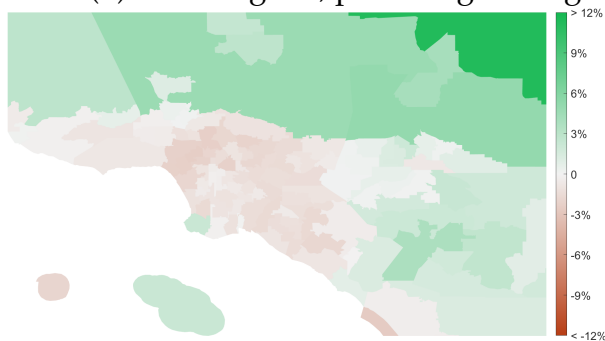


Figure A.5: Real Estate Prices

Panel (a): United States, percentage changes



Panel (b): Los Angeles, percentage changes



Panel (c): New York, percentage changes

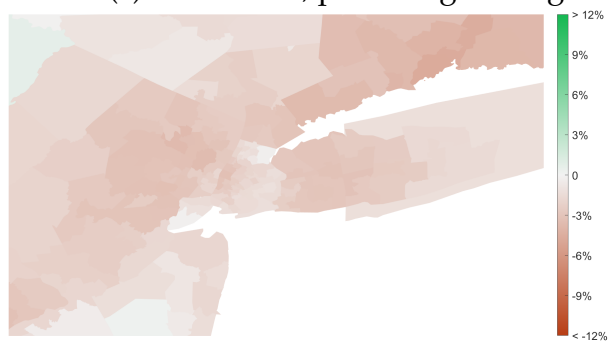
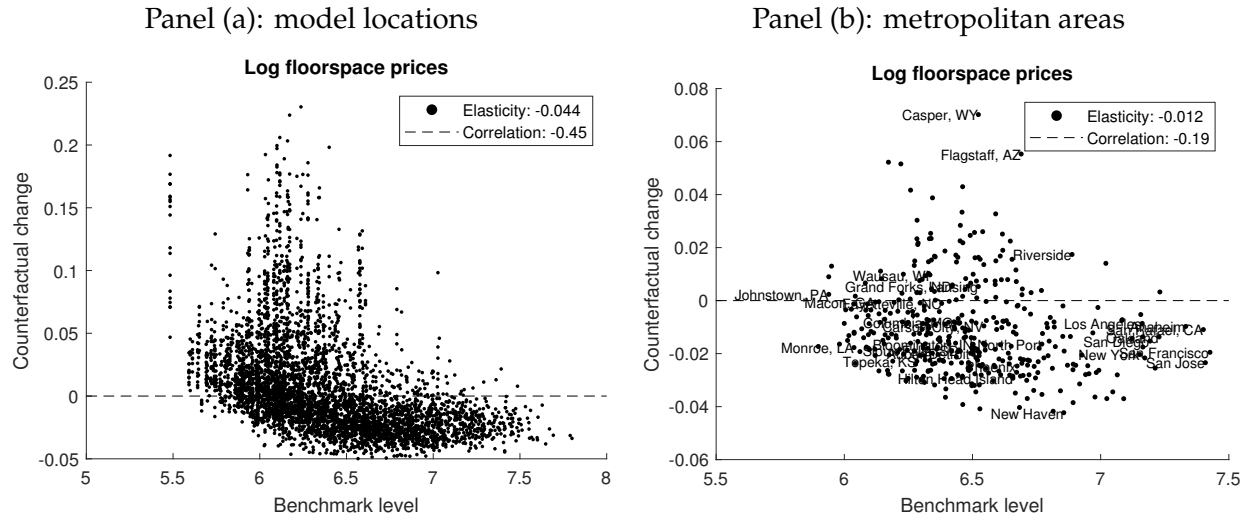
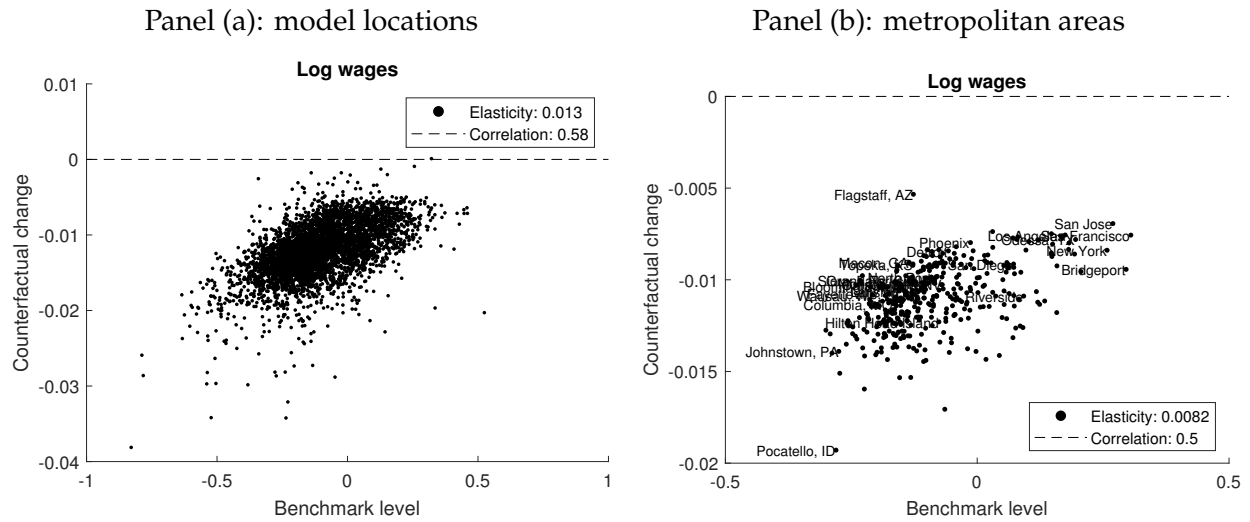


Figure A.6: Floorspace prices



Note: These scatterplots show the relationship between the benchmark log floorspace prices and the counterfactual change in log floorspace prices. “Elasticity” is the coefficient of the OLS regression of the variable on the vertical axis on the variable on the horizontal axis.

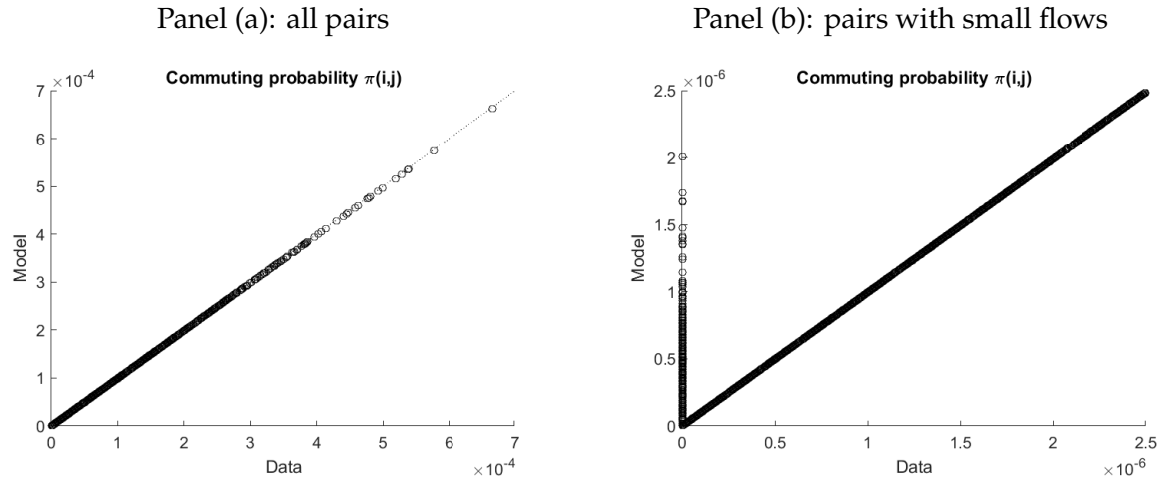
Figure A.7: Wages



Note: These scatterplots show the relationship between the benchmark log wages of commuters at the place of work, w_j^C , and the counterfactual change in log wages. “Elasticity” is the coefficient of the OLS regression of the variable on the vertical axis on the variable on the horizontal axis.

A.5 Additional Figures and Tables

Figure A.8: Commuting flows



Note: These scatterplots show the relationship between commuting probabilities in the LODS data and their counterparts in the model. Panel (a) shows all pairs, panel (b) shows pairs with $\pi_{ij} < 2.5 \times 10^{-6}$. The dotted line is the 45-degree line.