How Do Cities Change When We Work from Home?*

Matthew J. Delventhal†
Eunjee Kwon‡
Andrii Parkhomenko§

This version: June 30th, 2020.
Click here for the most recent version

Abstract

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

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

JEL codes: E24, J81, R31, R33, R41.

*We thank Gilles Duranton, Jeff Lin, and Jorge De la Roca, as well as seminar participants at USC for useful comments and discussions. The authors acknowledge generous grant funding from METRANS-PSR (grant number 65A0674) and the USC Lusk Center for Real Estate.
†The Robert Day School of Economics and Finance, Claremont McKenna College, 500 E. 9th Street, Claremont, CA 91711 mdelventhal@cmc.edu
‡Department of Economics, University of Southern California, Los Angeles, CA 90089 eunjeekw@usc.edu
§Department of Finance and Business Economics, Marshall School of Business, University of Southern California, Los Angeles, CA 90089 parkhome@usc.edu
1 Introduction

The potential savings in overhead costs and commuting time from remote work are significant.\(^1\) Technological conditions have been improving steadily for years, yet the fraction of Americans working from home has remained small. In 2019, just 4.2% of all workers worked from home. However, the trend since 1980 has been one of the persistent increases from an initial level of 1%. Now that the COVID-19 pandemic has forced many companies and organizations to pay a part of the fixed cost of transition to remote work, it seems reasonable to expect that the trend might accelerate. What if when COVID-19 leaves many of us to keep working remotely?\(^2\)

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

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

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

Second, average commuting times fall, while commuting distances increase. Since fewer

---

\(^1\)Mas and Pallais (2020) provides an overview of the current state of research. Bloom, Liang, Roberts, and Ying (2015) present experimental evidence that telework increases employee work satisfaction without necessarily reducing their productivity.

\(^2\)A survey by Gartner found that 74% of Chief Financial Officers planned to keep some of their employees working from home permanently (Gartner, 2020). Another survey conducted by S&P Global Market Intelligence found that 67% of IT firms expect work-from-home policies will remain in place permanently or at least for the long term (Bender, 2020). Notably, Facebook and Twitter announced that many of their employees would keep working remotely after the pandemic.
workers commute, traffic congestion eases, which increases average speed of travel. Commuters take advantage of this and also move farther away from their workplaces to live in locations with lower real estate prices. If the fraction of telecommuters were to increase to 33%, commuters would spend 2.5% less time on roads, while commuting 2.3% longer distances. Total miles traveled daily by all workers would fall by 29%.

Third, average real estate prices fall. As many workers move into distant suburbs, prices in the periphery increase. However, these price increases are more than offset by the decline of prices in the core. This decline is driven by two factors. The first is the decline in demand for residential real estate in core locations. The second is the reduced demand for on-site office space from workers who now telecommute. In the counterfactual where 33% of workers telecommute, average house prices fall by about 5.6%.

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

Ours is the first study of which we are aware to quantitatively assess the impact of telecommuting using a detailed general equilibrium model of an urban area with micro-level data. Our qualitative results conform fundamentally with previous theoretical findings by, for example, Safirova (2003) and Rhee (2008). Larson and Zhao (2017) calibrate a simple monocentric city model to quantify the effect of telework on energy consumption. They find somewhat smaller effects on welfare and time spent commuting, possibly because their models do not allow for changes in the employment location.

This paper builds upon our recent work, Delventhal, Kwon, and Parkhomenko (2020), in which we construct a quantitative model of the Los Angeles metro area to assess the impact of density-restricting zoning policies. It also follows a number of recent efforts to assess the impact on urban structure of urban policies and transport infrastructure, such as those by Ahlfeldt, Redding, Sturm, and Wolf (2015), Severen (2019), Tsivanidis (2019), Owens, Rossi-Hansberg, and Sarte (2020), and Anas (2020). Our paper uses a similar framework to assess the impact of a change to the underlying technology of production on urban structure.

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

Consider an urban area with a set of $I$ discrete locations and populated by workers, firms, and floorspace developers. The total employment of the urban area is fixed and normalized to 1.

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

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

This model is based on Delventhal, Kwon, and Parkhomenko (2020) and is similar in many respects to Ahlfeldt, Redding, Sturm, and Wolf (2015). The remainder of the section presents the model and Appendix B provides additional details.

2.1 Workers

Before choosing where to work and where to live, workers participate in a lottery which determines whether or not they will be a telecommuter. With probability $\psi \geq 0$, the worker becomes a “telecommuter.” With probability $1 - \psi$, the worker becomes a “commuter.” In what follows, variables specific to telecommuters and commuters are indexed by $T$ and $C$, respectively.
2.1.1 Commuters

Commuter \( n \) who resides in location \( i \in \{1, ..., I\} \) and works in location \( j \) enjoys utility \( U_{ijn}^C \) given by

\[
U_{ijn}^C = e^{-\kappa t_{ijn}} z_{ijn} \left( \frac{c_{ijn}^C}{1 - \gamma} \right)^{1-\gamma} \left( \frac{h_{ijn}^C}{\gamma} \right)^\gamma,
\]

(1)

where \( \gamma \in (0, 1) \) is the share of housing in expenditures, \( z_{ijn} \) represents an idiosyncratic preference shock for the \((i, j)\)-pair of locations, and the parameter \( \kappa > 0 \) determines the relationship between travel time and workers’ disutility from commuting. Consumption of the final good, \( c_{ijn}^C \), and consumption of residential floorspace, \( h_{ijn}^C \), are subject to the budget constraint

\[
(1 + \tau) w_j^C = c_{ijn}^C + q_{Ri} h_{ijn}^C,
\]

(2)

where \( w_j^C \) is the wage earned by working in location \( j \), \( q_{Ri} \) is the price of residential floorspace in location \( i \), and \( \tau \) is the proportional transfer which distributes income from land and the consumption good sold to real estate developers equally among all city workers. Idiosyncratic shocks \( z_{ijn} \) are drawn from a Fréchet distribution with elasticity \( \epsilon > 1 \) which has the following CDF:

\[
F(z_{ij}) = e^{-X_i E_j z_{ij}^{-\epsilon}}.
\]

(3)

In the above formulation, \( X_i \) is the average amenity derived from living in location \( i \), and \( E_j \) is the average amenity derived from working in location \( j \), which the worker takes as exogenous. The indirect utility of a commuter is

\[
u_{ijn}^C = e^{-\kappa t_{ijn}} z_{ijn} (1 + \tau) w_j^C q_{Ri}^{-\gamma}.
\]

(4)

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

2.1.2 Telecommuters

Telecommuters have the same utility function as commuters, except that they suffer from the disutility of commuting only during the fraction \( \theta \in [0, 1] \) of work days that they commute.
Telecommuter $n$ who resides in $i$ and works in $j$ enjoys utility $U_{ijn}^{T}$ given by

$$U_{ijn}^{T} = (\theta e^{-\kappa t_{ij}} + 1 - \theta) z_{ijn} \left( \frac{c_{ijn}^{T}}{1 - \gamma} \right)^{1-\gamma} \left( \frac{h_{ijn}^{T}}{\gamma} \right)^{\gamma}.$$  \hfill (5)

The telecommuters’ budget constraint is

$$(1 + \tau)w_{ij}^{T} = c_{ijn}^{T} + q R_{i} h_{ijn}^{T},$$  \hfill (6)

where $w_{ij}^{T}$ represents the effective wage paid to the telecommuter for work from home, net of expenses.

Telecommuters act as independent contractors who sell units of effective work to their employers at the equilibrium price $p_{j}^{T}$, which they take as given. When working on-site, the telecommuter combines their labor with commercial office space in their employer’s location, just as if they were a regular commuter. When working from home, the telecommuter combines their labor with home office space. A telecommuter with a job in $j$ and a residence in $i$ has a home production problem given by

$$\max_{h_{ij}^{T}, h_{ij}^{C}} \left\{ p_{j}^{T} \left[ \theta \left( h_{ij}^{C} \right)^{1-\alpha} + (1 - \theta) \nu \left( h_{ij}^{T} \right)^{1-\alpha_{T}} \right] - q_{j}^{W} h_{ij}^{C} - q_{i}^{R} h_{ij}^{T} \right\}$$  \hfill (7)

In the above problem, $h_{ij}^{T}$ represents the per-worker quantity of home office floorspace rented by the representative telecommuter, while $h_{ij}^{C}$ represents the per-worker quantity of on-site commercial floorspace rented. $\alpha_{T} \in (0, 1)$ is the labor share of distance work, and $\nu > 0$ represents the difference in total factor productivity between on-site and distance work.\(^3\) Ex-ante, we would expect that distance work is less floorspace intensive and has somewhat lower total factor productivity ($\alpha_{T} > \alpha$ and $\nu < 1$). However, we do not impose these restrictions in the analysis or the calibration.

Indirect utility for telecommuters is the same as that of on-site workers, after accounting for the differences in commuting disutility and labor income:

$$u_{ijn}^{T} = (\theta e^{-\kappa t_{ij}} + 1 - \theta) z_{ijn}(1 + \tau)w_{ij}^{T} - \gamma.$$  \hfill (8)

### 2.1.3 Location Choices

Let $\bar{u}_{ij}^{C} \equiv u_{ij}^{C} / z_{ijn}$ and $\bar{u}_{ij}^{T} \equiv u_{ij}^{T} / z_{ijn}$ be indirect utilities of a commuter and a telecommuter, respectively, net of the location preference shock. Optimal choices imply that the probability

\(^3\)Office work may make workers more productive thanks to in-person interaction and the availability of dedicated workspace, while working at home may be associated with more distractions.
that a worker of type $c \in \{C, T\}$ chooses to live in location $i$ and work in location $j$ is

$$\pi_{ij}^c = \frac{X_i E_j (\bar{u}_{ij}^c)^\epsilon}{\sum_{r=1}^l \sum_{s=1}^l X_r E_s (\bar{u}_{rs}^c)^\epsilon}.$$  \hspace{1cm} (9)

As a result, the equilibrium residential population in location $i$ is

$$N_{Ri} = N_{Ri}^C + N_{Ri}^T = (1 - \psi) \sum_{j=1}^l \pi_{ij}^C + \psi \sum_{j=1}^l \pi_{ij}^T,$$ \hspace{1cm} (10)

and the equilibrium employment in location $j$ is

$$N_{Wj} = N_{Wj}^C + N_{Wj}^T = (1 - \psi) \sum_{i=1}^l \pi_{ij}^C + \psi \sum_{i=1}^l \pi_{ij}^T.$$ \hspace{1cm} (11)

### 2.2 Firms

The final good is produced in each tract $j$ by perfectly competitive firms using a combination of on-site and telecommuting labor. In particular, a representative firm in tract $j$ produces the amount

$$Y_j^C = A_j (N_{Wj}^C)^\alpha H_{Wj}^{1-\alpha}$$ \hspace{1cm} (12)

of goods using on-site labor and the amount

$$Y_j^T = A_j Z_{j,T}$$ \hspace{1cm} (13)

using remote labor. The problem of the representative firm in location $j$ given by

$$\max_{N_{Wj}^C, H_{Wj}, Z_{j,T}} \left\{ A_j [(N_{Wj}^C)^\alpha H_{Wj}^{1-\alpha} + Z_{j,T}] - w_j^C N_{Wj}^C - q_{Wj} H_{Wj} - p_j^T Z_{j,T} \right\},$$ \hspace{1cm} (14)

where $A_j > 0$ represents total factor productivity. Firms hire $N_{Wj}^C$ on-site workers at a cost of $w_j^C$ per worker, and $H_{Wj}$ of commercial floorspace at a cost of $q_{Wj}$ per square foot. Additionally, they hire $Z_{j,T}$ units of effort from telecommuters acting as independent contractors, at a price of $p_j^T$. In equilibrium, $p_j^T = A_j$ and the amount of telecommuter effort hired by firms in location $j$ is equal to the supply of effort to location $j$,

$$Z_{j,T} = \nu \sum_i (N_{Wij}^T)^{\alpha_T} (h_{ij}^T)^{1-\alpha_T},$$ \hspace{1cm} (15)
where $h_{ij}^T$ is the optimal amount of home office floorspace rented by a telecommuter who resides in $i$ and works in $j$.

Profit maximization implies the following labor demand function,

$$N^C_{Wj} = \left( \frac{\alpha A_j}{w_j^C} \right)^{\frac{1}{1-\alpha}} H_{Wj}. \quad (16)$$

In equilibrium, the relationship between commuter and telecommuter wages is given by

$$w_{ij}^T = \theta w_j^C + (1 - \theta) \alpha_T \left( \nu A_j \right)^{\frac{1}{\alpha_T}} \left( \frac{1 - \alpha_T}{q_{Ri}} \right)^{\frac{1-\alpha_T}{\alpha_T}}, \quad (17)$$

and the relationship between commercial floorspace prices and commuter wages is

$$q_{Wj} = (1 - \alpha) \left( \frac{\alpha}{w_j^C} \right)^{\frac{1}{1-\alpha}} A_j^{\frac{1}{1-\alpha}}. \quad (18)$$

### 2.3 Developers

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

$$H_i = K_i^{1-\eta} (\phi_i(H_i) L_i)^{\eta}, \quad (19)$$

where $L_i \leq \Lambda_i$ and $K_i$ are the amounts of land and the final good used to produce floorspace, and $\eta$ is the share of land in production. $\Lambda_i$ is the exogenous supply of buildable land. Function $\phi_i(H_i)$ is defined as

$$\phi_i(H_i) = \bar{\phi} \left( 1 - \frac{H_i}{\bar{H}_i} \right), \quad (20)$$

and determines the local land-augmenting productivity of floorspace developers.\(^4\) Parameter $\bar{H}_i$ determines the density limit in tract $i$. When $H_i$ approaches $\bar{H}_i$, $\phi_i(H_i)$ approaches zero. As a result, it becomes very costly to build due to regulatory or political barriers, such as zoning, floor-to-area ratios, or local opposition to development.

Floorspace is divided into residential and commercial, $H_i = H_{Ri} + H_{Wi}$. Developers sell floorspace at price $\bar{q}_i = \min \{q_{Ri}, q_{Wi}\}$ to either residential or commercial users. However, the effective price that residents or firms pay for floorspace may differ from $\bar{q}_i$ due to zoning restrictions. The wedge between prices for residential and commercial floorspace is denoted by parameter $\xi_i > 0$. If $\xi_i < 1$, regulations increase the relative cost of supplying residential floorspace.

\(^4\)This function was also used in Favilukis, Mabille, and Van Nieuwerburgh (2019) to model density limits.
floorspace. If $\xi_i > 1$, regulations increase the relative cost of supplying commercial floorspace. Thus, the relationship between residential and commercial floorspace prices is\footnote{This equality does not need to hold if the supply of commercial or residential floorspace in a given tract is zero. In our quantitative model, however, these corner cases do not occur.}

$$q_{Wi} = \xi_i q_{Ri}.$$ \hspace{1cm} (21)

The demand for commercial floorspace ($H_{Wi}$) arises from the profit-maximizing choices of production firms. The demand for residential floorspace ($H_{Ri}$) comes from utility-maximizing choices of residents, as well as choices of telecommuters as to how much floorspace to hire for working from home. The equilibrium demand for floorspace also determines the demand for land which is in fixed supply. As a result, the equilibrium land price is equal to

$$l_i = \frac{\eta}{L_i} (q_{Ri} H_{Ri} + q_{Wi} H_{Wi}).$$ \hspace{1cm} (22)

### 2.4 Externalities

Total factor productivity in location $j$ is determined by an exogenous component, $a_j$, and an endogenous component that depends on the density of on-site workers in every other location $s$, weighted inversely by the travel time from that $j$ to $s$:

$$A_j = a_j \left[ \sum_{s=1}^{I} e^{-\delta t_{js}} \left( \frac{N^C_s + \theta N^T_s}{L_s} \right)^\lambda \right]$$ \hspace{1cm} (23)

On-site workers in location $s$ consist of the sum of regular commuters ($N^C_s$) and the fraction $\theta$ of telecommuters ($N^T_s$) who are in the office on any given day.

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

$$X_i = x_i \left[ \sum_{s=1}^{I} e^{-\rho t_{is}} \left( \frac{N_{Rs}}{L_s} \right)^\chi \right] \hspace{1cm} (24)$$

### 2.5 Equilibrium

A spatial equilibrium consists of commuter and telecommuter wages ($w^C_j$ and $w^T_{ij}$) that equalize labor demand and supply in each location and satisfy equation (17); residential and commercial floorspace prices ($q_{Ri}$ and $q_{Wi}$) that equalize floorspace demand and supply in each location and satisfy equation (21); commuting flows of commuters and telecommuters ($\pi^C_{ij}$ and
between each pair of locations; local supply of residential and commercial floorspace \((H_{Ri} \text{ and } H_{Wi})\); total factor productivities \((A_j)\) in each location; and local residential amenities \((X_i)\).

3 Calibration

The Los Angeles-Long Beach Combined Statistical Area had a total population of 18.7 million in 2018, distributed across a total land area of 88,000 square kilometers.\(^6\) It comprises five counties (Los Angeles, Orange, Riverside, San Bernardino, and Ventura) and 3,917 census tracts. To exclude nearly empty desert and mountain tracts with large land areas, which include tracts with a larger land area than all of Los Angeles County, we exclude any tracts that are below the 2.5th percentile of both residential and employment density. This excludes less than 1% of workers and leaves us with 3,846 tracts. We focus on the five years between 2012 and 2016. To construct tract-level data on the residence, employment, wages, prices of residential and commercial floorspace, and commuting times, we follow the methodology developed by Delventhal, Kwon, and Parkhomenko (2020). Please refer to Appendix A for more details.

The baseline probability of telecommuting, \(\psi\), is set to 0.0374. This number corresponds to the fraction of workers who report that they primarily work from home in the 2012–2016 individual-level data from the American Community Survey for the Los Angeles-Long Beach CSA. The fraction of time that telecommuters spend on an on-site workplace, \(\theta\), is set to 0.114, based on a survey questionnaire of Global Work-from-Home Experience Survey (Analytics, 2020).\(^7\) The elasticity of commuting time with respect to traffic volume, \(\varepsilon_V\), is set to 0.2, following Small and Verhoef (2007) (Appendix section E discusses robustness of results to different values of \(\varepsilon_V\)).

We calibrate the relative TFP of telecommuters, \(\nu\), so that the wages of commuters and telecommuters are identical in the benchmark economy.\(^8\) The floorspace share of telecommuters, \(\alpha_T\), is calibrated so that, on average, the home office of a telecommuter constitutes 20% of her house.\(^9\) The calibrated values of \(\nu\) and \(\alpha_T\) are equal to 0.71 and 0.934, respectively.

---

\(^6\)U.S. Census Bureau (2020)

\(^7\)The survey asked the number of days an employee worked from home per week. We classify workers as telecommuters if they work from home three or more days per week. According to the survey, 9% of workers work from home five days per week, 2% do this four days a week, and 3% work from home three days per week. Based on these numbers, we calculate the fraction of time spent on-site as \(1 - [0.09 \times (5/5) + 0.02 \times (4/5) + 0.03 \times (3/5)] / [0.09 + 0.02 + 0.03] = 0.114\).

\(^8\)Our empirical analysis finds that wages of telecommuters are higher than those of commuters, however, the wage premium disappears once we control for age, education, industry, and occupation. It is also unclear how the wage gap between the two types will change if many more workers start working remotely. As a result, we require that average wages are the same for both types in the benchmark economy.

\(^9\)The average house size was 2,430 square feet in 2010, according to Muresan (2016). Home-based teleworkers have, on average, 500 square feet larger homes than other workers (Nilles (2000)). Hence, telecommuters’ houses are about 20% larger. This gap may reflect differences in income, location within a city, and the need for designated workspace within a house. All of these factors are also present in our model.
We borrow values for the remaining city-wide parameters from previous studies in the literature. The share of housing in expenditures, $\gamma$, is equal to 0.25, following Davis and Ortalo-Magné (2011). The labor share in production, $\alpha$, is 0.8 (Valentinyi and Herrendorf, 2008), and the land share in construction, $\eta$, is 0.25 (Combes, Duranton, and Gobillon, 2018). Parameters that determine the strength of agglomeration forces and decay speed for productivity and residential amenities are borrowed from Ahlfeldt, Redding, Sturm, and Wolf (2015). In particular, we set $\lambda = 0.071$, $\delta = 0.3617$, $\chi = 1.0326$, and $\rho = 0.7595$. In addition, we borrow the variance of the Fréchet shocks and the elasticity of utility with respect to commuting from Ahlfeldt, Redding, Sturm, and Wolf (2015), and set $\epsilon = 6.6491$ and $\kappa = 0.0105$.

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

4 Counterfactuals

The COVID-19 outbreak in early 2020 has forced many workers to work from home. While before the epidemic around 4% of workers in Los Angeles metropolitan area worked from home, Dingel and Neiman (2020) estimate that as many as 33% of workers in Los Angeles have jobs that can be done remotely.

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

As the number of teleworkers increases, both firms and workers change their locations within the urban area. In response to the reallocation of firms and workers, the city also experiences endogenous adjustments in the supply of commercial and residential floorspace, as well as commuting speeds. In what follows, we discuss the effects on the spatial allocation of workers

---

10 Note that the parameter $\chi$ in our model corresponds to the product of the variance of the Fréchet shocks and the elasticity of residential amenities with respect to density in Ahlfeldt, Redding, Sturm, and Wolf (2015).

11 These two parameters, as well as the four parameters that determine amenity and productivity spillovers, were estimated for the city of Berlin, and we leave the estimation for Los Angeles for future work. Nonetheless, similar structural models with parameters estimated for other cities are characterized by similar magnitudes of productivity agglomeration effects and spatial spillovers. At the same time, the estimates of amenity agglomeration effects and spatial spillovers differ substantially across studies. See Berkes and Gaetani (2019), Heblich, Redding, and Sturm (2018), and Tsivanidis (2019), among others. The variance parameter of the Fréchet shock distribution for U.S. cities was estimated in Baum-Snow and Han (2019) and varies from 1.63 to 3.83, lower than the value used in this paper.
and firms, floorspace prices, commuting patterns, wages and land prices, and consumption and welfare.

4.1 Spatial Reallocation and Floorspace Prices

When workers are freed from the need to commute to their workplace, they tend to choose residences farther from the urban core in locations with more affordable housing. As the share of telecommuting workers rises, this drives a reallocation of residents from the core of the urban area towards the periphery. The upper panel of Figure 1 maps the predicted reallocation of residents when the fraction of telecommuters rises to 33%.

As residents decentralize, employment centralizes. There are three main factors driving this reallocation. First, the flipside of a telecommuter being able to access jobs even if they live far away, is that employers can access the labor of telecommuters even if they are located far from where they live. Therefore, as the fraction of telecommuters rises, employment shifts from locations which are less productive but closer to workers’ residences, toward locations closer to the core which have higher exogenous productivity and benefit from greater productivity spillovers. Second, the reallocation of residents increases demand for floorspace in peripheral locations and reduces it in the core, creating a cost incentive for jobs to move in the opposite direction. Third, the fact that telecommuters require less on-site office space further increases the cost-efficiency of firms in core locations with high productivity but high real estate prices. The lower panel of Figure 1 maps the predicted reallocation of jobs when the fraction of telecommuters rises to 33%.

The net effect of these reallocations is to reduce the price of floorspace in core locations and increase it in the periphery. On average, the price of real estate goes down. Figure 2 maps predicted changes in real estate prices when the fraction of telecommuters rises to 33%. Under this scenario, the average price of floorspace declines by 5.6%.

\[\text{In this model, residential and commercial prices move one to one. See equation 21.}\]
Figure 1: Reallocation of workers and firms

Note: Residential (upper figure) and employment (lower figure) density. Absolute change relative to benchmark economy in counterfactual with $\psi = 0.33$. See main text for details.

Figure 2: House prices

Note: Percentage change relative to benchmark economy in counterfactual with $\psi = 0.33$. See main text for details.
4.2 Commuting

A shift to telecommuting brings large benefits to those workers who do not have to come to the office every day anymore and therefore suffer less disutility from commuting. However, those who still have to commute benefit too, as traffic congestion drops and commuting speeds increase. As Figure 3 demonstrates, with lighter traffic and faster speeds, the average commuting time for those who still commute falls from 31 to around 30 minutes. At the same time, the average commute distance for commuters increases by nearly 1 km, as commuters use part of their increased travel speed to live farther away. However, the total amount of kilometers traveled falls by 29%, which suggests possible environmental benefits of the increase in telecommuting. The magnitudes of these effects depend importantly on the elasticity of speed with respect to traffic volume, $\varepsilon_V$. Simulations for alternative values of $\varepsilon_V$ can be found in Appendix E.

Figure 3: Commuting time and distance

![Figure 3: Commuting time and distance](image)

Note: Left panel displays the average commuting time for all workers and commuters, as a function of the share of telecommuters. Right panel shows the average commuting distance.

4.3 Income and Welfare

Wages and Income. As the share of telecommuters increases, two opposite forces influence average wages. On the one hand, jobs are being reallocated to more productive locations that benefit from higher agglomeration spillovers. On the other hand, a larger fraction of the workforce does not contribute to agglomeration spillovers. In our calibration, these two forces almost perfectly balance each other. As can be seen in the left panel of Figure 4, even a full increase in the fraction of telecommuters to 33% only leads to a 0.3% increase in average wages.

As can also be seen in the left panel of Figure 4, an increasing share of telecommuters is decisive for the average price of land. Residents reallocate themselves to less expensive locations, and firms with more telecommuters need less office space. If the fraction of telecommuters rose
to 33%, the income of landowners would fall by 8%.

How is the fall in property prices divided between the residential and commercial markets? The value of both types of real estate falls by roughly the same amount. As can be seen in the right panel of Figure 4, when the change in the amount of telecommuting is relatively small, the decrease in residential prices is somewhat larger. After the fraction of telecommuters passes 28%, commercial prices are hit harder. Prices of each type of real estate fall by roughly 6% when $\psi$ increases all the way to 33%.

**Figure 4: Wages, land and floorspace prices**

![Wages, land and floorspace prices](image)

*Note:* The left panel displays the percentage change in average wages and land prices relative to the benchmark economy, as a function of the share of teleworkers. The right panel shows the percentage change in residential and commercial floorspace prices.

**Consumption and Welfare.** When all the changes are taken together, we find that an increase in the share of telecommuters raises the welfare of the average worker considerably. As can be seen in the right panel of Figure 5, this holds true regardless of which aspects of welfare are considered. In the scenario where the fraction of telecommuters increases to 33%, welfare derived purely from the consumption of goods and housing increases by 4.1%; and welfare derived from consumption of goods and housing, but also taking account of commuting time, increases by 13.5%. Taking account also of residential amenities and idiosyncratic preferences as they are specified in our model, total welfare in the maximal scenario increases by nearly 20%.

These net increases in overall welfare have three components. First, the welfare of the average telecommuter is significantly higher than that of the average commuter, due to reduced disutility from commuting, access to lower-cost housing, and access to better-paying jobs and amenities. This welfare advantage remains as the fraction of telecommuters increases to 33%, making the shift of workers from commuting to telecommuting is the single largest source of the welfare increases shown in the right panel of Figure 5. Second, because an increase in the
fraction of telecommuters reduces traffic congestion, commuters who continue to commute also benefit from reduced time commuting, access to lower-cost housing, and access to better-paying jobs and amenities, but to a lesser extent than switchers. Gains for this sub-group can be seen in the left panel of Figure 5. Third, telecommuters who were already telecommuting do not benefit from the increase in their mode of work. On the contrary, they need to compete with an increasing fraction of the workforce for residence and job sites that were previously accessible only to them. These losses can be seen in the middle panel of Figure 5.

Figure 5: Welfare

![Graph showing changes in welfare for commuters, telecommuters, and all workers.]

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

4.4 Discussion

What are the main factors driving these results? One important driver of welfare gains for commuters is access to jobs. In large, sprawled and congested cities, such as Los Angeles, good jobs are often inaccessible for households who live on the periphery. To study how a shift to telecommuting impacts job access, we calculate commuter market access for each tract as $CMA_i = \sum_j (w_j e^{-\kappa t_j})^\epsilon$.\(^{13}\) We find that an increase in the fraction of telecommuters improves average job access for those who keep commuting by 16%. We also find that the elasticity of floorspace prices with respect to market access at the tract level falls from 0.31 to 0.14, meaning

\(^{13}\)For more information, see Tsivanidis (2019).
that places with better access to jobs command a lower price premium. Further details of these calculations as well as other results can be found in Appendix D.

As for changes at the tract level, we find that a tract’s distance from the Los Angeles central business district (CBD) is an important predictor. There is also a large fraction of the variation in outcomes that cannot be accounted for using this simplistic, monocentric viewpoint. We find that distance from the center can account for around 60% of the variation in changes in floorspace prices, around 40% of the variation in changes in employment, and 50% of the variation in changes in residence across space. We also find that location-specific characteristics such as exogenous local productivity and residential amenity play a significant role in accounting for reallocations. Further details on these calculations can be found in Appendix F.

5 Conclusion

In this paper we have used a detailed quantitative model of internal city structure to study what happens in large urban areas, such as Los Angeles, if telecommuting becomes popular over the long run. We have found substantial changes to the city structure, wages and real estate prices, and commuting patterns. We have concluded that a more widespread telecommuting could bring significant welfare benefits.

At the same time, our analysis overlooks several important channels which could mute or amplify our findings. First, in our model all workers are ex-ante identical and have the same chances of being able to telecommute. In reality, the ability to telecommute is correlated with occupation, industry and income. We are therefore unable to speak to some distributional effects which may arise from an increase in telecommuting. Second, we calibrated the productivity gap between commuters and telecommuters to ensure that their average wages are the same in the benchmark economy. However, as telecommuting becomes more widespread, technological changes may shift the productivity gap between the two types of workers. Third, we do not distinguish between transportation modes in the model. The reduction in traffic congestion brought by more common telecommuting could be offset if, after COVID-19, some transit users start commuting by car. Finally, we do not allow migration in and out of the city. In practice, as some workers gain the ability to work remotely, they may choose to leave Los Angeles and move to a different city, or even a different country. On the other hand, telecommuters from elsewhere may move into Los Angeles to enjoy local amenities.
References


A Data Appendix

A.1 Property Price Data

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

We categorize properties as commercial or residential based on their reported use. Examples of residential use include “condominium”, “single family residence”, and “duplex”. Examples of commercial use include “hotel/motel”, “restaurant”, and “office building”. Table 1 provides descriptive statistics. Table 2 provides the number of observations in each county over the period of 2007–2016. Note that the commercial transactions are far less frequent than residential transactions.

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

\[
\ln(P_{pjt}) = \alpha + \beta X_p + \tau_t + \eta_j + \epsilon_{pjt},
\]

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

Because commercial transactions are less numerous, for many Census tracts we only observe very few or no transactions in the period of interest. To overcome this issue, we calculate commercial property indices at the Public Use Microdata Area (PUMA)-level.\(^\text{14}\) There are 123 PUMAs in our sample. For a commercial property transaction of a property \( p \), in tract \( j \) of PUMA \( g \) in year-month \( t \), we estimate

\[
\ln(P_{pgjt}) = \alpha + \beta X_p + \tau_t + \zeta_g + \upsilon_{pgjt},
\]

where \( P_{pgjt} \) is the price per square foot; \( X_p \) is property characteristics including property use; and \( \tau_t \) is the year-month fixed effect. The commercial price index in PUMA \( g \) corresponds to \( \zeta_g \), which is the PUMA fixed effect.

\(^{14}\)PUMA is a geographic unit used by the US Census for providing statistical and demographic information. Each PUMA contains at least 100,000 people.
Table 1: Descriptive Statistics

Panel A. Residential Properties

<table>
<thead>
<tr>
<th>County</th>
<th>sqft (mean)</th>
<th>sqft (median)</th>
<th>sales price, $ (mean)</th>
<th>sales price, $ (median)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Los Angeles</td>
<td>1752.25</td>
<td>1499</td>
<td>774734.19</td>
<td>389000</td>
</tr>
<tr>
<td>Orange</td>
<td>1969.92</td>
<td>1578</td>
<td>714043.38</td>
<td>495000</td>
</tr>
<tr>
<td>Riverside</td>
<td>2046.06</td>
<td>1855</td>
<td>489885.35</td>
<td>246649</td>
</tr>
<tr>
<td>San Bernardino</td>
<td>1759.41</td>
<td>1584</td>
<td>345662.41</td>
<td>200000</td>
</tr>
<tr>
<td>Ventura</td>
<td>1860.88</td>
<td>1626</td>
<td>569042.40</td>
<td>410000</td>
</tr>
</tbody>
</table>

Panel B. Commercial Properties

<table>
<thead>
<tr>
<th>County</th>
<th>sqft (mean)</th>
<th>sqft (median)</th>
<th>sales price, $ (mean)</th>
<th>sales price, $ (median)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Los Angeles</td>
<td>20687.28</td>
<td>5203</td>
<td>5661399.99</td>
<td>1300000</td>
</tr>
<tr>
<td>Orange</td>
<td>16447.48</td>
<td>5329</td>
<td>3879699.73</td>
<td>1260000</td>
</tr>
<tr>
<td>Riverside</td>
<td>1329.38</td>
<td>1201</td>
<td>1813988.76</td>
<td>590000</td>
</tr>
<tr>
<td>San Bernardino</td>
<td>19486.08</td>
<td>3541</td>
<td>2472923.09</td>
<td>522000</td>
</tr>
<tr>
<td>Ventura</td>
<td>12087.09</td>
<td>4565</td>
<td>3513023.97</td>
<td>982500</td>
</tr>
</tbody>
</table>

Table 2: Number of Transactions by County and Property Type

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

A.2 Wage Data

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 years 2012 to 2016. We use the variable “earnings in the past 12 months (2016 $), for the workers 16-year-old and over,” which is based on the respondents’ workplace locations. The variable provides the estimates of the number of people in each earning bin in each workplace tract. Table 3 provides an overview of the number of observations in each bin for the five counties included in our study.

We calculate mean tract-level labor earnings as

$$\hat{w}_j = \frac{\sum b nworkers_{b,j} \times meanw_b}{\sum b nworkers_{b,j}},$$

(27)

where $nworkers_{b,j}$ is the number of workers in bin $b$ in tract $j$, and $meanw_b$ is mean earnings in bin $b$ for the entire L.A. urban area, calculated from the ACS microdata.

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

$$\hat{w}_j = \alpha + \beta_1 age_j + \beta_2 sexratio_j + \sum_r \beta_2,r race_{r,j} + \sum_i \beta_3,i,ind_{i,j} + \sum_o \beta_4,o,occ_{o,j} + \epsilon_j,$$  

(28)
Table 3: Number of observations in each earnings bin

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

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

where \(age_j\) is the average age of workers; \(sexratio_j\) is the proportion of males to females in the labor force; \(race_{r,j}\) is the share of race \(r \in \{Asian, Black, Hispanic, White\}\); \(ind_{i,j}\) is the share of jobs in industry \(i\); \(occ_{o,j}\) is share of jobs in occupation \(o\) in tract \(j\).\(^{15}\) Finally, the estimated tract-level wage index corresponds to the sum of the constant and the tract fixed effect, \(\hat{\alpha} + \hat{\epsilon}_j\).

Table 4 presents summary statistics for the estimated tract-level earnings.

Table 4: Descriptive statistics: the estimated tract-level earnings, by county

<table>
<thead>
<tr>
<th></th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Los Angeles</td>
<td>2,339</td>
<td>61203.81</td>
<td>13589.54</td>
<td>21376.82</td>
<td>170987.1</td>
</tr>
<tr>
<td>Orange</td>
<td>582</td>
<td>63455.76</td>
<td>11197.14</td>
<td>24120.39</td>
<td>113428.8</td>
</tr>
<tr>
<td>Riverside</td>
<td>452</td>
<td>61477.51</td>
<td>13606.08</td>
<td>17286.49</td>
<td>138802.9</td>
</tr>
<tr>
<td>San Bernardino</td>
<td>369</td>
<td>59823.33</td>
<td>12741.49</td>
<td>21101.49</td>
<td>132544.9</td>
</tr>
<tr>
<td>Ventura</td>
<td>172</td>
<td>61034.83</td>
<td>10709.51</td>
<td>29174.4</td>
<td>89796.23</td>
</tr>
</tbody>
</table>

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

\(^{15}\)We use the following industry categories: Agricultural; Armed force; Art, entertainment, recreation, accommodation; Construction; Education, health, and social services; Finance, insurance, real estate; Information; Manufacturing; Other services; Professional scientific management; Public administration, Retail. We use the following occupation categories: Architecture and engineering; Armed Forces; Arts, design, entertainment, sports, and media; Building and grounds cleaning and maintenance; Business and financial operations specialists; Community and social service; Computer and mathematical; Construction and extraction; Education, training, and library; Farmers and farm managers; Farming, fishing, and forestry; Food preparation and serving related; Healthcare practitioners and technicians; Healthcare support; Installation, maintenance, and repair; Legal; Life, physical, and social science; Management; Office and administrative support; Personal care and service; Production;Protective service; Sales and related.
A.3 Commuting Time Data

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

Table 5: Commuting time coverage, by distance

<table>
<thead>
<tr>
<th>N. of trajectories</th>
<th>% covered by time data</th>
<th>% w/ observed positive flows</th>
<th>N. of commuters</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt; 1 km</td>
<td>10,105</td>
<td>60.8%</td>
<td>239,188</td>
</tr>
<tr>
<td>&lt; 2 km</td>
<td>36,205</td>
<td>40.5%</td>
<td>410,571</td>
</tr>
<tr>
<td>&lt; 5 km</td>
<td>188,047</td>
<td>24.4%</td>
<td>1,088,797</td>
</tr>
<tr>
<td>&lt; 10 km</td>
<td>649,005</td>
<td>15.0%</td>
<td>2,248,646</td>
</tr>
<tr>
<td>&lt; 20 km</td>
<td>2,099,417</td>
<td>8.2%</td>
<td>3,995,134</td>
</tr>
<tr>
<td>&lt; 40 km</td>
<td>5,549,775</td>
<td>4.3%</td>
<td>5,508,736</td>
</tr>
<tr>
<td>&lt; 80 km</td>
<td>10,752,785</td>
<td>2.5%</td>
<td>6,515,595</td>
</tr>
<tr>
<td>All</td>
<td>15,342,889</td>
<td>1.8%</td>
<td>6,935,765</td>
</tr>
</tbody>
</table>

Table 6: Commuting time coverage, by N. of commuters

<table>
<thead>
<tr>
<th>N. of trajectories</th>
<th>% covered by time data</th>
<th>N. of commuters</th>
</tr>
</thead>
<tbody>
<tr>
<td>&gt; 100 commuters</td>
<td>1,778</td>
<td>94.4%</td>
</tr>
<tr>
<td>&gt; 50 commuters</td>
<td>8,678</td>
<td>89.9%</td>
</tr>
<tr>
<td>&gt; 25 commuters</td>
<td>27,833</td>
<td>82.2%</td>
</tr>
<tr>
<td>&gt; 10 commuters</td>
<td>96,177</td>
<td>63.7%</td>
</tr>
<tr>
<td>&gt; 5 commuters</td>
<td>220,555</td>
<td>46.5%</td>
</tr>
<tr>
<td>&gt; 1 commuters</td>
<td>1,108,755</td>
<td>17.9%</td>
</tr>
<tr>
<td>All &gt; 0</td>
<td>5,647,791</td>
<td>4.8%</td>
</tr>
</tbody>
</table>

Table 5 summarizes CTPP data coverage by trajectory distance. Table 6 summarizes CTPP data coverage by trajectory and the number of commuters observed using that trajectory. These tables show that CTPP has the greatest coverage of high-volume short-distance trajectories, just as Spear (2011) observes and just as would be expected from a dataset based on a partial sample.

The CTPP data places commuting times into 10 bins: less than 5 minutes, 5 to 14 minutes, 15 to 19 minutes, 20 to 29 minutes, 30 to 44 minutes, 45 to 59 minutes, 60 to 74 minutes, 75 to 89 minutes, 90 or more minutes, and work from home. In order to get as accurate commute times as possible for the set of primitive connections of the network, we drop all home-workers, who are irrelevant for transit times. We drop workers in the top time bin, because this bin has no upper bound and so the mean may vary substantially across trajectories. We assign mean commute times to all the remaining bins as the mid-points between the bin bounds. We
then drop all observations which report an average commuting speed that is either less than 8 kilometers per hour, a brisk walking pace, or more than 70 miles per hour (112.7 kilometers per hour), the standard rural freeway speed limit in the United States. Finally, we calculate tractpair mean commuting times as the average of the mean commuting times in each bin weighted by the share of commuters on that tractpair reporting times in each bin. Table 7 provides a summary of the overall share of commuters in each bin before and after the cleaning steps described above, and the mean commute time assigned to each bin.

Table 7: Commuting time bins

<table>
<thead>
<tr>
<th>share in raw data</th>
<th>share in cleaned data</th>
<th>bin mean time</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt; 5 min</td>
<td>1.6%</td>
<td>0.9%</td>
</tr>
<tr>
<td>5-14 min</td>
<td>19.4%</td>
<td>18.9%</td>
</tr>
<tr>
<td>15-19 min</td>
<td>14.0%</td>
<td>15.7%</td>
</tr>
<tr>
<td>20-29 min</td>
<td>19.1%</td>
<td>22.5%</td>
</tr>
<tr>
<td>30-44 min</td>
<td>20.5%</td>
<td>24.4%</td>
</tr>
<tr>
<td>45-59 min</td>
<td>8.0%</td>
<td>9.6%</td>
</tr>
<tr>
<td>60-74 min</td>
<td>6.1%</td>
<td>6.9%</td>
</tr>
<tr>
<td>75-89 min</td>
<td>0.9%</td>
<td>1.0%</td>
</tr>
<tr>
<td>&gt; 90 min</td>
<td>2.8%</td>
<td>0</td>
</tr>
<tr>
<td>work from home</td>
<td>7.6%</td>
<td>0</td>
</tr>
</tbody>
</table>

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

The final directed network contains 447,277 directed paths. We use the Dijkstra’s algorithm to calculate the fastest path through this network for each origin-destination pair. We assume that these calculated times represent the time require to travel from tract centroid to tract centroid. We then add time to each trajectory to represent the time need to travel from place of residence within tract to residence tract centroid, and from workplace tract centroid to workplace within the tract. Naturally, these times are proportional to tract land area–larger tracts should on average require more internal travel time. Specifically, we assume that the “internal” distance traveled on each end of the trip is equal to the hypothetical average

\[ 162 \times \sqrt{\frac{\text{landarea}}{\pi}} \]
straight-line distance from any point in the tract to the tract centroid, if the tract were a circle.\footnote{\(\sqrt{\frac{\text{landarea}}{\pi}}\)} We then assume that each of these distances is traveled at twice the overall average commuting speed in the cleaned data of 31.3 kilometers per hour. For the vast majority of tracts this adds a negligible amount to commuting time—two minutes or less. For a handful of very large tracts it adds considerable travel time—up to half an hour. We think that this is reasonable given the time that is required to travel within these much larger tracts. These origin-destination distribution effects are also applied to self-commute times, so that a worker that lives and works in the same tract will still have to spend some time travelling to their workplace—more time for larger tracts.

### A.4 Summary

Table 8 gives summary statistics by tract for seven key variables: residential density; employment density; wage by workplace weighted by employees; average constant-quality price of one square foot of residential floorspace; average constant-quality price of one square foot of commercial floorspace; average commute time by residence tract; and average commute distance by residence tract.

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

### B Model Details

#### B.1 Floorspace Markets

##### B.1.1 Floorspace Supply

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

\[
H_i = \phi_i(H_i) \left((1 - \eta)\bar{q}_i\right)^{\frac{1-\eta}{\eta}} L_i. \tag{29}
\]
Solving this expression for $H_i$ and using the definition of construction efficiency in (20), yields

$$H_i = \frac{\bar{\phi} \left((1-\eta)\bar{q}_i\right)^{\frac{1+\eta}{\eta}} L_i}{1 + \bar{\phi} \left((1-\eta)\bar{q}_i\right)^{\frac{1+\eta}{\eta}} L_i/\bar{H}_i}.$$ (30)

**B.1.2 Floorspace Demand**

From equation 9, the probability that a commuter works in $j$, conditional on living in $i$, is given by

$$\pi_{ij}^{C} = \frac{E_j (w^j e^{-\kappa t^j})^\epsilon}{\sum_{s=1}^I E_s (w^s e^{-\kappa t^s})^\epsilon}.$$ (31)

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

$$\bar{w}_i \equiv \sum_{j=1}^I \left[ \pi_{ij}^{C} w^j_i \frac{N_{Rj}^C}{N_{Ri}} + \pi_{ij}^{T} w^T_i \frac{N_{Rj}^T}{N_{Ri}} \right].$$ (32)

The demand for commercial floorspace is given by

$$H_{Wj} = \left(\frac{(1-\alpha)A^j}{q_{Wj}}\right)^{\frac{1}{\alpha}} \left(N_{Wj}^C + \theta N_{Wj}^T\right).$$ (33)

The demand for residential floorspace is given by

$$H_{Ri} = \frac{\gamma (1+\tau)\bar{w}_i}{q_{Ri}} N_{Ri} + (1-\theta) \sum_{j=1}^I \left(\frac{(1-\alpha_T)\nu A_j}{q_{Ri}}\right)^{\frac{1}{\alpha_T}} N_{ij}^T,$$ (34)

where the first component on the right-hand side is the demand for housing and the second component is the demand for home office space. $N_{ij}^T = \psi \pi_{ij}^T$ is the number of telecommuters who live in $i$ and work in $j$.

**B.2 Factor Incomes and Transfers**

The city-wide total land income is

$$\sum_{i=1}^I l_i \Lambda_i.$$ (35)

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

\[
\tau = \frac{\sum_i (l_i \Lambda_i + K_i)}{\sum_i \tilde{w}_i N_{Ri} + \sum_i (l_i \Lambda_i + K_i)}.
\]

### B.3 Welfare

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

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

(37)

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

A consumption-equivalent measure of change in welfare is given by \( \Delta \). This quantity represents the percentage amount by which the composite consumption of goods and housing, \( e^{1-\gamma} h^\gamma \), must change in order to make the expected utility in the benchmark economy equal to the expected utility in the counterfactual economy. Note that in this model the composite consumption is proportional to wages (see equations 6 and 8). Let "\( \hat{\cdot} \)" represent variables in the counterfactual economy. Then \( \Delta \) must satisfy

\[
\left[ \sum_{r=1}^{I} \sum_{s=1}^{I} X_r E_s \left[ (1 - \psi) \left( e^{-\kappa \hat{t}_{rs}} (1 + \hat{\tau}) \hat{w}_s \hat{q}_{Rr}^{-\gamma} \right)^\epsilon + \psi \left( (1 - \theta + \theta e^{-\kappa \hat{t}_{rs}}) (1 + \hat{\tau}) \hat{w}_{T_{rs}} \right) \right] \right]^{\frac{1}{\epsilon}}.
\]

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

\[
\Delta = \frac{\hat{U}}{U} - 1.
\]

### C Structural Residuals

The amounts of commuting workers and residents are related as

\[
N_{Wj}^C = \sum_{i=1}^{I} \pi_{ij}^C N_{Ri}^C,
\]

(39)
From equations (31) and (39), $E_j$ can be defined implicitly as:

$$E_j = N_{Wj} \left( \sum_{i=1}^{I} \frac{e^{-\epsilon\kappa t_{ij} \omega_j}}{N_{Ri} \sum_{s=1}^{I} E_s e^{-\epsilon\kappa t_{is} \omega_s} N_{Ri}} \right)^{-1}, \quad (40)$$

where $N_{Wj}$ and $N_{Ri}$ are observed tract-level employment and residential populations, and $t_{ij}$ are observed average commuting times from tract $i$ to tract $j$. Since we do not observe how many workers telecommute in each tract and since the share of telecommuters in the data is small (3.74% of workforce), we perform this and the following calculations assuming that all workers commute to their jobs. A vector $\hat{E}$ is solved recursively using equation (40) and then the vector of residuals $E$ is recovered as $E_j = \hat{E}_j / w_j$, using observed tract-level wages.

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

$$\hat{X}_i = N_{Ri} \left( \sum_{j=1}^{I} \frac{e^{-\epsilon\kappa t_{ij} \omega_j}}{N_{Wj} \sum_{r=1}^{I} \hat{X}_r e^{-\epsilon\kappa t_{ir} \omega_j} N_{Wj}} \right)^{-1}. \quad (41)$$

A vector $\hat{X}$ is solved recursively using equation (41) and then the vector of residuals $X$ is recovered as $X_j = \hat{X}_j q_{\gamma Rj}$, using observed tract-level prices of residential floorspace. Then the exogenous part of local amenities, $x_j$, can be recovered using equation (24) and the data on local residential population and land area.

The vector of local productivities $A$ can be solved for using (18) and the data on wages and commercial floorspace prices as follows:

$$A_j = \left( \frac{w_j}{\alpha} \right)^{\alpha} \left( \frac{q_w j}{1 - \alpha} \right)^{1-\alpha}. \quad (42)$$

Then the exogenous part $a$ can be recovered using equation (23) and the data on local employment and land area.

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

$$\xi_i = \frac{q_{W_i}}{q_{R_i}}. \quad (43)$$

Finally, in order to recover $\bar{H}_i$, we use market clearing conditions for land and floorspace ($L_i = \Lambda_i$ and equation 30). Combining them, we can recover $\bar{H}_i$ from the following relationship:

$$\bar{H}_i = \frac{\bar{\phi} \left( (1 - \eta) \bar{q}_i \right)^{\frac{1-\eta}{\nu}} L_i}{\bar{\phi} \left( (1 - \eta) \bar{q}_i \right)^{\frac{1-\eta}{\nu}} L_i / H_1^P - 1}, \quad (44)$$
where $H^D_i$ is the total demand for floorspace in tract $i$ given by

$$H^D_i = H^D_{Ri} + H^D_{Wi} = \frac{\gamma(1 - \tau)\bar{w}_i}{q_{Ri}} N_{Ri} + \left(\frac{(1 - \alpha)A_i}{q_{Wi}}\right)^{1/\alpha} N_{Wi}.$$  

(45)

D Additional Results of Counterfactual Experiments

D.1 Land Use

When the fraction of telecommuters rises, land use becomes more specialized. Figure 6 shows that in the economy with more widespread telework, commercial development becomes relatively more prevalent in core areas and virtually disappears in the periphery. In addition, both types of development become more concentrated in space. As a consequence, the numbers of primarily residential and primarily commercial tracts increase, while the number of mixed tracts goes down (right panel of Figure 7).\footnote{We label a tract as \textit{commercial} if the share of commercial floorspace in the tract is more than 3 times the share of the average tract. Similarly, we label a tract as \textit{residential} if the share of commercial floorspace in the tract is less than 1/3 of the share of the average tract. All other tracts are labeled \textit{mixed}.}
Figure 6: Land Use

![Land Use Map](image1)

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

Figure 7: Land Use Specialization

![Land Use Specialization](image2)

**Note:** The figure shows the number of commercial and residential tracts, as a function of the share of teleworkers. See main text for details.
D.2 Job access

In large, sprawled and congested cities, such as Los Angeles, good jobs are often inaccessible for households who live on the periphery. To study how a shift to telecommuting impacts job access, we calculate commuter market access for each tract as \( CMA_i = \sum_j (w_j e^{-kt_{ij}}) \).\(^\text{19}\) We find that, as the number of teleworkers grows, the average job access increases for those who keep commuting (left panel of Figure 8). Moreover, in the counterfactual economy the elasticity of housing prices with respect to the market access halves, meaning that places with better access to jobs command a lower price premium (right panel of Figure 8).

Figure 8: Access to jobs

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

E Elasticity of Speed to Traffic Volume

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

\[
\frac{\text{speed}^{\text{CF}}_{ij} - \text{speed}^{\text{BM}}_{ij}}{\text{speed}^{\text{BM}}_{ij}} = -\varepsilon_V \frac{VMT^{\text{CF}} - VMT^{\text{BM}}}{VMT^{\text{BM}}},
\]

assuming that the road capacity remains unchanged and only taking into account the change in total vehicle miles traveled (\( VMT \)) in the city. Then we recover commuting times as \( t^{\text{CF}}_{ij} = \frac{\text{distance}_{ij}}{\max\{\text{speed}^{\text{CF}}_{ij}, 65\text{mph}\}} \). The maximum operator caps speeds at 65 mph which is the speed limit on most highways in California. Since \( t_{ij} \) and \( VMT \) endogenously depend on each

\(^{19}\)For more information, see Tsivanidis (2019).
other, when solving for an equilibrium in a counterfactual economy, we iterate the model until \( VMT \) converges.

**Robustness.** Since the results of the counterfactual experiments described in Section 3 crucially depend on changes in commuting speeds, we investigate whether our results are robust to the value of \( \varepsilon_V \). While 0.2 is a standard value in the traffic modeling literature, other studies used higher values.\(^{20}\) At the same time, a low value of \( \varepsilon_V \) ensures that many of our counterfactual results are conservative.

To understand how sensitive our results are to the value of \( \varepsilon_V \), we compute the counterfactual economy with fraction \( \psi = 0.33 \) telecommuters at different levels of \( \varepsilon_V \) ranging from 0 to 1. Our three main sets of results remain robust to the value of \( \varepsilon_V \). First, regardless of the value of \( \varepsilon_V \), the economy exhibits the decentralization of residents and centralization of jobs. Second, commuters’ trips are characterized by shorter times and longer distances (Figure 9). Third, residential and commercial floorspace prices fall for all values of \( \varepsilon_V \) (Figure 10).

Figure 9: Commuting time and distance

![Graph showing commuting time and distance](image)

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

\(^{20}\)For example, Akbar, Couture, Duranton, and Storeygard (2020) used values of 0.2 and 0.3. Bento, Hall, and Heilmann (2020) estimate a value of about 0.9 for Los Angeles. The latter estimate, however, is a peak-hour elasticity.
Note: The figure displays the counterfactual change in average residential and commercial floorspace prices, as a function of the elasticity of commuting speed with respect to traffic volume.

At the same time, quantitative implications of more telecommuting for wages and welfare are sensitive to the value of $\varepsilon_V$. In our main counterfactual with $\varepsilon_V = 0.2$, the average commuter market access (CMA) increases by about 17%. However, as $\varepsilon_V$ approaches 1, commutes become speedier and the average CMA increases by nearly 80% (left panel of Figure 11). In addition, the higher the elasticity of speed, the stronger will be spatial productivity spillovers. Hence, when $\varepsilon_V$ goes to 1, wage gains for commuters are much larger and wage losses for telecommuters turn into small gains (right panel of Figure 11).

Note: Left panel displays the average commuter market access for commuters, as a function of the elasticity of commuting speed with respect to traffic volume. Right panel shows average wages and land prices.
As a result, with higher values of $\varepsilon_V$, welfare gains are larger (Figure 12). In particular, as $\varepsilon_V$ goes to 1, commuters see their welfare increase by almost 10% (compared to 2.2% at $\varepsilon_V = 0.2$), telecommuters experience a 2% increase (compared to a 2.5% loss), and overall welfare increases by nearly 25% (compared to 18.9%).

Figure 12: Welfare

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

F Accounting for Spatial Variation in Outcomes

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

Interestingly, this measure picks out downtown LA as the most central location on the
Figure 13: Quantiles of Centrality and Initial Allocations

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

map. It also turns out to be highly correlated with both straight line distance and travel time to downtown LA (Pearson’s correlation coefficient 0.97 for each). Figure 13 shows the evolution of some key variables along the centrality gradient.\(^{21}\) Real estate prices, the density of employment, and the density of residence all increase on average the closer one gets to the center. The time required to reach the downtown LA is also, naturally, lower near the center.

In Figure 14, we plot the changes that take place in the counterfactual exercise in the same manner as in Figure 13. Here again we see that on average jobs move towards the center and residents move away from it, and that there are big property price increases in the periphery. We can also see that there is a great deal of variation that is unexplained.

Accounting for counterfactual changes. In order to have a more complete idea of what is driving the variation in counterfactual outcomes, we expand our view to consider not only a location’s initial centrality, but also the change in centrality between the baseline and

\(^{21}\)The x-axis is scaled to quantiles of the centrality measure, weighted by land area. In other words, 0.5 on the x-axis represents the single square meter of land area such that 50% of the land area in the metro area is less central (and 50% is more central.)
counterfactual due to changes in average speed, and the exogenous local characteristics $a_i$, $E_i$ and $x_i$. We run a multivariate regression at the tract level, weighted by land area, of these five variables on the log differences between counterfactual and baseline floorspace prices, employment density, and residential density. From the estimated coefficients of these regressions we can infer the sign of each relationship. We then use the Shapley method to decompose the coefficient of determination ($R^2$) for each regression. The share assigned to each explanatory variable is a measure of its importance in accounting for the variation across space in each counterfactual outcome.

Table 9 shows the results of this exercise for the change in floorspace prices. The negative estimated coefficient on centrality confirms the core-periphery gradient of price changes, with prices falling in the core and rising in the periphery. Once this is accounted for, locations whose centrality increases due to change in speed in the counterfactual also see a more positive overall change in prices. The negative coefficients on $a_i$ indicates that the relative value of real estate in locations with high productivity falls, which is to be expected as workers on average need

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

---

Table 9: Accounting for counterfactual floorspace price changes

<table>
<thead>
<tr>
<th>Coeff.</th>
<th>Var. expl.</th>
</tr>
</thead>
<tbody>
<tr>
<td>constant</td>
<td>0.274 (0.063)</td>
</tr>
<tr>
<td>centrality</td>
<td>0.022 (0.015)</td>
</tr>
<tr>
<td>Δ centrality</td>
<td>3.918 (0.389)</td>
</tr>
<tr>
<td>$a_i$</td>
<td>-0.270 (0.012)</td>
</tr>
<tr>
<td>$E_i$</td>
<td>-0.018 (0.001)</td>
</tr>
<tr>
<td>$x_i$</td>
<td>0.024 (0.001)</td>
</tr>
<tr>
<td>Total</td>
<td>84.33%</td>
</tr>
</tbody>
</table>

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

Table 10: Accounting for counterfactual employment changes

<table>
<thead>
<tr>
<th>Always commuter</th>
<th>New telecommute</th>
<th>Always telecommute</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>constant</td>
<td>-1.292 (0.199)</td>
<td>-7.139 (0.362)</td>
<td>-0.924 (0.119)</td>
</tr>
<tr>
<td>centrality</td>
<td>-0.138 (0.049)</td>
<td>-1.384 (0.089)</td>
<td>-0.149 (0.029)</td>
</tr>
<tr>
<td>Δ centrality</td>
<td>-15.619 (1.237)</td>
<td>-40.542 (2.253)</td>
<td>-10.146 (0.737)</td>
</tr>
<tr>
<td>$a_i$</td>
<td>1.012 (0.039)</td>
<td>2.508 (0.070)</td>
<td>0.534 (0.023)</td>
</tr>
<tr>
<td>$E_i$</td>
<td>0.057 (0.004)</td>
<td>0.189 (0.008)</td>
<td>0.022 (0.003)</td>
</tr>
<tr>
<td>$x_i$</td>
<td>-0.041 (0.003)</td>
<td>-0.015 (0.005)</td>
<td>-0.010 (0.002)</td>
</tr>
<tr>
<td>Total</td>
<td>84.36%</td>
<td>39.04%</td>
<td>78.95%</td>
</tr>
</tbody>
</table>

For employment density and residential density, we further break the overall changes down into changes in the average choices made by three groups of workers. These groups are: those that commute both in the baseline and the counterfactual (67% of all workers), those that switch from commuting to telecommuting (29.3%), and those that telecommute both in the baseline and the counterfactual (3.7%). Table 10 shows the results for changes in employment density and Table 11 shows the same for changes in resident density. Workers who continue
commuting take jobs closer to the urban core and also choose residences that are, on average, closer to the core. New telecommuters, with the new-found freedom, do the opposite: they choose jobs and residence that are, on average, farther from the core than before. Continuing telecommuters make smaller shifts overall, taking jobs a bit closer to the core and moving their residences a bit farther from it. Across all categories of workers there is a strong shift from commercial to residential use of land in locations where there is a larger increase in centrality due to commuting speed changes.

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

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