Spatial Implications of Telecommuting*

Matthew J. Delventhal† and Andrii Parkhomenko‡

February 23, 2022

Abstract

We build a quantitative spatial model in which some workers can substitute on-site effort with work done from home. Ability and propensity to telecommute vary by education and industry, and telework mitigates the disutility of living far from the job site. We quantify our framework to match the distribution of jobs and residents across 4,502 U.S. locations. A permanent increase in the attractiveness of telework results in a rich pattern of reallocations within and across cities. There are winners and losers: income and welfare go up for workers who can telecommute, and down for those who cannot. This framework robustly predicts changes in residents observed 2020–2021. We use our model to evaluate two competing interpretations of the 2020 remote work shock, and conclude the change in preferences was more important than the change in technology.

Key Words: urban, work at home, commuting, spatial equilibrium
JEL Codes: E24, J81, R31, R33, R41

*We are thankful to Amanda Ang, Daniel Angel, and Seongmoon Cho for excellent research assistance. We thank Jan Brueckner, Thomas Chaney, Morris Davis, Jonathan Dingel, Fabian Eckert, Vadim Elenev, Eunjee Kwon, Monica Morlacco, Jamil Nur, Weihua Zhao, as well as seminar and conference participants at USC Marshall, CSU Fullerton, ASSA 2021, AUM Global Workshop, PSR Congress, UEA European Meeting, Family Macro Group, AREUEA National Meeting, Barcelona GSE Summer Forum, WEAI, EEA-ESEM, UEA North American Meeting, University of Nebraska, SAEe Barcelona, and Missouri State University for helpful discussions, comments, and suggestions. We are also grateful to Nate Baum-Snow and Lu Han for sharing estimates of local housing supply elasticities; to Jose-Maria Barreiro, Nick Bloom, and Steven Davis for sharing survey data on expectations about work from home; and Alexander Bick and Adam Blandin for sharing survey data on work from home during the Covid-19 pandemic. Finally, we gratefully acknowledge financial support provided by the USC Lusk Center for Real Estate and the U.S. Department of Transportation. First draft: October 2, 2020.

†Claremont McKenna College, Claremont, CA 91711, delventhal.m@gmail.com.

‡University of Southern California, Los Angeles, CA 90089, parkhomenko.andrii@gmail.com.

1 Introduction

Telecommuting, once a fond dream of techno-utopians, came roaring to the forefront of the American workplace in the spring of 2020. While no more than 8% of work was done remotely in 2019, shutdowns and social-distancing policies introduced at the onset of the Covid-19 pandemic pushed more than 1 out of every 3 American workers to telecommute. The sudden, enforced prominence of telework, and the surge of experimentation with ways to make it possible, has led many to wonder what role it might play in our future. Surveys indicate that employers plan to allow employees more leeway to work from home than before, with many previously office-bound positions even going fully remote. There may never be a better time to think seriously about the role remote work plays in the economy, and the reallocations it could trigger within and across cities.

In this paper we build a quantitative model of location choice and commuting with endogenous remote work. Unique in this literature, our model allows for both the opportunity to telecommute, and the telecommuting behavior of remote-capable workers, to vary by education and industry in a non-trivial way. This is consistent with the data, which show a significant presence of remote work at all education levels and in all industries, but higher rates of both opportunity and uptake among college-educated workers and in industries with tradable output. Our framework is also consistent with observed wage differences between remote and on-site workers, and the observed spatial distribution of remote workers relative to their employers. Dividing the continental United States into 4,502 locations, our framework seamlessly accounts for both the inter-city and intra-city distribution of jobs and residents.

We simulate a permanent increase in remote work in the United States, and find results which are nuanced and non-monotonic. Workers who can work from home decentralize, ending up 75% farther on average from their jobs. Those who cannot work remotely move closer to their workplaces. Jobs in non-tradable industries follow the mass of residents towards suburbs and small cities. In tradable industries, broader geographic competition for remote workers allows both low-density and the very most central locations to add jobs. Most big cities lose population but those with especially competitive city centers, like New York City, grow. We show that these results are a robust predictor of population shifts seen between February 2020 and November 2021, even at the most disaggregated level.

Our quantitative and disaggregated approach allows us to address a major open question in the remote work literature–was Covid-19 more of a technology shock, or a preference shock?[1] We show that assuming increases in telecommuting are caused solely by an increase in remote work productivity leads to implausible wage predictions, and population movements that are poorly correlated with the 2020–2021 data. We therefore conclude that our baseline assumption, which loads all of the increase on a fall in remote work aversion, is the more plausible one; and that the more important effect of the Zoompocalypse of 2020 was a shift in norms and attitudes, rather than improvements in productivity.

A closely related recent study is Davis, Ghent, and Gregory (2021). They use American Time Use Survey data to estimate an elasticity of substitution between remote and on-site work, which we borrow in our own study. They build a model with two residential locations in which all jobs are located in the central business district and cannot move, and in which low-skilled workers cannot telecommute. They simulate an increase in remote work due to an increase in remote work productivity. Our results contrast with theirs in several ways. We find quantitatively important movements of jobs, and non-monotonic movements of residents that cannot be captured by a two-location model. Our inequality predictions are substantively different and break between remote-capable and non-, rather than between high- and low-skilled. Our results make clear that the intensity of spatial reallocation–whether telecommuters move only a small distance or very far away–is quantitatively important. And we also find that idiosyncratic preferences for *particular* central or peripheral locations, necessarily omitted when one central and one peripheral location are made to stand in for all, are an important motivation amplifying decentralization of remote capable workers.

Several other recent papers also study the effects of remote work on cities. Behrens, Kichko, and Thisse (2021), Brueckner, Kahn, and Lin (2021), and Kyriakopoulou and Picard (2021) develop stylized spatial equilibrium models with on-site and remote work, and study the implications of greater work from home on the demand for floorspace, productivity, income inequality, and city structure. Lennox (2020) builds a quantitative spatial model of Australia and studies a fall in transport costs as a proxy for an increase in remote work. Delventhal, Kwon, and Parkhomenko (2021) builds a quantitative spatial model of the Los Angeles area, in which workers are homogeneous and work from home behavior is exogenous.

Monte, Redding, and Rossi-Hansberg (2018) analyze the U.S. system of cities using a model in which workers may commute between counties–an approach which we extend by including many small locations within each urban county to study intra-city, as well

[1] Barrero, Bloom, and Davis (2021), e.g. promote the primacy of a shift in norms and attitudes, while Davis, Ghent, and Gregory (2021) argue for a shock to productivity.

as inter-city, adjustments. 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). Our study contributes to this literature by extending the toolbox to include a full-fledged model of working from home.

Our paper also follows an earlier literature studying the impact of communication technologies and telework from a theoretical standpoint, which includes contributions from Gaspar and Glaeser (1998), Safirova (2003), Glaeser and Ponzetto (2007), Rhee (2008), and Larson and Zhao (2017).

Yet another strand of recent research empirically studies movement of residents and changes in real estate prices during the pandemic. Examples include Althoff, Eckert, Ganapati, and Walsh (2021), Haslag and Weagley (2021), Li and Su (2021), Gupta, Peeters, Mittal, and Van Nieuwerburgh (2021), Liu and Su (2021), Rosenthal, Strange, and Urrego (2021), and De Fraja, Matheson, and Rockey (2021), among others.

The remainder of the paper is organized as follows. Section 2 documents key facts about pre-2020 remote work, and presents evidence related to its future trajectory. Section 3 describes the theoretical framework. Section 4 describes the data and the methodology used to quantify the model, and demonstrates how the model is congruent with the facts shown in Section 2. Section 5 presents the results of the counterfactual experiments, tests the predictions of our model against local changes in residents since March 2020, and provides evidence for the preference shock as the driver of the rise in work from home during Covid-19. Section 6 concludes.

2 Remote Work: Past and Present

In this section we establish facts about telecommuting prior to 2020, and present evidence to support our interpretation of Covid-19 as a shock to the preference for remote work. This will motivate the way we build the model as well as how we approach the counterfactual exercise.

2.1 The Who, What and Where of U.S. Telework

In order to construct a sensible model of remote work in the U.S. context, we should first make ourselves familiar with some basic facts. First of all, *who* can telecommute, and of those, who actually does? Second, *what* does this telecommuting entail? In particular, how frequently do remote workers work from home, and what are their average wages relative to non-remote workers? Third, *where* do telecommuters tend to live?

To address the first question, we subdivide the work force by education level and by industry. *College* workers have obtained a four-year degree or more, and *non-college* have not. *Tradable* industries are 2-digit NAICS categories whose products are often sold far from the location of origin, while *non-tradable* industries are categories whose products are mostly sold locally.[2] Using data on full-time workers in the 48 contiguous United States and Washington, D.C. from the American Community Survey (ACS), we calculate that the U.S. workforce between 2012–2016 was composed of 28.9% college workers, 12.3% in tradable and 16.6% in non-tradable industries; and 71.1% non-college workers, 28.8% in tradable and 42.3% in non-tradable industries.

Telecommutability, i.e., the ability to telecommute, differs sharply between these categories. Combining occupational classifications from Dingel and Neiman (2020) with our data, we find that 33.6% of workers in our sample have jobs that can be done from home. We also find that college workers and those in tradable industries are more likely to have such a job–an observation we label **Stylized Fact #1**. As shown in Figure 1, 68.8% of college workers in tradable industries have jobs that can be done mostly or completely from home, compared to just 18.9% of non-college workers in non-tradable industries.[3]

These differences are compounded by further gaps in telecommuting *uptake*. To measure uptake, we use data from the 2018 Survey of Income and Program Participation (SIPP); see Appendix Section C.1 for more details. Focusing on full-time workers who are not self-employed, we find that 38% of college workers in tradable industry with telecommutable occupations actually do work from home at least one full paid day a week; while uptake for non-college, non-tradable workers is only 21%.[4] We dub these gaps by education and industry **Stylized Fact #2**.

With what frequency do remote workers dial it in from home? Table 1 provides an answer. Using the data from SIPP, we find that a notable feature of the distribution for each worker category is *bi-modality*: most are full-time on-site or full-time at home, with few workers in between. We call this **Stylized Fact #3**.

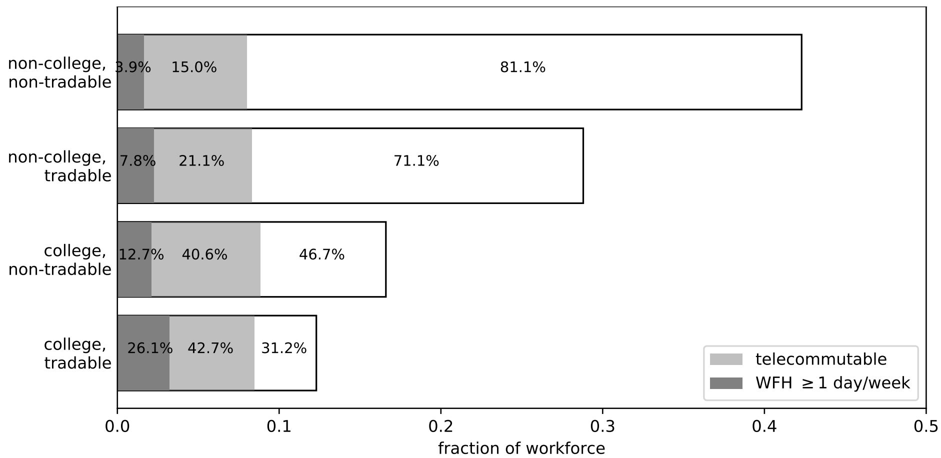
How do the earnings of telecommuters compare to those who work full-time in the office? In Table 2 we report that at least from 2012–2016, they did not appear to earn any

[2]*Tradable:* BEA 2012 NAICS categories Agriculture, forestry, fishing and hunting, and mining; Manufacturing; Wholesale trade; Transportation and warehousing, and utilities; Information; Finance, insurance, real estate and rental and leasing; and Professional, scientific, management, administrative, and waste management services. *Non-tradable:* Educational, health and social services; Arts, entertainment, recreation, accommodation and food services; Other services (except public administration); and Public administration. *Excluded:* Armed Forces.

[3]Differences in telecommutability by industry and education have been previously documented by Dingel and Neiman (2020) and Mongey, Pilossoph, and Weinberg (2020).

[4]$26.1/(26.1 + 42.7) \approx 0.38$, and $3.9/(3.9 + 15.0) \approx 0.21$, from Figure 1.

Figure 1: Telecommutability and uptake



Note: Total bar length corresponds to the share of each worker type in the labor force. Dark-gray areas represent workers who report at least one paid full day/week worked from home. Light-gray areas represent workers with telecommutable professions who do not work from home. White areas represent workers in non-telecommutable occupations. Percentages on the graph report the fraction of each worker type with each commuting status.

Table 1: Frequencies of working from home, 2018

		College		Non-college	
WFH frequency	Overall	Tradable	Non-Tradable	Tradable	Non-tradable
5 days per week	5.6%	15.0%	6.7%	5.2%	2.7%
4 days per week	0.2%	0.5%	0.5%	0.2%	0.1%
3 days per week	0.3%	0.9%	0.4%	0.3%	0.1%
2 days per week	0.7%	1.9%	1.4%	0.5%	0.3%
1 day per week	2.3%	7.8%	3.7%	1.6%	0.7%
<1 day per week	90.8%	73.9%	87.3%	92.3%	96.2%

Note: The table summarizes the share of all workers, as well as workers in each education-industry group, that report having a certain number of paid full days a week worked from home from SIPP. Self-employed workers are excluded.

less on average than their counterparts who belonged to a telecommutable occupation but worked on-site full time, even after controlling for a wide array of observable characteristics including age, occupation, industry, and geographic location; see Appendix Section C.3 for more details on the data. On the contrary, for every category except for non-college workers in non-tradable industries, we observe a modest work from home wage premium. We call this **Stylized Fact #4**.[5]

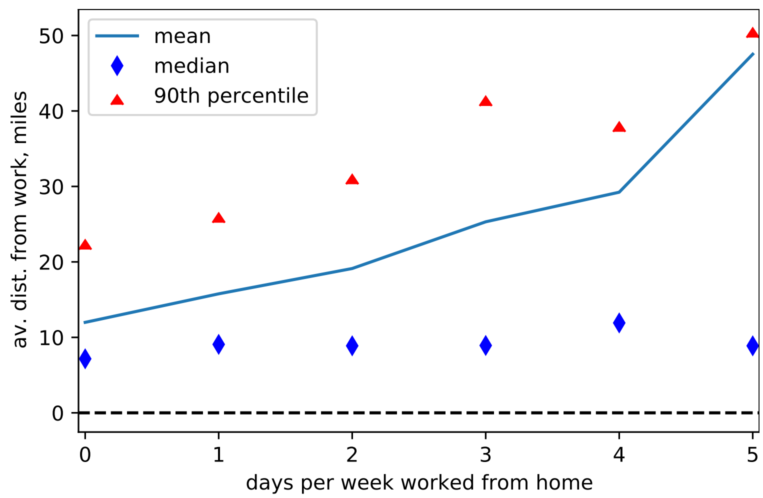
[5]This observed premium is consistent with a wide variety of causes, including unobserved differences between remote and non-remote workers, and a possible work-from-home productivity bonus. Survey evidence from Barrero, Bloom, and Davis (2021) provides some support for the latter possibility. They find that workers forced to work from home during 2020–2021 reported a nearly 8% increase in productivity on average.

Table 2: Relative earnings of telecommuters

	Non-college	College
Non-tradable	- 1.5%	+2.4%
Tradable	+ 2.6%	+5.2%

Note: Hourly earnings of those who entirely worked from home last week, versus those who did not. ACS 2012-2016, only for workers in telecommutable occupations, controlling for age, sex, race, industry, occupation, and geographical location using a linear regression.

Figure 2: Telecommute frequency versus distance to workplace



Note: Calculated from NHTS. 5 days/week: worked from home more than 90% of the days in a 21.67 day average work month; 4 days: between 90% and 70%, 3 days: between 70% and 50%, etc.

Finally, does the ability to telecommute affect workers' location choices? Using data from the 2017 National Household Transportation Survey (NHTS), we find a positive relationship between work-from-home frequency and distance to job site, as shown in Figure 2; see Appendix Section C.4 for more details on the data.[6] We shall refer to this relationship as **Stylized Fact #5**. It is consistent with telework being a way of reducing the effective commuting cost.

2.2 Covid-19: A Telework Shock

When the Covid-19 pandemic began in early 2020, lockdowns and distancing policies moved over one-third of the U.S. workforce from offices to their homes. Prior to the pandemic, no more than 8% of paid full workdays were remote.[7] By early May 2020,

[6] Zhu (2012) also found that telecommuters live at a farther distance from work than commuters.
[7] Based on 2018 SIPP data. This is in the upper range of numbers in Mas and Pallais (2020).

35% of workers who commuted daily before Covid-19 switched to working remotely (Brynjolfsson, Horton, Ozimek, Rock, Sharma, and TuYe, 2020).

This sudden upheaval sparked consternation in many but, in survey after survey of workers and managers, an interesting pattern emerged. It was all going rather better than almost anyone had expected. Companies and workers had found ways to adjust without losing too much productivity, and many found a lot to like about remote work. So much so, that surveys by Barrero, Bloom, and Davis (2021) suggest a full 22% of paid workdays will be remote even after the pandemic.[8]

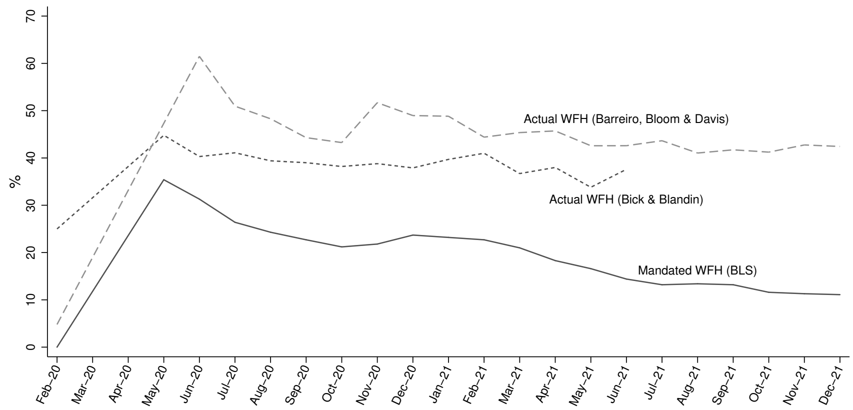
There are at least four hypotheses as to what the Covid-19 telework shock really was. None are mutually exclusive, though some may be more important than others. And the implications of each for the future of remote work are quite distinct.

First, there is the view that working from home during the pandemic is a purely transitory phenomenon, and that once people are allowed to and feel safe they will flock straight back to the office. Second, there is the view that we have experienced a shock to *preferences* around working from home. Barrero, Bloom, and Davis (2021) take the position that working from home was always great but social norms and stigma limited it. They also document a positive change in attitude by the average worker towards telework after having actual experience with working from home. Third, events of the past two years may amount to a *technology shock*. The early months after March 2020 saw a burst of innovation directed at making remote work, work. New software was developed and widely adopted, new policies and procedures were put in place, and individuals and organizations did a great deal of learning by doing. This was on top of a sizeable investment in remote-complementary physical capital. Fourth, it could be that work mode is a coordination game with multiple equilibria–if everyone is in the office, workers want to be there, but if enough people go remote, workers prefer to stay home.

The first hypothesis does not seem to be supported by the progression shown in Figure 3. The share of *mandated* remote work has fallen from 35% in May 2020 to 11% by December 2021. Over the same time period, two measures of *actual* working from home–Bick and Blandin's and Barrero, Bloom, and Davis's–have remained roughly constant at around 40%. We therefore believe it is highly likely that some combination the latter three hypotheses are playing a role. In Section 5, we will present evidence that a *preference shock* is more plausible as a primary explanation for changes in work-from-home behavior than a *technology shock*. We leave the possible role of workplace coordination as a potential topic of future research.

[8]Other surveys indicate that remote work will be more common post-pandemic: Bartik, Cullen, Glaeser, Luca, and Stanton (2020), Ozimek (2020), Bick, Blandin, and Mertens (2021), inter alia.

Figure 3: Work from home during the Covid-19 pandemic



Note: Solid line: the fraction of employed persons who worked remotely for pay during the last 4 weeks because of the coronavirus pandemic, per a Bureau of Labor Statistics survey. Short-dashed line: the fraction of persons who work at home at least some of the time, per the Real Time Labor Market survey by Bick and Blandin (2021). This survey was discontinued in June 2021. Long-dashed line: the fraction of paid full days worked at home, per the survey by Barrero, Bloom, and Davis (2021).

3 Model

Consider a national economy which consists of a finite set $\mathcal{I}$ of discrete locations. Each location is populated by a continuous measure of workers who are distinguished by two characteristics. First, each worker has a skill-level $s \in \{H, L\}$. College-educated workers ($s = H$) provide High-skilled labor to employers, and non-college-educated workers ($s = L$) provide Low-skilled labor. Second, a worker belongs to one of two types of occupations, $o \in \{T, N\}$. Some occupations are Telecommutable ($o = T$), i.e., amenable to remote work, while other occupations are Non-telecommutable ($o = N$) and must be performed on-site.[9] The four types that are the product of $\{H, L\}$ and $\{T, N\}$ are taken to be exogenous and immutable. The economy-wide fraction of workers with education s and occupation o is denoted by l^{so}. Total employment of all types of workers is fixed and normalized to one, so that $\mathrm{l}^{HN} + \mathrm{l}^{LN} + \mathrm{l}^{HT} + \mathrm{l}^{LT} = 1$.

Three types of output are produced in each location: tradable goods and services, non-tradable goods and services, and floorspace, $m \in \{G, S, F\}$. Tradable output ($m = G$) is produced by combining college- and non-college labor with floorspace, and may be sold in any other location without paying a shipping cost. Non-tradable output ($m = S$) is produced using the same three inputs, but can only be sold in the location of origin.[10]

[9] Examples of telecommutable occupations are architects and call center representatives. Examples of non-telecommutable occupations include dentists and plumbers.

[10] Tradable output is indexed $m = G$ as in our data it consists largely (though not entirely) of Goods, while

Floorspace is produced by combining land with tradable goods, and may only be used in the same location it is built.

Work at home is modeled as an option of telecommutable workers to split their work time between their job site and their residence. The productivity of work from home relative to on-site work, as well as a preference parameter that we call the aversion to work from home, vary across education levels and industries. A worker chooses to spend more time working at home when remote work is relatively productive, when the aversion to it is relatively low, floorspace at home is relatively cheap, and the commute to the job site is long.

3.1 Workers

All workers make three types of choices. First, they choose which industry to work in; second, the locations of their job and their residence; and third, how to divide their resulting disposable income between spending on tradables, non-tradables and housing. Those belonging to telecommutable professions make one additional decision after choosing industry, job and residence location: how to divide their labor time between working in the office and working at home.

The first three types of choices are not unusual in a quantitative spatial model, so our discussion of them will be brief. Consumption preferences are Cobb-Douglas. Optimal consumption choices for individual worker ι of education level s and occupation o, conditional on a choice of location i as a residence, j as a worksite, and a choice of m as an industry, imply the indirect utility of $\mu_{m,\iota}\xi_{ij,\iota}v^{so}_{mij}(\theta)$. Here $\theta \in [0,1]$ is the fraction of time worked on-site, for the moment left undetermined; $\mu_{m,\iota}$ represents idiosyncratic preferences over industry, drawn from a Fréchet distribution $\Phi_{\text{ind}}(\mu) = \exp(-\mu^{-\sigma})$; and $\xi_{ij,\iota}$ represents idiosyncratic preferences over residence and job location pairs, drawn from $\Phi_{\text{loc}}(\xi) = \exp\left(-\xi^{-\epsilon}\right)$. The common component of indirect utility is

$$v^{so}_{mij}(\theta) \equiv \frac{X^s_{mi}E^s_{mj}}{g_{ij}d^{so}_{mij}(\theta)}\frac{\tilde{w}^{so}_{mij}(\theta)}{p_i^\beta q_i^\gamma}. \tag{3.1}$$

In this expression, p_i is the price of non-tradables, q_i is the price of floorspace, and $\beta, \gamma \in (0,1)$ are the expenditure shares of these two categories. X^s_{mi} is a residential amenity and E^s_{mj} is an employment amenity. Disposable income $\tilde{w}^{so}_{mij}$ depends on θ in a way which we will discuss later in this section. The disutility of commuting $d^{so}_{mij}(\theta)$ also depends on θ

non-tradable is indexed $m = S$ for Services, for the same reason.

and is given by

$$d^{so}_{mij}(\theta) \equiv \theta e^{\kappa t_{ij}} + (1-\theta)\varsigma^{s}_{m}, \tag{3.2}$$

where t_{ij} is the time in minutes required to commute from location i to location j; $\kappa > 0$ is the elasticity of the disutility to commute time; and $\varsigma^s_m > 0$ represents the relative preference of an s-educated worker in industry m to work in the office, as opposed to at home. In what follows, we will sometimes refer to this as the "aversion to telecommuting."[11] The worker only experiences the part of this disutility which comes from commuting on the days she commutes: the first term ranges from 0 when $\theta = 0$, to $e^{\kappa t_{ij}}$ when $\theta = 1$. The second term, representing disutility from remote work, has the opposite relationship with θ, ranging from 0 when $\theta = 1$ to ς^s_m when $\theta = 0$.

We also allow for reasons not directly related to commuting to cause workers to prefer shorter commutes between work and home.[12] We represent these with the distance penalty $g_{ij} \equiv e^{\tau t_{ij}}$, with $\tau > 0$ determining the strength of distance dependence.[13] This dependence is necessary for model predictions to conform with the distance-commute frequency relationship reported in Section 2: even workers who rarely come to the office tend to live at commutable distances from their job site.[14]

Let us designate the optimal choice of θ, discussed later, as θ^{so}_{mij}; and the associated indirect utility, disposable income, and disutility of commuting as v^{so}_{mij}, $\tilde{w}^{so}_{mij}$, and d^{so}_{mij}. Given indirect utilities characterized by equation (3.1), and the Fréchet distribution of shocks, it is straightforward to show that the measure of workers of education level s and occupation o who choose industry m, residence i and job site j is given by

$$\pi^{so}_{mij} = \mathrm{I}^{so}\pi^{so}_{m}\pi^{so}_{ij|m}, \tag{3.3}$$

where π^{so}_m is the probability that a worker with education level s and occupation o chooses

[11] Assuming that ς^s_m takes a value greater than 1 (as it does for all worker categories in our calibration), it lends itself to a range of interpretations. It could represent average worker tastes; or worker concerns about career advancement, which may be easier to achieve in the office; or restrictions against work-from-home imposed by convention, or bias, or employer regulations.

[12] We see three possible interpretations: (1) Spatial frictions in the process of finding jobs and forming attachments to residential locations, leading to spatial covariance in idiosyncratic preferences. (2) Employees with longer tenure on-site, who have already established residential attachments nearby, may be more likely to begin remote work. (3) Company policies may discourage moving far away, perhaps due to the option value of occasional office visits.

[13] An alternative specification could embed this distance penalty in the distribution of preference shocks, so that workers are less likely to draw a shock with high value for a pair of distant locations.

[14] In Appendix Section G.1 we recalibrate the benchmark model and repeat our main counterfactual exercise (as described in Sections 4.2.3 and 5.1) assuming that $g_{ij} = 1$ so the whole cost of distance is loaded onto commuting. This means that high-frequency telecommuters live farther from their job sites, so the same calibrated increase in telecommuting leads to more dramatic reallocations.

industry m, and $\pi^{so}_{ij|m}$ is the probability that such a worker chooses the location pair (i, j), conditional on having chosen industry m. These two probabilities are given by

$$\pi^{so}_{m} = \frac{\left[\sum_i \sum_j \left(v^{so}_{mij}\right)^{\epsilon}\right]^{\frac{\sigma}{\epsilon}}}{\sum_{m'}\left[\sum_i \sum_j \left(v^{so}_{m'ij}\right)^{\epsilon}\right]^{\frac{\sigma}{\epsilon}}} \qquad \text{and} \qquad \pi^{so}_{ij|m} = \frac{(v^{so}_{mij})^{\epsilon}}{\sum_{i'}\sum_{j'}(v^{so}_{mi'j'})^{\epsilon}}. \tag{3.4}$$

Choice probabilities π^{so}_{mij} allow us to characterize aggregate allocations of residents and jobs. For example, the residential population (indexed by R) of type (s, o) workers in location i is

$$N^{so}_{Ri} = \sum_m \sum_j \pi^{so}_{mij}. \tag{3.5}$$

Also, the supply of on-site work days (indexed by WC) by workers of skill level s at job site j and the supply of remote work days (indexed by WT) are given by

$$N^{s}_{WCj} = \sum_m \sum_i \left[\theta^{sT}_{mij}\pi^{sT}_{mij} + \pi^{sN}_{mij}\right] \qquad \text{and} \qquad N^{s}_{WTj} = \sum_m \sum_i (1-\theta^{sT}_{mij})\pi^{sT}_{mij}. \tag{3.6}$$

Finally, the expected utility (and our measure of welfare) of a worker with education s and occupation o is

$$V^{so} = \Gamma\left(\frac{\epsilon-1}{\epsilon}\right)\Gamma\left(\frac{\sigma-1}{\sigma}\right)\left[\sum_m \left[\sum_i \sum_j \left(v^{so}_{mij}\right)^{\epsilon}\right]^{\frac{\sigma}{\epsilon}}\right]^{\frac{1}{\sigma}}, \tag{3.7}$$

where $\Gamma(\cdot)$ is the Gamma function.

3.1.1 Allocation of Time Between On-Site and Remote Work

Workers supply one unit of work time inelastically. This is a common assumption. What is different in our model is that some workers–those in telecommutable occupations–choose how to divide their work time between the job site and home. Those in non-telecommutable occupations do not have a choice–for them $\theta = 1$.

In a given work location, whether on-site or at home, labor time n is combined with floorspace h in a Cobb-Douglas production function to produce effective labor: $n^{\alpha}h^{1-\alpha}$, where the share of labor time α is the same across work locations and in tradable and non-tradable industries.[15]

We assume that while some tasks may be as easily done at home, others are more easily accomplished at the job site; and there may even be tasks for which work time at home is

[15]The need for home offices is consistent with Stanton and Tiwari's (2021) finding that, conditional on location, income, and family structure, telecommuters own larger houses.

more productive. Reflecting this, overall effective labor supply of a worker is a constant elasticity of substitution combination of labor on-site and at home, with the elasticity of substitution $\zeta > 1$:[16]

$$z_m^{so}(\theta, h_C, h_T) = \left[\left(\theta^\alpha h_{WC}^{1-\alpha}\right)^{\frac{\zeta-1}{\zeta}} + \left(\nu_m^s (1-\theta)^\alpha h_{WT}^{1-\alpha}\right)^{\frac{\zeta-1}{\zeta}} \right]^{\frac{\zeta}{\zeta-1}}. \tag{3.8}$$

Parameter $\nu_m^s > 0$ is the relative productivity of working from home. It represents all possible reasons why a given worker may produce a different quantity of output while working at home, such as a different work environment, lack of supervision, or the difficulty of coordinating with co-workers. Variables h_{WC} and h_{WT} are the amounts of on-site and home floorspace, respectively, rented by the worker.[17] A worker of education level s in industry m takes as given that they will be paid a wage w_{mj}^s for each unit of effective labor they supply to their employer. Thus, the worker's disposable income is the compensation paid by the firm less floorspace expenses, $\tilde{w}_{mij}^{so}(\theta) \equiv w_{mj}^s z_m^s(\theta, h_{WC}, h_{WT}) - q_j h_{WC} - q_i h_{WT}$.

Income-maximizing choices imply the following floorspace expenditures of a worker with education s in occupation o who lives in location i, works in industry m in location j, and commutes to the job site a fraction θ of time:

$$q_j h_{mij,WC}^{so}(\theta) = \left((1-\alpha) w_{mj}^s\right)^{\frac{1}{\alpha}} \left[\left(\theta^\alpha q_j^{-(1-\alpha)}\right)^{\zeta-1} \Omega_{mij}^s(\theta) \right]^{\frac{1}{1+\alpha(\zeta-1)}}, \tag{3.9}$$

$$q_i h_{mij,WT}^{so}(\theta) = \left((1-\alpha) w_{mj}^s\right)^{\frac{1}{\alpha}} \left[\left(\nu_m^s (1-\theta)^\alpha q_i^{-(1-\alpha)}\right)^{\zeta-1} \Omega_{mij}^s(\theta) \right]^{\frac{1}{1+\alpha(\zeta-1)}}, \tag{3.10}$$

where

$$\Omega_{mij}^{so}(\theta) \equiv \left[\left(\theta^\alpha q_j^{-(1-\alpha)}\right)^{\frac{\zeta-1}{1+\alpha(\zeta-1)}} + \left(\nu_m^s (1-\theta)^\alpha q_i^{-(1-\alpha)}\right)^{\frac{\zeta-1}{1+\alpha(\zeta-1)}} \right]^{\frac{1}{\alpha}\frac{1+\alpha(\zeta-1)}{\zeta-1}}. \tag{3.11}$$

Then the optimal effective labor of a worker who rents optimal amounts of floorspace and commutes to work with frequency θ is $z_{mij}^{so}(\theta) = \left((1-\alpha) w_{mj}^s\right)^{\frac{1-\alpha}{\alpha}} \Omega_{mij}^{so}(\theta)$, while his disposable income is

$$\tilde{w}_{mij}^{so}(\theta) = \alpha (1-\alpha)^{\frac{1-\alpha}{\alpha}} (w_{mj}^s)^{\frac{1}{\alpha}} \Omega_{mij}^{so}(\theta). \tag{3.12}$$

In order to choose how much time to work on-site and at home, a telecommutable worker compares the benefits and costs of working on-site. On the one hand, working at

[16]Imperfect substitution between on-site and remote work implies that all workers in telecommutable occupations choose an interior θ.

[17]For simplicity of exposition, we specify floorspace rent as a choice by the worker; firms' payments to workers compensate both labor and floorspace. There exists an isomorphic specification in which firms rent floorspace directly.

the job site may yield higher disposable income if on-site work is relatively productive (low ν_m^s) and on-site floorspace is relatively affordable (low q_j/q_i), as implied by equation (3.12). Working at the job site also yields higher utility when the aversion to remote work ς_m^s is high, as suggested by equation (3.2). On the other hand, working on premises requires costly commuting (t_{ij}) which reduces utility, as implied by equation (3.2). The optimal choice of θ that balances this tradeoff is

$$\theta_{mij}^{sT} = \frac{1}{1 + \left(\nu_m^s \left(\frac{q_j}{q_i}\right)^{1-\alpha}\right)^{\zeta-1} \left(\frac{e^{\kappa t_{ij}}}{\varsigma_m^o}\right)^{1+\alpha(\zeta-1)}}. \tag{3.13}$$

3.2 Firms

In each location there are many perfectly competitive firms producing tradable products, and likewise producing non-tradable products. Each of these firms hires the effective labor of college and non-college workers and combines them in a constant elasticity of substitution production process. Total output of industry m in location j is

$$Y_{mj} = A_{mj}\left[\omega_{mj}\left(y_{mj}^L\right)^{\frac{\xi-1}{\xi}} + (1-\omega_{mj})\left(y_{mj}^H\right)^{\frac{\xi-1}{\xi}}\right]^{\frac{\xi}{\xi-1}}, \tag{3.14}$$

where y_{mj}^s represents the total effective labor rented from workers with education s, ω_{mj} determines the weight of non-college labor in the production function, A_{mj} is the productivity of industry m in location j, and ξ is the elasticity of substitution between college and non-college labor. In our setup, the decision of how to divide labor time between on-site and at-home work is made by the worker, and the firm is ready to purchase however much effective labor results from the worker's choices.

The firm chooses labor inputs y_{mj}^s so as to maximize profit: $p_{mj}Y_{mj} - w_{mj}^L y_{mj}^L - w_{mj}^H y_{mj}^H$. Since firms in the tradable sector are able to sell their product in any location without facing any transport costs, there is an economy-wide equilibrium price for tradable products, normalized to 1: $p_{Gj} = 1$ for all j. Firms in the non-tradable sector can only sell their product locally and thus $p_{Sj} \equiv p_j$ varies by location.

Profit maximization and zero profits imply the following equilibrium relationship between non-college wages and output prices in each industry,

$$\frac{w_{mj}^L}{p_{mj}} = A_{mj}\omega_{mj}^{\frac{\xi}{\xi-1}}\left[1 + \left(\frac{1-\omega_{mj}}{\omega_{mj}}\right)^{\xi}\left(\frac{w_{mj}^L}{w_{mj}^H}\right)^{\xi-1}\right]^{\frac{1}{\xi-1}}. \tag{3.15}$$

Meanwhile, optimal use of inputs implies that in each industry m and each location j, the college premium has the following relationship to the relative input level of each skill type:

$$\frac{w^H_{mj}}{w^L_{mj}} = \frac{1-\omega_{mj}}{\omega_{mj}} \left(\frac{y^L_{mj}}{y^H_{mj}} \right)^{\frac{1}{\xi}}. \tag{3.16}$$

3.3 Developers

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

$$H_i = K_i^{1-\eta_i} \left(\phi_i L_i\right)^{\eta_i}, \tag{3.17}$$

where K_i and L_i are the inputs of the tradable good and land, and η_i is the location-specific share of land in the production function. We make a simplifying assumption that the production of floorspace does not employ labor directly. Each location is endowed with Λ_i units of buildable land which 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.[18] Let q_i be the equilibrium price of floorspace. Then the equilibrium supply of floorspace in location i is

$$H_i = \phi_i (1-\eta_i)^{\frac{1-\eta_i}{\eta_i}} q_i^{\frac{1-\eta_i}{\eta_i}} L_i. \tag{3.18}$$

3.4 Market clearing

There are five markets that need to clear in each location in an equilibrium: the market for college labor, the market for non-college labor, the market for non-tradable output, the market for floorspace, and the market for land.[19]

Labor markets clear when the demand for effective labor of each education level equals the supply, $y^s_{mj} = \sum_o \sum_i \pi^{so}_{mij} z^{so}_{mij}$, which implies that equilibrium effective labor supply is

$$y^s_{mj} = \left((1-\alpha) w^s_{mj}\right)^{\frac{1-\alpha}{\alpha}} \sum_o \sum_i \pi^{so}_{mij} \Omega^{so}_{mij}. \tag{3.19}$$

Applying equation (3.19) to equation (3.16), we obtain the equilibrium college wage pre-

[18] The productivity may depend on terrain, climate, land use regulations, etc.

[19] By Walras' Law, the economy-wide market for tradables will clear as long as the other $I \times 5$ local markets clear.

mium,

$$\frac{w_{mj}^H}{w_{mj}^L} = \left(\frac{1-\omega_{mj}}{\omega_{mj}}\right)^{\frac{\alpha\xi}{1+\alpha(\xi-1)}} \left(\frac{\sum_o \sum_i \pi_{mij}^{Lo}\Omega_{mij}^{Lo}}{\sum_o \sum_i \pi_{mij}^{Ho}\Omega_{mij}^{Ho}}\right)^{\frac{\alpha}{1+\alpha(\xi-1)}}. \tag{3.20}$$

Wage levels can then be found by plugging in this expression in equation (3.15).

Profit-maximization and zero profits imply the following equilibrium supply of the non-tradable product in location j,

$$p_{Sj}Y_{Sj} = \left(p_{Sj}A_{Sj}\right)^{\frac{1}{\alpha}} (1-\alpha)^{\frac{1-\alpha}{\alpha}} \omega_{Sj}^{\frac{\xi}{\alpha(\xi-1)}} \left(\sum_o \sum_i \pi_{Sij}^{Lo}\Omega_{Sij}^{Lo}\right)\left[1+\left(\frac{1-\omega_{Sj}}{\omega_{Sj}}\right)^{\xi}\left(\frac{w_{Sj}^L}{w_{Sj}^H}\right)^{\xi-1}\right]^{\frac{1+\alpha(\xi-1)}{\alpha(\xi-1)}}. \tag{3.21}$$

Let total disposable income in residential location i be $W_i \equiv \sum_s \sum_o \sum_m \sum_j \pi_{mij}^{so}\tilde{w}_{mij}^{so}$. Non-tradables are demanded only by workers for consumption and total spending on the non-tradable output in any residential location i is βW_i. This allows us to construct the following market-clearing condition in the market for non-tradables:

$$p_{Sj}A_{Sj} = \frac{(\beta W_i)^{\alpha}}{(1-\alpha)^{1-\alpha}\omega_{Sj}^{\frac{\xi}{\xi-1}}\left(\sum_o \sum_i \pi_{Sij}^{Lo}\Omega_{Sij}^{Lo}\right)^{\alpha}}\left[1+\left(\frac{1-\omega_{Sj}}{\omega_{Sj}}\right)^{\xi}\left(\frac{w_{Sj}^L}{w_{Sj}^H}\right)^{\xi-1}\right]^{-\frac{1+\alpha(\xi-1)}{\alpha(\xi-1)}}. \tag{3.22}$$

Floorspace is demanded by workers both for residential use and as a production input. Expenditure on residential floorspace in location i is $H_{Ri} = \gamma W_i$. Expenditure on on-site office space is $H_{WCi} = q_i \sum_s \sum_o \sum_m \sum_j \pi_{mji}^{so} h_{mji,WC}^{so}$, and the expenditure on home office space is $H_{WTi} = q_i \sum_s \sum_m \sum_j \pi_{mij}^{sT} h_{mij,WT}^{sT}$. Then, total local floorspace expenditure is

$$H_i = H_{Ri} + H_{WCi} + H_{WTi}. \tag{3.23}$$

Floorspace demand also determines the demand for land. Land is owned by landlords and, since there are no alternative uses of land, it is optimal for landlords to sell all buildable land to developers: $L_i = \Lambda_i$ for all i. Land owners receive a share η_i of the total revenues from floorspace sales, H_i. The price per unit of land must then be equal to total earnings divided by the quantity of land:

$$l_i = \frac{\eta_i H_i}{\Lambda_i}. \tag{3.24}$$

Landlords use proceeds from land sales to consume the tradable good, as in Monte, Redding, and Rossi-Hansberg (2018). Thus, we can account for changes in land values when computing welfare effects: the welfare of landlords is simply the total value of land in the economy, $\sum_i l_i \Lambda_i$. Finally, optimal decisions of floorspace developers imply the following relationship between land prices and floorspace prices:

$$q_i = \frac{1}{\eta_i^{\eta_i}(1-\eta_i)^{1-\eta_i}} \left(\frac{l_i}{\phi_i}\right)^{\eta_i} . \tag{3.25}$$

3.5 Externalities

The productivity of industry m in location j is determined by an exogenous component, a_{mj}, and an endogenous component that is increasing in the density of on-site and remote employment in this location:

$$A_{mj} = a_{mj} \left(\frac{N_{WCj} + \psi N_{WTj}}{\Lambda_j}\right)^{\lambda} . \tag{3.26}$$

Parameter $\lambda > 0$ is the elasticity of productivity with respect to local employment density, while $\psi \in [0,1]$ 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 welfare effects of telecommuting.

Similarly, the residential amenity in location i is determined by an exogenous component, x^s_{mi}, and an endogenous component that depends on the density of residents:

$$X^s_{mi} = x^s_{mi} \left(\frac{N_{Ri}}{\Lambda_i}\right)^{\chi} , \tag{3.27}$$

where $\chi > 0$ represents the elasticity of amenities with respect to the local density of residents.[20] The positive relationship between residential density and amenities represents in reduced form the greater propensity for amenities, such as parks or schools, to locate in proximity to greater concentrations of potential users. All workers, regardless of commuting frequency, contribute equally to amenity externalities at their location of residence.[21]

[20]We abstract from spatial spillovers of productivity or amenities across locations. They are highly localized, as found in Ahlfeldt, Redding, Sturm, and Wolf (2015) and other studies. Given that locations in our quantitative model are relatively large, the effect of these spillovers may not be first-order.

[21]It is also possible that those who work at home more often contribute more to local amenities by spending more time in the area of their residence. We abstract from this channel.

3.6 Equilibrium

Definition 3.1. Given local fundamentals, a_{mj}, x^s_{mi}, E^s_{mj}, ϕ_i, η_i, and Λ_i; bilateral commute times, t_{ij}; population shares, ℓ^{so}; and economy-wide parameters, ν^s_m, ς^s_m, ℓ^{so}, ψ, α, β, γ, ϵ, σ, ζ, ξ, κ, τ, λ, and χ; a *spatial equilibrium* consists of allocations of workers to industries, residences, and job-sites, π^{so}_{mij}; allocations of work time between on-site and remote, θ^{so}_{mij}; productivities, A_{mj}; residential amenities, X^s_{mj}; college and non-college wages, w^H_{mj} and w^L_{mj}; effective labor supplies, y^s_{mj}; prices and supplies of floorspace, q_i and H_i; prices and supplies of non-tradable goods, p_i and Y_{Si}; and land prices, l_i; such that equations (3.3), (3.13), (3.26), (3.27), (3.15), (3.20), (3.19), (3.25), (3.18), (3.22), (3.21), and (3.24) are satisfied.

Existence and uniqueness. While our model has a number of extensions compared to a "standard" quantitative spatial equilibrium model with commuting such as Ahlfeldt, Redding, Sturm, and Wolf (2015), our main innovation is the introduction of work from home. In Appendix Section A, we evaluate equilibrium properties of a simplified model with exogenous floorspace supply, single industry, and no heterogeneity in education or occupation, but with work from home. We show that, in general, the introduction of telecommuting makes it less likely that the equilibrium is unique. In a standard model, the extent to which a location with high exogenous productivity attracts employment is amplified via agglomeration externalities but is dampened as the number of workers willing to commute to this location daily is limited. In a model with work from home, such locations have a greater firm market access (or "catchment area") and can attract more workers since they do not have to commute daily. As a result, even modest values of the productive externality parameter λ can lead to multiple equilibria.

4 Quantification

In this section we describe how we build our model into a quantitative description of industry, residence, workplace, and telecommuting decisions made by U.S. workers in the years leading up to 2020. We focus our analysis on the 48 contiguous United States and the District of Columbia.

We define a model location as the intersection of a Census Public Use Microdata Area (PUMA) and a county.[22] In densely populated areas, where there are many PUMAs to a county, each PUMA is a model location. This allows us to take advantage of

[22]The Census Bureau designs PUMAs to have between 100,000 and 200,000 residents. Thus, large metropolitan areas have many model locations: the New York metro area has 147 distinct model locations, and there are 10 locations in Manhattan alone.

geographically-detailed data and depict patterns of commuting within metro areas. In rural areas, where there may be several counties in a single PUMA, each location is a county. Defining locations as described above and dropping two locations with missing wage data, we end up with 4,502 model locations.

4.1 Data

Our next step is to populate these locations with relevant data. For each location, we use information on the resident population, the number of jobs, wages, floorspace prices, and non-tradable output prices. We also use information on bilateral commuting flows and times. We focus on the five-year period of 2012–2016.[23] The total number of workers by education level and occupation type, I^{so}, is calculated from ACS data as described in Section 2.

Residents, jobs, and commuting. To obtain information on resident population, jobs, and commuting flows, we turn to the LEHD Origin-Destination Employment Statistics (LODES) database. We use averaged data for the years 2012–2016. LODES provides workplace and residence job counts separately by education level or by industry at the Census block level, which we aggregate up to the level of our model locations. We divide NAICS categories into tradable and non-tradable industries and divide education levels into "college" and "non-college" in the same way that we describe in Section 2. LODES also provides commuting flows between each pair of locations, which we use to estimate the Fréchet elasticity of preference shocks.

Wages. We use the Census Transportation Planning Products (CTPP) database and American Community Survey (ACS) microdata for 2012–2016 to obtain estimates of average wage by industry m and education s for each location j: $\hat{w}^s_{mj}$. We then convert $\hat{w}^s_{mj}$ into their model counterpart w^s_{mj} by applying commuting flows and effort predicted by the model. To estimate wage differences between on-site workers and telecommuters, we also use the ACS data. The data and our methodology are described in Appendix Sections C.2 and C.3.

Non-tradable goods prices. We use the Bureau of Economic Analysis Regional Price Parities for the "Services other than real estate" category as a proxy for non-tradable output prices. We use data at the metropolitan statistical area (MSA) level, if available, and apply the same price level to all locations within a single MSA. For the remaining locations, we apply the state non-metropolitan price level from the database. For each location we take the average across the years from 2012–2016.

[23]The choice of the time period is motivated by the fact that our wage and commuting time data is aggregated at five-year intervals and this is the most recently available interval prior to the pandemic.

Floorspace prices. To obtain local rental prices of floorspace, we estimate hedonic rent indices for each PUMA using self-reported housing rents from the ACS for the period from 2012 to 2016. Appendix Section C.5 provides more details.

Commute times. Bilateral travel times are obtained from the CTPP survey data for the period 2012–2016, with some imputations to fill in missing trajectories. Details can be found in Appendix Section C.6.

4.2 Parameterization

The parameters of our model can be divided into three sets: those we set externally and those we estimate (both summarized in Table 3), as well as those we calibrate internally (summarized in Table 5).

4.2.1 Externally Set Parameters

We set the consumption share of housing, $\gamma = 0.24$, following Davis and Ortalo-Magné (2011). Valentinyi and Herrendorf (2008) estimate that the combined share of land and structures in the U.S. is equal to 0.18. Thus, we set the labor share in the production of tradable and non-tradable goods, α, equal to 0.82. The elasticity of substitution between college and non-college labor, ξ, is set to 2, in the middle of the range between 1.5 and 2.5 reported by Card (2009). We set the Fréchet elasticity of the distribution of industry choice shocks, σ, equal to 1.4, following Lee (2020). 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 $\chi = 0.172$. To evaluate the sensitivity of our results to these values, we run counterfactual experiments where each of these values is set to zero (see Section 5.3). 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 the productive externalities, ψ. Instead, we will consider counterfactual scenarios with two extreme values: $\psi = 0$ and $\psi = 1$.

In our model, the expected utility of a worker is decreasing in commute time for two reasons. First, greater commuting time increases the disutility of commuting (with elasticity κ). Second, it increases the distance penalty (with elasticity τ). Note that most existing urban models with commuting did not have remote work and, in terms of our model, had all workers have $\theta = 1$. Therefore, because for a worker with $\theta = 1$ we have $g_{ij}d^{so}_{mij} = e^{(\kappa+\tau)t_{ij}}$, the term $\kappa + \tau$ in our model is analogous to the elasticity of the commuting cost with respect to commuting time in a model without remote work. Using the same functional form of the commuting cost, Ahlfeldt, Redding, Sturm, and Wolf

Table 3: Externally determined and estimated parameters

Parameter	Description	Value	Comments
γ	consumption share of housing	0.24	Davis and Ortalo-Magné (2011).
α	labor share in production	0.82	Valentinyi and Herrendorf (2008)
ξ	elasticity of substitution between college and non-college labor	2	middle of the 1.5–2.5 range in Card (2009)
σ	Fréchet elasticity of industry shock	1.4	Lee (2020)
ϵ	Fréchet elasticity of location shock	4.026	estimated–see Section 4.2.2
λ	elasticity of local productivity to employment density	0.086	Heblich, Redding, and Sturm (2020)
χ	elasticity of local amenity to population density	0.172	Heblich, Redding, and Sturm (2020)
ψ	contribution of telecommuters to productivity externalities	{0,1}	we run separate counterfactuals with $\psi = 0$ and $\psi = 1$
$\kappa + \tau$	elasticity of commuting cost to commuting time	0.011	average of estimates from Ahlfeldt, Redding, Sturm, and Wolf (2015) and Tsivanidis (2019)
ζ	elasticity of substitution between on-site and remote labor time	5	Davis, Ghent, and Gregory (2021)
η_i	price elasticity of floorspace supply	various	Baum-Snow and Han (2021)

Note: The table lists parameters determined externally to the calibration process.

(2015) estimate the elasticity of about 0.01, while Tsivanidis (2019) estimates a value of 0.012. We set $\kappa + \tau = 0.011$, the average of these two estimates. Below we calibrate τ and thus identify the value of κ.

In choosing a parameter value for ζ, the elasticity of substitution between on-site and remote labor, we follow the recent work by Davis, Ghent, and Gregory (2021) who estimate values between 3 and 7 using data from the American Time Use Survey. We set $\zeta = 5$, the midpoint of their estimates.

To allow for the possibility that in our counterfactuals floorspace development responds differently to changes in demand across locations, we let the elasticity of floorspace supply, $(1 - \eta_i)/\eta_i$, vary by location. Baum-Snow and Han (2021) estimate elasticities of floorspace supply with respect to prices for Census tracts in over 300 metro areas.[24] We aggregate these to the level of our model locations using population weights. A nationwide map of elasticities can be found in Appendix Figure I.5. The advantage of these estimates is their geographic granularity. At the same time, they are significantly lower than previous stud-

[24]The model locations for which no estimates exist are mostly rural. Since, according to Baum-Snow and Han (2021), there is a strong negative relationship between elasticity and population density, we assume that the elasticity in these places takes the maximum observed value.

ies have found.[25] In Appendix Section G.3 we show that the results of our counterfactuals change little if we use higher values of the elasticity.

4.2.2 Estimation of the Fréchet Elasticity of Location Choice.

We estimate the Fréchet elasticity ϵ using Poisson pseudo maximum likelihood (PPML).[26] The log-likelihood function combines the number of commuters for each (i, j) link and the probability of commuting along this link and is defined as

$$\ln \mathcal{L} \equiv \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{I}} N_{ij} \ln \left[\frac{\bar{X}_i \bar{E}_j e^{-(\kappa+\tau)\epsilon t_{ij}}}{\sum_{i' \in \mathcal{I}} \sum_{j' \in \mathcal{I}} \bar{X}_{i'} \bar{E}_{j'} e^{-(\kappa+\tau)\epsilon t_{i'j'}}} \right], \tag{4.1}$$

where N_{ij} is the number of commuters from i to j in the LODES data, $\bar{X}_i$ and $\bar{E}_j$ are origin and destination fixed effects that subsume all relevant local variables that appear in the conditional location choice probability (equation 3.4), and t_{ij} is the commuting time from i to j.[27] Prior to estimation, we set $N_{ij} = 0$ for all pairs with commuting times of more than 3 hours one way.[28]

Table 4 reports estimation results. Note that we cannot separately identify $\kappa + \tau$ and ϵ. Hence, we first estimate the product $(\kappa + \tau)\epsilon$ and obtain 0.0443. Then, to recover ϵ we use the chosen value $\kappa + \tau = 0.011$, as discussed above. Our estimate of ϵ is therefore equal to $4.026 = 0.0443/0.011$.

[25] At the level of our model locations, elasticities vary from 0 to 0.95, and the population-weighted mean is 0.45. Thus, η_i ranges from 0.51 to 1 and the mean is 0.72. For comparison, Saiz (2010) estimates the elasticities to be on average 1.75 at the metro area level. Baum-Snow and Han (2021) discuss the reasons for this discrepancy. Moreover, in our model the parameter η_i also determines the land share in the production. Thus, the mean land share in our model is higher than most existing estimates: e.g., Albouy and Ehrlich (2018) find that the land share is about 1/3 for the U.S.

[26] The primary reason why we use the PPML approach rather than more common OLS estimation is that 98.4% of location pairs in our data have zero flows. As Dingel and Tintelnot (2020) show, the sparse nature of commuting matrices may result in biased OLS estimates of the Fréchet elasticity and poor model fit. We use the Stata package *ppmlhdfe* of Correia, Guimarães, and Zylkin (2020).

[27] Because LODES and CTPP do not distinguish commuters and telecommuters, we estimate this relationship assuming that all observations commute to the job site all the time, i.e., are workers with $\theta = 1$. Moreover, because we only observe employment levels but not flows by either industry or education, we cannot estimate the Fréchet elasticity separately for different worker types.

[28] Out of around 139 mln commuters we observe in LODES, 9.8 mln travel between locations that are over 3 hours apart. While some of these observations could be full-time telecommuters who live far from their employers, due to reasons outlined in Graham, Kutzbach, and McKenzie (2014), many of these long commutes arise due to errors in assigning work or residence locations. In addition, the evidence in Figure 2 shows that most telecommuters do not live extremely far from their employers and therefore are unlikely to be dropped from our analysis.

Table 4: Estimation of the gravity equation

t_{ij}	-0.04428
	(0.00013)
Observations	20,268,004
Pseudo R^2	0.967

Note: This table reports estimated coefficients for equation (4.1). Standard errors are in parentheses. Estimation includes residence and workplace fixed effects.

4.2.3 Model Calibration and Inversion

Relative productivity and aversion to remote work for each worker category, ν_m^s and ς_m^s, are primarily determined by two sets of targets. The first are the relative wages of remote workers. In our model, we calculate, for workers in each industry and education group, the average wage of telecommutable workers who work on-site less than 10% of the time, $\bar{w}_m^{sT}(\theta < 0.1)$; and the average wage of telecommutable workers who work on-site more than 90% of the time, $\bar{w}_m^{sT}(\theta > 0.9)$. We target each ratio $\bar{w}_m^{eT}(\theta < 0.1)/\bar{w}_m^{eT}(\theta > 0.9)$ to the corresponding number from Table 2. The second set of targets are mean fractions of time worked on-site for workers in each industry and education group $\bar{\theta}_m^s \equiv \sum_o \sum_i \sum_j \pi_{mij}^{so} \theta_{mij}^{so} / \sum_o \sum_i \sum_j \pi_{mij}^{so}$. We target each ratio to match the type-specific averages calculated from SIPP data, as described in Section 2. The calibrated values of work-from-home productivity and aversion are shown in Table 5.

Next, we calibrate the elasticity of the distance penalty to the commuting time, τ, as follows. If a person is unable to telecommute, it is observationally equivalent for them to live close to their work because of the commute cost d_{ij} or because of distance penalty g_{ij}. Once workers can telecommute, however, the distinction becomes very important. If commuting cost is all that matters, our model predicts that the average telecommuter will live very far from their workplace. If, on the other hand, distance penalty is all that matters, there is no substantive difference between commuters and telecommuters in terms of residential location choices. Either of these extremes would be inconsistent with the *stylized fact #4* presented in Section 2. Thus, we first calculate the average distance in kilometers between residence i and job site j, dist_{ij}, separately for "full-time commuters" (defined as those with $\theta > 0.9$) and telecommuters ($\theta \leq 0.9$). Then, we calibrate τ so that the ratio of average distances,

$$\frac{\sum_s \sum_o \sum_m \sum_i \sum_j \mathbb{1}\{\theta_{mij}^{so} > 0.9\} \pi_{mij}^{so} \text{dist}_{ij}}{\sum_s \sum_o \sum_m \sum_i \sum_j \mathbb{1}\{\theta_{mij}^{so} \leq 0.9\} \pi_{mij}^{so} \text{dist}_{ij}}, \tag{4.2}$$

Table 5: Internally calibrated parameters

Parameter	Description	Value	Target
β	Consumption share of non-tradables	0.688	The ratio between average wages in the tradable and non-tradable sectors = 1.23
τ	Elasticity of distance penalty g_{ij} to commuting time	0.0031	The ratio between distance to work for non-telecommuters and telecommuters = 0.338
	Productivity of remote work:		WFH mean wage differentials:
ν_S^L	non-college, non-tradable	0.975	$\bar{w}_S^{LT}(\theta < 0.1)/\bar{w}_S^{LT}(\theta > 0.9) = 0.985$
ν_G^L	non-college, tradable	1.101	$\bar{w}_G^{LT}(\theta < 0.1)/\bar{w}_G^{LT}(\theta > 0.9) = 1.026$
ν_S^H	college, non-tradable	1.019	$\bar{w}_S^{HT}(\theta < 0.1)/\bar{w}_S^{HT}(\theta > 0.9) = 1.024$
ν_G^H	college, tradable	1.136	$\bar{w}_G^{HT}(\theta < 0.1)/\bar{w}_G^{HT}(\theta > 0.9) = 1.052$
	Disutility of work from home:		Average commuting frequency:
ς_S^L	non-college, non-tradable	2.621	$\bar{\theta}_S^L = 0.97$
ς_G^L	non-college, tradable	2.414	$\bar{\theta}_G^L = 0.94$
ς_S^H	college, non-tradable	2.681	$\bar{\theta}_S^H = 0.91$
ς_G^H	college, tradable	2.371	$\bar{\theta}_G^H = 0.82$

Note: The table lists parameters determined internally during the calibration process.

is the same in the model and in the data.

Spending on non-tradable goods is an important determinant of wages in the non-tradable sector. Therefore, we calibrate β, the expenditure share on non-tradable goods, so that the ratio between the mean wages in the tradable and non-tradable sectors,

$$\frac{\sum_s \sum_o \sum_i \sum_j \pi_{Gij}^{so} w_{Gij}^{so} / \sum_s \sum_o \sum_i \sum_j \pi_{Gij}^{so}}{\sum_s \sum_o \sum_i \sum_j \pi_{Sij}^{so} w_{Sij}^{so} / \sum_s \sum_o \sum_i \sum_j \pi_{Sij}^{so}}, \tag{4.3}$$

is the same in the model and in the data.

We also need to quantify several vectors of location-specific fundamentals, and we do this by inverting the model. These fundamentals are $\tilde{a}_{mi} \equiv a_{mi}\Lambda_i^{-\lambda}$, $\tilde{x}_{mi}^s \equiv x_{mi}^s \Lambda_i^{-\chi}$, $\tilde{\phi}_i \equiv \phi_i \Lambda_i$, X_{mi}^s, E_{mj}^s, and ω_{mj}.[29] In the data we observe total residents and employment by industry or education for each location, but not by both characteristics at the same time. This requires us to assume that residence and workplace amenities can be decomposed into education- and industry-specific components as $X_{mi}^s = X_{mi} X_i^s$ and $E_{mj}^s = E_{mj} E_j^s$. The following result states that, given observed data and economy-wide parameters, there are unique vectors of location-specific fundamentals, consistent with the equilibrium of the model.

[29]Separate identification of land area Λ_i is not required for the model. This is desirable because Λ_i represents the land available for floorspace development and thus is difficult to measure.

Proposition 1. *Given the data, $N_{R,mi}$, $N_{W,mj}$, $N^s_{R,i}$, $N^s_{W,j}$, $\mathfrak{l}^{so}$, $\hat{w}^s_{mj}$, q_i, p_i, t_{ij}, estimated local land shares η_i, and economy-wide parameters, α, β, γ, ϵ, ζ, κ, λ, ν^s_m, ς^s_m, ξ, σ, τ, χ, and ψ, there exists a unique set of vectors, $\tilde{a}_{mi}$, $\tilde{x}^s_{mi}$, $\tilde{\phi}_i$, X_{mi}, X^s_i, E_{mj}, E^s_j, and ω_{mj}, that is consistent with the data being an equilibrium of the model.*

Proof. See Appendix Section H.2 □

4.3 Model Fit

Stylized Facts about Telecommuting. How does our model do in matching the four stylized facts laid out in Section 2? For *stylized fact #1*, the model matches the telecommutability gap between college and non-college workers by construction (59.9% to 23.0%), and endogenously produces a gap across industries. The industry telecommutability gap is smaller than observed in the data: 35.1% to 33.4%, versus 40.9% to 28.6%. This is not surprising as industry is a free choice in our model and we do not have any parameter to represent the structural links between certain occupations and certain industries that almost certainly drive most of the gap in the data. For *stylized fact #2*, our model successfully produces a substantial gap in telecommuting *uptake* across both education levels and industries: 47.3% to 37.8% for college/non-college (versus 29.8% to 23.2% in the data); and 61.1% to 28.9% for tradable/non-tradable (versus 30.2% to 21.5% in the data). The model ably reproduces *stylized fact #3*, as is made plain by Figure 4. We think it is remarkable that by only targeting the mean frequency for each education/industry pair, the model is able to reproduce well the entire distribution of frequencies for each of the four pairs (including their bi-modal nature) and also reproduce *stylized fact #2*'s uptake gaps. *Stylized facts #4 and #5* we match by construction, as the relative wages and relative distance to the job site of telecommuters are calibration targets.

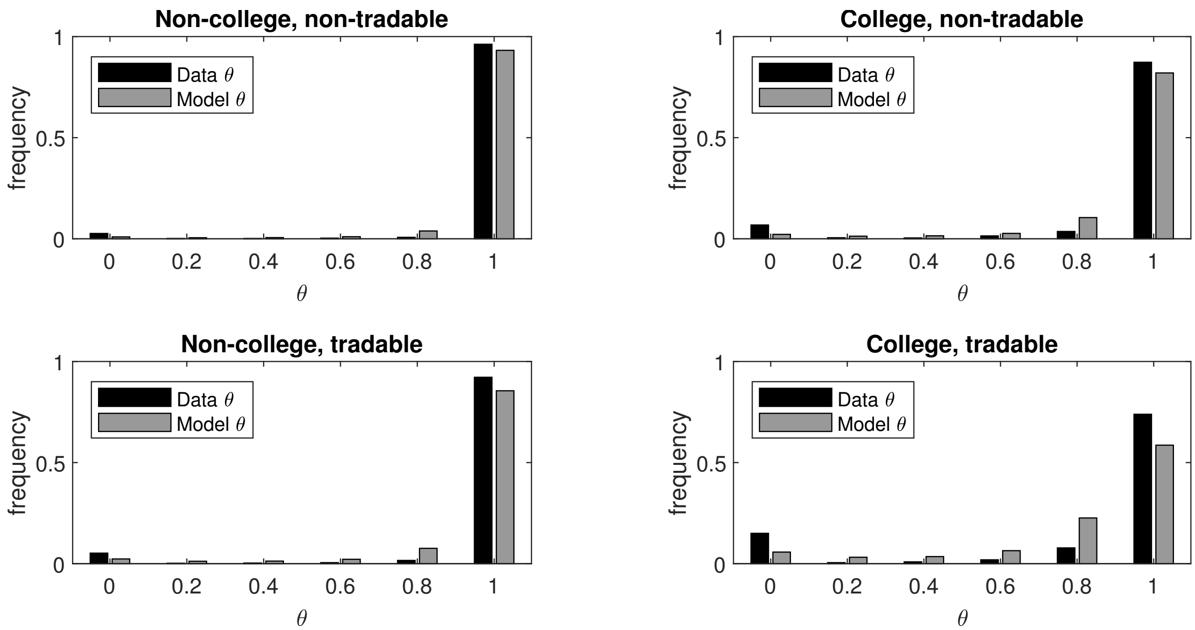
Commuting Flows. We match residents and jobs by education and industry in each location, but leave the model free to predict commuting flows between locations. This means that $\pi_{ij} \equiv \sum_s \sum_o \sum_m \pi^{so}_{mij}$ is an untargeted moment that we can use to evaluate our model.[30] Appendix Figure I.1 shows that the correlation between model and data flows is 0.93.

4.4 Plausibility of calibrated remote work productivity bonuses

The calibrated productivity differences between on-site and remote work in the non-tradable sector are small. But in the tradable sector the calibrated productivity bonuses

[30]Flows by industry, occupation, education are unobserved and cannot be compared to model flows.

Figure 4: Telecommute frequency, data vs. benchmark model

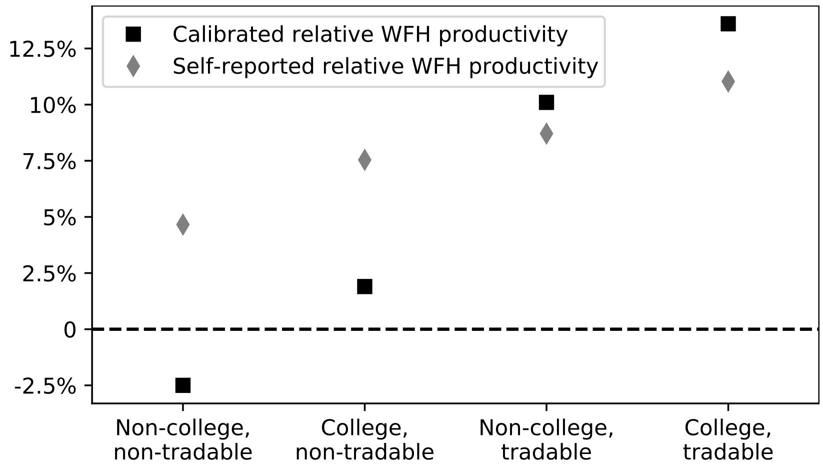


Note: "Data" reflects averages from SIPP, as described in Section 2. "Model" shows values predicted by the calibrated model.

for workers of both education levels are greater than 10%. Are these calibrated numbers plausible in light of existing evidence?

In our view, yes, they are. In a carefully controlled experiment, Bloom, Liang, Roberts, and Ying (2015) find that Chinese call center workers were 13% more productive working from home. This is a result for a narrow category of worker, but the estimated productivity bonus, interestingly, is very close to our own calibrated numbers for workers in the tradable sector. Furthermore, surveys conducted by Barrero, Bloom, and Davis (2021) since March 2020 indicate that workers of all types self-evaluate that they are, on average, more productive working from home. Figure 5 compares these self-reported differences in productivity with our calibrated relative productivity of remote work. It shows that first, for the tradable sector, these self-evaluated values are remarkably close to our calibrated values. Second, the ranking of values across categories for both our calibration and the survey is identical.

Figure 5: Work from home productivity



Note: Black squares: calibrated relative productivity of work from home, ν_m^s. Gray diamonds: Self-reported difference in work-from-home productivity compared to the on-site productivity from Barrero, Bloom, and Davis (2021).

5 Implications of an Increase in Telecommuting

In this section, we study the long-run impact of the rise in work from home as a result of a permanent preference shock which reduces worker distaste for working from home. We explore the shifts in residence, jobs, prices, and commuting patterns predicted by our model, as well as welfare implications of these changes. To validate our approach, we show that our model has considerable success in predicting changes in population that have already occurred since March 2020.

Finally, we provide evidence that the preference component of the Covid-19 telework shock is likely more significant than the technology shock component. We calculate an alternative counterfactual, in which preferences are held constant but the productivity of remote work permanently increases to achieve the same average increases in working from home. We show that the results of this alternative counterfactual are a significantly worse predictor of observed changes in population since March 2020 and produce unrealistically large wage gains.

5.1 Counterfactual Setup

Our baseline assumption is that the increase in remote work is driven by falls in the aversion to telecommuting experienced by workers of each skill/industry combination:

ς_m^s for $s \in \{H, L\}$ and $m \in \{G, S\}$.[31] How do we determine the size of the changes in these four parameters? Barrero, Bloom, and Davis (2021) conducted repeated surveys of workers where they self-report their employers' plans for whether a worker is expected to work remotely zero, one, two, three, four or five days a week post-Covid. The survey is representative of the U.S. labor force. From these data we calculate a post-pandemic mean on-site working frequency for each worker type, and decrease the aversion to remote work to match it. Importantly, we assume that remote workers do not contribute to productive externalities: i.e., we set $\psi = 0$. We examine the implications of this assumption in Section 5.3.

Figure 6 compares the distributions of commuting frequency indicated by the Barrero, Bloom, and Davis (2021) survey with those predicted in the counterfactual. In spite of the fact that only one moment–the mean–from each distribution is targeted, the two sets of distributions line up very well.

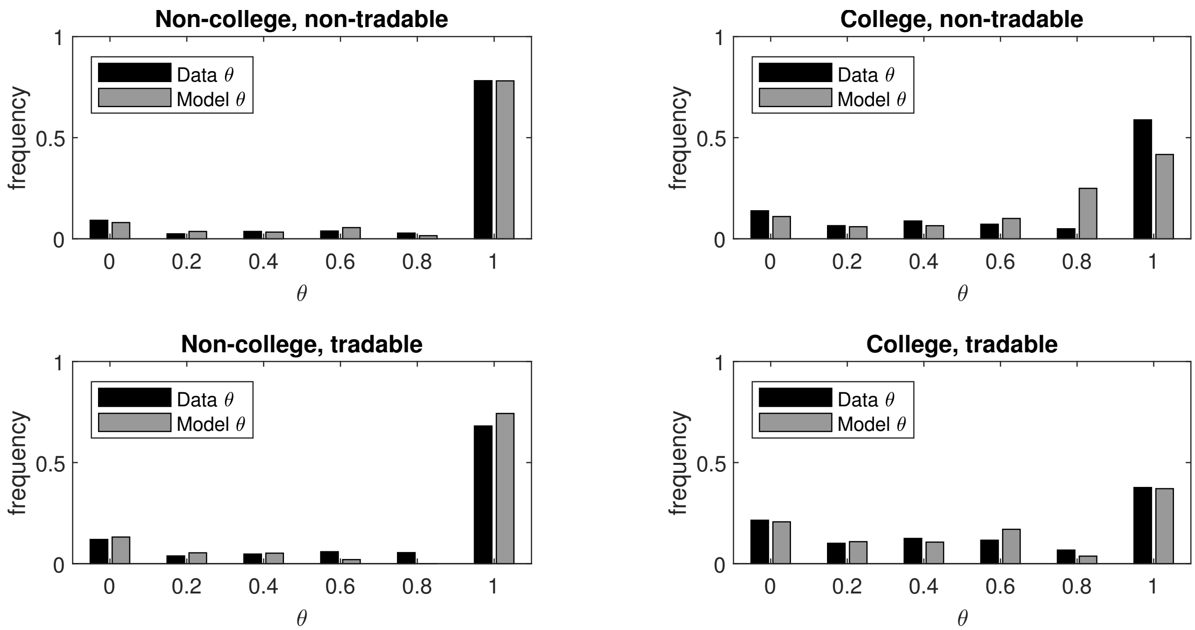
Table 6 shows the change in the aversion to telecommuting for each worker type that was necessary to achieve the targeted increases in telecommuting. In the benchmark economy the aversion to remote work is somewhat higher for non-tradable sector workers of both education levels than it is for workers in the tradable sector. In the counterfactual non-college-educated workers in both sectors see large drops in their aversion to telecommuting, while college-educated workers see smaller drops, ending up with higher levels of aversion than their non-college counterparts. One possible interpretation of this result is that even once the technological and cultural barriers to remote work are removed, college workers have some reasons to want to come to the office–possibly knowledge spillovers and networking for career advancement–that may be less important for non-college workers. In Appendix Section G.2, we study a counterfactual in which all types of workers experience the same change in work-from-home aversion. This does not change any qualitative results.

5.2 Results

Permanently decreasing the aversion for remote work triggers important shifts in the spatial distribution of residents, jobs and real estate prices. These add up to a significant effect on aggregate productivity and welfare. We will describe the spatial shifts first, and then proceed to analyze the aggregate effects.

[31] As discussed in Section 3.6, the equilibrium of the model need not be unique. We follow Tsivanidis (2019) in focusing on the counterfactual equilibrium that is computed using the benchmark equilibrium as the starting point and turns out to be unique. Such counterfactual equilibria may be more likely to occur, for instance, due to path dependence (Allen and Donaldson, 2020).

Figure 6: Telecommute frequency, survey prediction vs. counterfactual model



Note: "Data" reflects averages calculated from the survey by Barrero, Bloom, and Davis (2021) on work from home expectations after Covid-19. "Model" shows values predicted by the calibrated counterfactual model.

Table 6: Relative aversion for remote work, baseline vs. counterfactual

Description	Variable	Benchmark	Conterfactual
non-college, non-tradable	ς_S^L	2.6211	1.3586
non-college, tradable	ς_G^L	2.4137	1.2794
college, non-tradable	ς_S^H	2.6808	1.7357
college, tradable	ς_G^H	2.3711	1.5503

Note: The table shows calibrated values of the relative aversion for remote work.

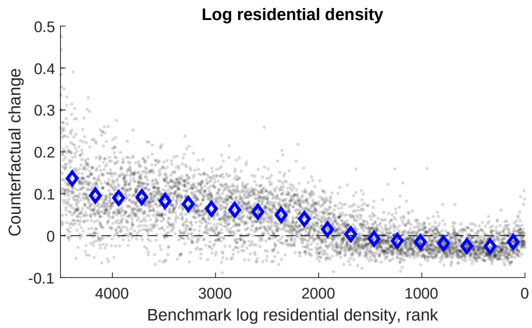
5.2.1 Spatial shifts

Distribution of residents. As panels (a) and (b) in Figure 7 show, increased productivity of remote work leads to a reallocation of residents away from the densest locations and biggest cities, towards sparser locations and smaller cities. While there is much heterogeneity in the changes which is not explained by the crude ranking of locations and cities, the *average* trend is monotonic. In the five largest metro areas, New York's population grows 1%, Chicago's stays nearly the same, and Los Angeles, Dallas and Houston each lose 2%. Appendix Table I.1 provides details for changes in residents in 40 largest metro areas, while Appendix Figure I.2 displays predicted changes in residents on a map.

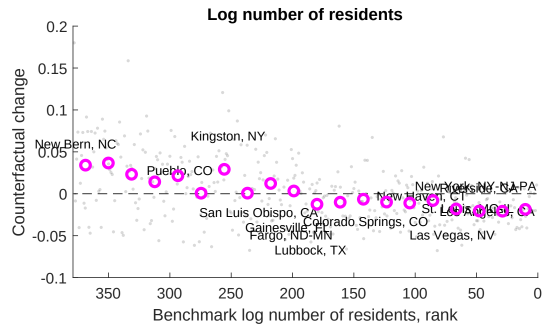
Our base of residents is made up of two distinct groups who react very differently to the

Figure 7: Change in Residents

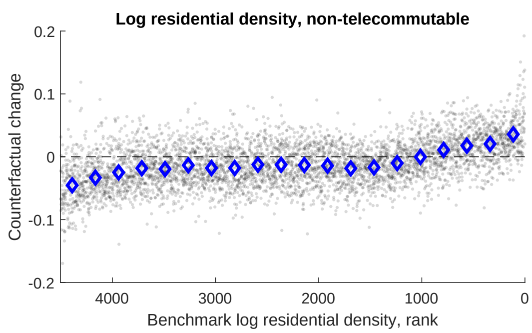
Panel (a): All residents



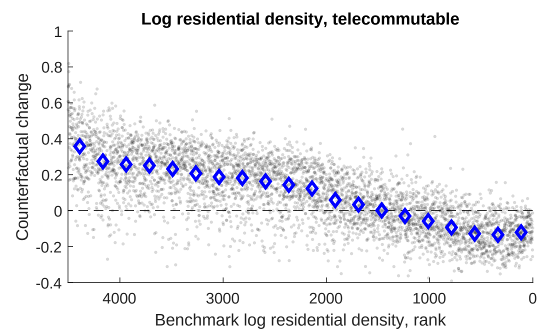
Panel (b): All residents, metropolitan areas



Panel (c): Non-telecommutable



Panel (d): Telecommutable

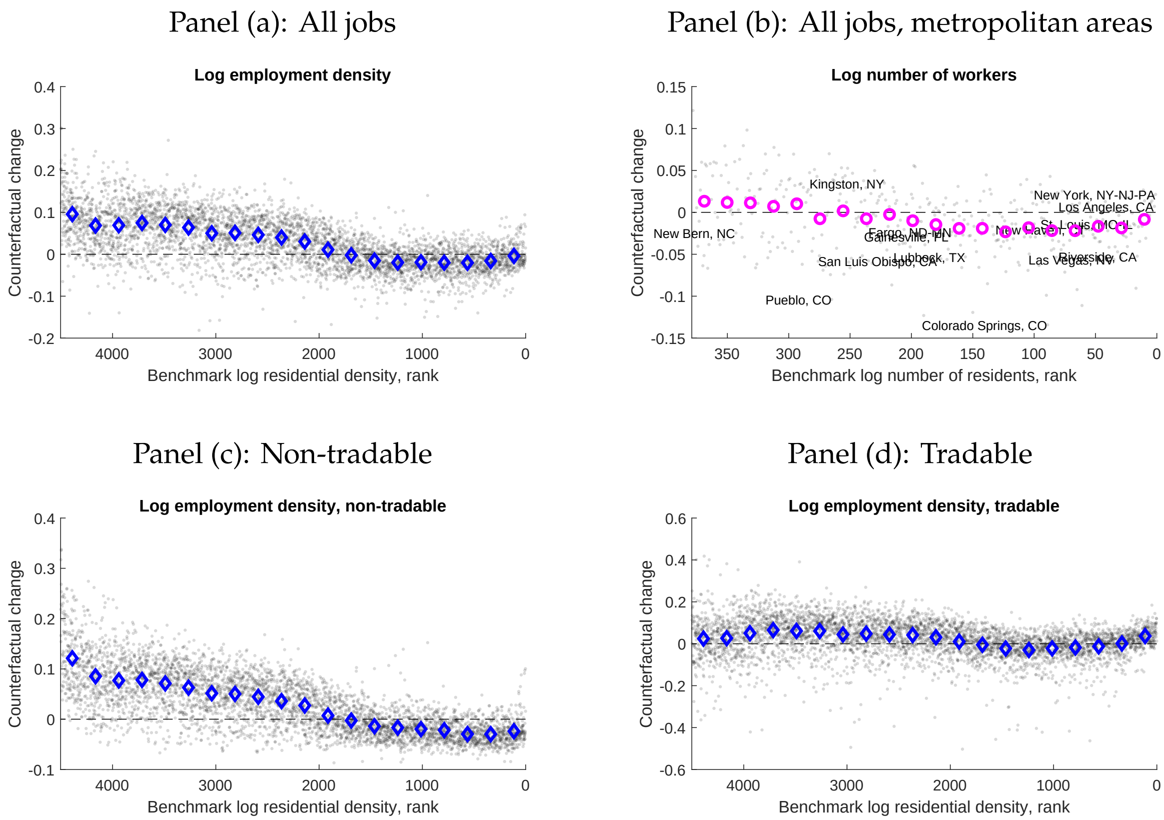


Note: Panel (a) shows the relationship between residential density rank for model locations and counterfactual change in log residential density. Panel (b) shows the relationship between total resident rank for metro areas and the counterfactual change in log total residents. Panel (c) repeats the exercise for non-telecommutable residents by model location, while panel (d) does the same for telecommutable residents. Scatterplots in gray show individual model locations or MSAs, while diamonds or circles represent averages by ventile: i.e. below the 5^{th} percentile, from the 5^{th} to the 10^{th}, etc.

change. Panel (c) shows that non-telecommutable residents shift from less dense locations and smaller cities towards the center. At the same time, panel (d) shows telecommutable residents moving away from denser places towards the periphery. This is because workers who cannot work remotely take advantage of falling prices in city centers and larger cities to relocate closer to better-paying jobs. Meanwhile, remote-capable workers, now facing fewer obstacles to working at home, follow lower prices out of city centers and from larger to smaller cities. The latter trend is stronger and dominates the overall shift in residents–in spite of the fact that telecommutable workers are outnumbered nearly 2 to 1.

Distribution of jobs. In contrast to the overall pattern in the distribution of residents, the shift in the overall distribution of jobs displays some non-monotonicity. As panel (a) in Figure 8 demonstrates, the density of jobs increases on average in locations which are below the median density, while decreasing in locations which are above the median, and

Figure 8: Change in Employment



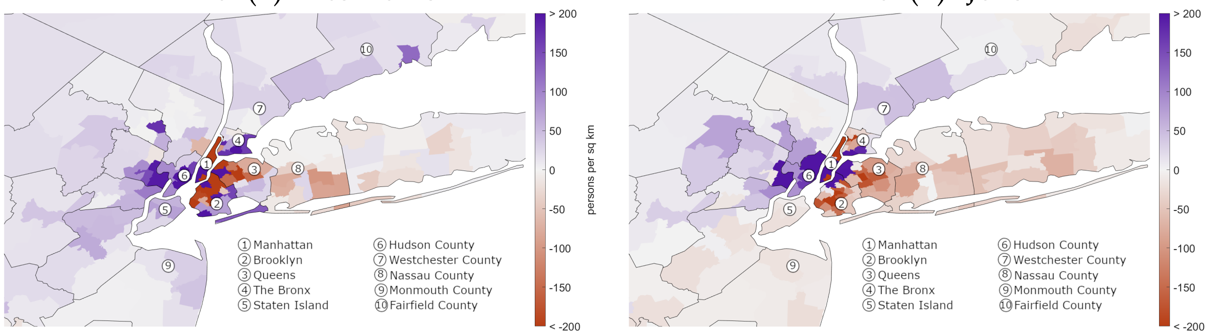
Note: Panel (a) shows the relationship between residential density rank for model locations and counterfactual change in log job density. Panel (b) shows the relationship between total resident rank for metro areas and the counterfactual change in log total jobs. Panel (c) repeats the exercise for non-tradable jobs by model location, while panel (d) does the same for tradable jobs. Scatterplots in gray show individual model locations or MSAs, while diamonds or circles represent averages by ventile: i.e. below the 5th percentile, from the 5th to the 10th, etc.

showing little change in the most-dense locations. A similar pattern is observed at the metro area level, as shown in panel (b). Appendix Table I.2 provides details for changes in jobs in 40 largest metro areas, while Appendix Figure I.3 displays predicted job changes on a map.

Decomposing the changes in job location into the two sectors, we see a differential pattern underlying the aggregate shifts. Panel (c) shows that shifts in non-tradable jobs are monotonic, from less- to more-dense locations. Since demand for non-tradable output comes entirely from the local population, these jobs simply follow the residents. The non-monotonicity in the pattern of job shifts comes from the tradable sector. As can be seen in panel (d), locations below the median gain tradable sector jobs, and so do the very densest locations in the 95th percentile and above. This is because the increased productivity of remote work effectively reduces spatial frictions in the labor market, and two types of

Figure 9: New York metro area, predicted movements of residents and jobs

Panel (a): Residents Panel (b): Jobs



Note: The maps show absolute changes in the number of residents (panel a) or jobs (panel b) per square kilometer in the main counterfactual exercise.

locations win out in this expanded competition. One is low-density locations with low real estate costs. The other is the highest-density locations, with high productivity, and also the biggest reduction in real estate costs, as we will see in our discussion of price changes below.[32]

Zooming in: New York metropolitan area. A closer look at the New York metro area can give us a more concrete idea of how predicted changes in jobs and residents play out at the intra-city level. In panel (a) of Figure 9 we can see that there is a large predicted movement of residents out of most of Manhattan, Brooklyn, and Queens. The Bronx, Staten Island, and isolated locations in Manhattan and Queens see significant inflows. Counties in New Jersey and Connecticut and outlying counties in New York state gain residents. This donut-shaped pattern is consistent with the aggregate patterns we reviewed earlier.

Panel (b) shows changes in jobs. Downtown and midtown Manhattan, the the parts of Brooklyn, Queens, the Bronx, and New Jersey which are closest to Manhattan, all see strong job gains. Employment growth in highly productive areas like these is largely driven by the growth in telecommutable jobs in the tradable sector. The immediate suburbs to the north of the city see moderate gains, while Long Island and suburbs to the south of the city see job losses. Further maps and discussion of results for the New York metro area can be found in Appendix Section F.

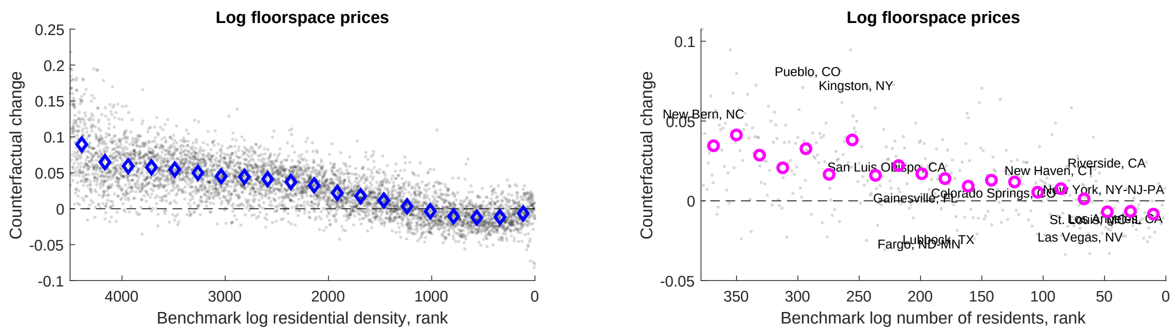
Real estate prices. As a result of reallocation of many residents and some jobs to less dense locations, changes in floorspace prices show a clear negative slope in initial density, as can be seen in Figure 10.[33] Prices increase on average in locations below the top

[32]The correlation between log productivity in the tradable sector and log residents per square km is 0.66.

[33]This prediction is consistent with the evidence documented during the pandemic. Gupta, Peeters,

Figure 10: Floorspace prices

Panel (a): model locations | Panel (b): metropolitan areas



Note: Panel (a) shows the relationship between residential density rank for model locations and counterfactual change in floorspace prices. Panel (b) shows the relationship between total resident rank for metro areas and the counterfactual change in floorspace prices. Scatterplots in gray show individual model locations or MSAs, while diamonds or circles represent averages by ventile: i.e. below the 5$^{\text{th}}$ percentile, from the 5$^{\text{th}}$ to the 10$^{\text{th}}$, etc.

quartile, and decrease in most top-quartile locations.[34] Both the location-level and metro-level patterns are consistent with the previously-seen shift of residents and non-tradable jobs to less-dense locations on average driving up demand for floorspace.

5.2.2 Aggregate Results and Welfare Effects

Table 7 summarizes aggregate results for the main counterfactual scenario, broken down by worker type. In what follows, we will discuss each row in turn.

Income. Workers' income rises by 1.2%, averaging gains by those who can work from home against losses by those who cannot. Among non-telecommutable workers, we see that losses are higher for the college-educated, while among the remote-capable, gains are higher for the highly-educated. In section 5.3 we compare counterfactuals with alternative assumptions, allowing us to infer the reasons for these disparities.

Commuting. As a result of the reduction in aversion for remote work, the average worker lives 29.7% farther, in terms of commuting time, from their workplace, but spends 17.7% less time commuting, because their frequency of work from home has increased by 0.8 days per 5-day work week. Workers who cannot work from home, especially college-educated, move closer to their workplaces and enjoy somewhat shorter commutes. Those

Mittal, and Van Nieuwerburgh (2021) and Liu and Su (2021) find a significant "flattening" of the relationship between prices/rents and distance to the center in major metro areas for residential real estate, while Rosenthal, Strange, and Urrego (2021) report similar relationship for commercial real estate. Althoff, Eckert, Ganapati, and Walsh (2021) also show that rents fell in the densest and went up in the least dense areas.

[34] Appendix Figure I.4 displays predicted rent changes on a map. The right-hand panel shows a similar negative gradient across metro areas, also reversing slightly for the largest metros.

who can work remotely, on the other hand, increase their distance to work by around 51% for college or 85% for non-college, and cut their total commuting time by 48 to 71 percent.

Prices. Average floorspace prices drop by 0.3%. This can be attributed to two complementary forces. First, the increased desire for remote work increases demand for office space in residence locations where prices, on average, are lower than in the dense downtown areas where most jobs are. Second, demand for residential floorspace moves to less dense, more supply-elastic locations which tend to be farther from central areas, and which now face lower effective commuting costs. This relocation of demand is counteracted by the overall rise in worker income, which puts upward pressure on prices. The average price paid for residential floorspace paid by telecommutable workers falls by 1.3% for college-educated and 2.2% for non-college-educated. Non-telecommutable workers move to denser locations. Even though prices are falling on average in these denser locations, they are still more expensive than the peripheral locations they are moving from, leading to slightly higher average floorspace prices for this group.

Non-tradable prices increase by around 2% for everybody. This can be attributed to a combination of the increase in income, and a movement of non-tradable demand to less-dense places which tend to also have lower workplace amenities for the non-tradable sector.[35]

Workers' welfare and landowners' income. Consumption of goods and housing go up for telecommuters and down for non-telecommuters, so that consumption for the average worker declines slightly, by 0.3%. This is the net result of the 1.2% increase in income and the 0.3% fall in floorspace prices, outweighed by the 2.1% increase in the price of non-tradables. Utility loss from lower consumption is more than offset by gains from less time spent commuting–when adding commute times to changes in utility, the average worker comes out 1.7% ahead. Gains from reduced commute times are unevenly distributed, being very large for non-college workers in telecommutable occupations, while non-telecommutable workers gain just 0.1 or 0.3 percentage points.[36] The average worker gains access to slightly better residential amenities. Telecommutable workers actually reduce the quality of their amenities, due to the fact that they move to less dense (and, in our model, lower amenity) locations–effectively trading low housing costs, and possibly a better idiosyncratic match, for lower amenities.

Overall welfare–expected utility prior to the realization of preference shocks–increases by an average of 5.2%. This is the net result of large gains for telecommutable workers and

[35]These are locations where, all else equal, it is harder to attract workers due to lower calibrated employment amenities. Hence, non-tradable firms must pay higher wages and pass on that cost to the consumer.

[36]Since our model does not allow for endogenous reduction in traffic due to less frequent commuting, these welfare gains may be understated.

Table 7: Aggregate results

		non-college			college		
	all workers	all	non-tel.	tel.	all	non-tel.	tel.
Income, % chg	1.2	0.7	-0.3	3.6	2.1	-2.2	4.6
Average time to work, % chg	29.7	27.1	-0.2	84.7	35.2	-0.6	50.6
Time spent commuting, % chg	-17.7	-14.4	-0.2	-71.2	-26.7	-0.6	-48.0
Average WFH days/week, chg	0.8	0.6	–	2.8	1.1	–	2.9
Floorspace prices, % chg	-0.3	-0.1	0.5	-2.2	-0.7	0.3	-1.3
Non-tradables prices, % chg	2.1	2.2	2.2	2.0	2.1	2.2	2.1
Welfare, % chg							
consumption only	-0.3	-0.8	-2.0	2.5	0.7	-3.8	3.2
+ commuting	1.7	0.7	-1.9	8.5	3.5	-3.5	7.7
+ amenities	2.0	0.9	-0.8	5.9	3.7	-1.4	6.7
total welfare	5.2	2.5	-1.4	32.9	16.5	-2.8	22.8

Note: The table shows results of the main counterfactual exercise, as described in the text. "tel." refers to telecommutable workers, and "non-tel." to non-telecommutable workers. Price changes refer to the change in the average price faced by a member of the indicated group of workers.

small changes for the rest.[37] One important reason why welfare gains for those who can telecommute are so large is that, thanks to less frequent commutes, they are able to choose location pairs with higher values of Fréchet shocks, thus satisfying their idiosyncratic preferences for locations. Non-college workers who cannot work from home end up with a 1.4% reduction in overall welfare, while their college-educated counterparts lose 2.8%. This is mostly because a greater proportion of college workers are telecommutable, so the supply of skilled labor falls more for skilled than unskilled labor, meaning that high-skilled wages rise relative to low-skilled. Overall, college workers gain more than non-college ones. This is because even though telecommutable non-college workers gain the most, their numbers are relatively small; while telecommutable workers make up a relatively large proportion of the college-educated group. More details on how we compute welfare changes can be found in Appendix Section B.

One more adjustment to consider is the impact of increased telecommuting on the income earned by landlords. Overall demand for floorspace goes up by 1.4% and, even though it reallocates to places with higher supply elasticity (and, therefore, lower land share), land prices go up by 0.8%. While we do not take a stance on the weight of landlords

[37] Because we do not take a position on whether the calibrated "aversion to telecommuting" parameters, ς^s_m, reflect genuine worker preferences or other kinds of non-pecuniary barriers to remote work, we exclude the shift in these parameters from all welfare change calculations.

in the social welfare function, it is obvious that this increase in landowners' income would amplify aggregate welfare gains from increased remote work.

5.3 Alternative Scenarios

We have presented results from the counterfactual in which all endogenous variables adjust and remote work does not generate productive externalities ($\psi = 0$). To understand the relative roles of each of the channels, we also run a series of alternative counterfactuals in which we first shut down all of the margins of adjustment, and then re-activate them one by one.

We start with a world in which the aversion to telecommuting decreases but workers are unable to move and floorspace supply does not change. Then we switch on the reallocation of workers to new residences and jobs. After that, floorspace supply adjusts. Next, residential amenities and then local productivity adjust. This last stage brings us all the way up to our original focus point–the long run with full adjustment.

Table 8 reports results for each scenario. In counterfactual (1), we see that average welfare rises as soon as remote work becomes more accessible, even before workers can move and floorspace supply can change. However, gains are only experienced by telecommutable workers. These enjoy higher income from a more productive combination of at-home and on-site time, and less time spent commuting. Among those who cannot work from home, non-college workers are slightly better off while college workers have 1.4% lower welfare. This can be attributed to the impact of general equilibrium labor supply changes on income for each group. A larger proportion of college workers are remote-capable, and they are slightly more productive working at home. In the counterfactual this leads to an aggregate increase in the supply of college-educated labor. This bolsters the wages of non-college workers, their complements; and puts downward pressure on the wages of non-telecommutable college workers, who compete directly.

In counterfactual (2), when workers are allowed to choose new jobs and residences but floorspace allocations remain the same, non-telecommutable workers are able to increase their income by moving into jobs in central locations left behind by remote workers. Non-telecommutable workers also take advantage of reduced floorspace demand in central areas to move slightly closer to their jobs, reducing their time spent commuting by 0.4%. We also see a gap emerge between the income gains of college remote-capable workers, and the gains of their non-college counterparts. This can be attributed to an industry composition effect: a greater proportion of college workers are employed in the tradable sector, and are thus able to take advantage of easier remote work to match with

Table 8: Aggregate results, alternative counterfactuals

WFH aversion falls:	✓	✓	✓	✓	✓	✓
Residents and jobs reallocate:	–	✓	✓	✓	✓	✓
Floorspace adjusts:	–	–	✓	✓	✓	✓
Residential amenities adjust:	–	–	–	✓	✓	✓
Labor productivity adjusts:	–	–	–	–	✓	✓
Telecommuters add to productivity:	–	–	–	–	–	✓
	(1)	(2)	(3)	(4)	(5)	(6)
Income, % chg						
all workers	2.7	4.8	2.9	2.9	1.2	2.9
non-college, non-telecommutable	0.3	4.4	1.3	1.4	-0.3	1.4
non-college, telecommutable	7.4	4.7	5.4	5.4	3.6	5.4
college, non-telecommutable	-1.1	3.2	-0.5	-0.5	-2.2	-0.6
college, telecommutable	6.2	6.5	6.4	6.3	4.6	6.3
Floorspace prices, % chg						
residential	1.2	14.2	1.3	0.9	-0.3	0.5
commercial	-3.9	-14.1	–	–	–	–
Non-tradable goods prices, % chg	0.2	1.4	2.2	2.1	2.1	2.1
Average time to work, % chg	0.0	25.6	29.3	29.8	29.7	30.2
Time spent commuting, all workers, % chg	-15.2	-16.1	-17.8	-17.7	-17.7	-17.5
Time spent commuting, commuters ($\theta = 1$), % chg	0.0	-0.4	-0.5	-0.2	-0.3	0.0
Distance traveled, all workers, % chg	-15.2	-16.5	-18.3	-17.9	-18.1	-17.6
Average WFH days/week, chg	0.6	0.7	0.8	0.8	0.8	0.8
Welfare, % chg						
all workers	5.5	5.4	6.6	6.7	5.2	6.8
non-college, non-telecommutable	0.1	0.4	0.0	0.0	-1.4	0.1
non-college, telecommutable	30.4	27.5	34.5	34.9	32.9	35.1
college, non-telecommutable	-1.4	-0.5	-1.4	-1.4	-2.8	-1.4
college, telecommutable	18.6	18.3	24.3	24.5	22.8	24.6
Landlord income, % chg	1.7	21.5	2.6	2.5	0.8	2.4
due to change in demand	1.7	23.2	3.1	3.1	1.4	3.1
due to reallocation to low η_i	0.0	-1.7	-0.5	-0.6	-0.6	-0.7

Note: Columns (1)–(6) present results from counterfactuals with different margins of adjustment turned on, as specified in the header of the table. Welfare changes in columns (2)–(6) are measured as changes in expected utility (equation 3.7). Since in the first counterfactual workers cannot move, welfare changes in column (1) are measured as changes in the utility from consumption and commuting.

more productive job sites. Non-tradable employment, however, follows residents to less productive locations, as evidenced by the increase in non-tradable prices. This reduces income gains for non-college remote workers. This counterfactual also leads to the most extreme shifts in floorspace prices of any of the scenarios we consider–under-utilized, centrally located commercial floorspace faces deep price cuts, while surging demand for residential floorspace drives steep price increases.[38]

In counterfactual (3), allowing floorspace supply to adjust sharply cuts income gains by non-telecommutable workers, as center-city offices are downsized and more employment shifts to less central locations. This also brings double-digit shifts in floorspace prices and land income down to a 1.3% and a 2.6% increase, respectively. The main impact of allowing residential amenities adjust in counterfactual (4) is to cause non-telecommutable workers to choose residences that are slightly farther away from their jobs, as some of the amenities have now followed remote workers out to the suburbs. In counterfactual (5), our main counterfactual, we see the impact of reduced agglomeration externalities from having workers out of the office. Income gains are cut by 1.7 percentage points across the board, in each category of worker.

Finally, we run a counterfactual in which working at home contributes to productive externalities in the main job site as much as working on site ($\psi = 1$). This could happen if remote interaction technology advances to the point that it can fully simulate the experience of being co-located with one's collaborators thus eliminating any disadvantage remote work has in sparking spontaneous spillovers.[39] Comparing columns 6 and 4 of Table 8, we can see that income losses from reduced productivity are neatly reversed under this alternative assumption.

Appendix Section D reproduces a version of Figures 7 and 8 for these alternative counterfactuals, and further discusses the reallocation of residents and jobs in each.

5.4 Evidence During Covid-19

The long-run effects of the Covid-19 shock are yet to be seen, but many changes have already taken place since March 2020. How do the predictions of our model compare to the shifts we have already observed?

To test our model's predictions regarding movement of residents, we use Safegraph data on locations of cell phone devices. For each device, Safegraph assigns a "home location" based on where this device is observed spending the night over a period of six weeks; more details on the data can be found in Appendix Section C.7. Column (1) of Table 9 shows that our predicted changes have a positive and significant relationship with observed changes in the data. Moreover, this correlation does not merely pick up

[38]We are able to distinguish between commercial and residential prices because in this counterfactual floorspace supply is fixed.

[39]The "holodeck" from *Star Trek: The Next Generation* also comes to mind.

Table 9: Change in population during Covid-19, model vs. data

Dependent variable: $\Delta \ln N_{Ri}$, Feb'20–Nov'21	(1)	(2)
$\Delta \ln N_{Ri}$, model	0.9183	0.1229
	(0.0368)	(0.0471)
ln density		-0.0327
		(0.0013)
Observations	4,502	4,502
R^2	0.121	0.227

Note: The table shows estimates from the regressions of log change in residents between Feb. 2020 and Nov. 2021 from the Safegraph data on the log change in residents in the model and log residential density in 2012–2016 (panel b). Standard errors are in parentheses.

the negative relationship between initial residential density and the change in rents.[40] As Column (2) shows, even after controlling for residential density in 2012–2016 our model predictions retain positive and significant correlation with the data. This suggests that structural reasons beyond density, such as changes in the commuter market access, can explain migration patterns during the pandemic.

5.5 Covid-19: a shock to preferences, or technology?

Various authors, including Barrero, Bloom, and Davis (2021), have emphasized the importance of shifting norms and preferences in explaining planned changes in work-from-home behavior following March 2020. At the same time, we believe that there is strong circumstantial evidence for a technology-shock component to the pandemic. At the very least, large investments in remote-complementary capital have been made, and a great deal of learning-by-doing has occurred. Another recent study of working from home, by Davis, Ghent, and Gregory (2021), conducts a simulation of the effects of an increase in working from home which is driven entirely by improved remote-work productivity. We attempt the same within our own framework, and find it to be a highly implausible assumption.

If we assume that planned increases in working-from-home are due to increased remote productivity, instead of changes in preferences, some counterfactual patterns do not change much. We still see an overall decentralization of population and jobs. But the correlation between model predictions of changes in residents and actual shifts in residen-

[40] Althoff, Eckert, Ganapati, and Walsh (2021) and Haslag and Weagley (2021) previously documented a reallocation of residents from the densest to the least dense locations during the pandemic and, as Figure 7 shows, our model also predicts a movement to locations with low density.

tial population observed since February 2020 becomes much lower. And the predicted increases in wages for telecommutable professions–over 40% for college-educated, and over 90% for non-college-educated–are flatly unrealistic.

More details of the results of this alternative counterfactual can be found in Appendix Section E. We believe that it is very likely that both norms/preferences and productivity for remote work have changed, and that the most precise option would be to model both, along with targets that can plausibly identify each effect independently. But based on the evidence from these exercises, we conclude that if the choice is between one cause or the other, it is much more plausible to assume that preferences and norms have driven the bulk of changes in planned working from home behavior.

6 Conclusions

In this paper we have sought to better understand a phenomenon which could reshape our work lives and our cities: telecommuting. We built a quantitative spatial equilibrium model of commuting and remote work crafted to conform with key empirical facts of pre-2020 telework.

We propose that enforced 2020 workplace distancing was primarily a durable shock to attitudes and policies surrounding remote work, which can be represented in a reduced form way as a shock to workers' preferences. We calibrate a counterfactual where surveys of workers' long-run remote work plans come true. Counterfactual predictions for local changes in residents line up well with actual changes observed 2020–2021. Our model foresees decentralization of workers who can work from home, partially counterbalanced by a weaker centralization of those who cannot; a decentralization of non-tradable employment, partially offset by an increase in tradable employment in the densest, most productive places; and a slight reduction in average real estate prices. Those who can work from home benefit greatly, while those who cannot experience welfare losses, especially when remote workers do not contribute to workplace agglomeration externalities.

Furthermore, we provide evidence that a shock to preferences is more plausible as a sole driver of the move to remote work than a technology shock, by showing that an alternative counterfactual in which workers' change in telecommuting plans is due to increased productivity performs poorly in predicting actual changes from 2020 to 2021. We believe that this is a particularly relevant finding, given the lack of agreement among recent papers on remote work as to how the March 2020 shock should be modeled.

To sum up, the impact of remote work may be large, but is unlikely to be catastrophic. There will be no "end to big cities." The average big metro area loses about 2.5% of its population, but the very biggest, New York, actually grows by 1%. Many of the largest, most productive cities will be able to take advantage of geographically expanded competition to lure additional talent from other cities, and call in remote workers from more distant suburbs.

Finally, we believe the substantial impacts of increased telecommuting, both observed and potential, suggest this will be an important consideration for quantitative spatial models in the future.

Bibliography

ACS (2016): American Community Survey, U.S. Census Bureau. https://usa.ipums.org/usa/. Accessed through IPUMS USA, September 2020.

Ahlfeldt, G. M., S. J. Redding, D. M. Sturm, and N. Wolf (2015): "The Economics of Density: Evidence From the Berlin Wall," *Econometrica*, 83(6), 2127–2189.

Albouy, D., and G. Ehrlich (2018): "Housing productivity and the social cost of land-use restrictions," *Journal of Urban Economics*, 107, 101 – 120.

Allen, T., C. Arkolakis, and X. Li (2020): "On the Equilibrium Properties of Network Models with Heterogeneous Agents," Working Paper 27837, National Bureau of Economic Research.

Allen, T., and D. Donaldson (2020): "Persistence and Path Dependence in the Spatial Economy," Working Paper 28059, National Bureau of Economic Research.

Althoff, L., F. Eckert, S. Ganapati, and C. Walsh (2021): "The Geography of Remote Work," Working paper.

Barrero, J. M., N. Bloom, and S. J. Davis (2021): "Why Working from Home Will Stick," Working Paper 28731, National Bureau of Economic Research.

Bartik, A. W., Z. B. Cullen, E. L. Glaeser, M. Luca, and C. T. Stanton (2020): "What Jobs are Being Done at Home During the Covid-19 Crisis? Evidence from Firm-Level Surveys," NBER Working Paper 27422.

Baum-Snow, N., and L. Han (2021): "The Microgeography of Housing Supply," Working Paper.

Behrens, K., S. Kichko, and J.-F. Thisse (2021): "Working from Home: Too Much of a Good Thing?," Working Paper.

Bick, A., and A. Blandin (2021): "Real Time Labor Market Estimates During the 2020 Coronavirus Outbreak," Working paper.

Bick, A., A. Blandin, and K. Mertens (2021): "Work from Home Before and After the COVID-19 Outbreak," Working paper.

Bloom, N., J. Liang, J. Roberts, and Z. J. Ying (2015): "Does working from home work? Evidence from a Chinese experiment," *The Quarterly Journal of Economics*, 130(1), 165–218.

Brueckner, J., M. E. Kahn, and G. C. Lin (2021): "A New Spatial Hedonic Equilibrium in the Emerging Work-from-Home Economy?," Working Paper 28526, National Bureau of Economic Research.

Brynjolfsson, E., J. J. Horton, A. Ozimek, D. Rock, G. Sharma, and H.-Y. TuYe (2020): "COVID-19 and Remote Work: An Early Look at US Data," NBER Working Paper 27344.

Card, D. (2009): "Immigration and Inequality," *American Economic Review*, 99(2), 1–21.

Correia, S., P. Guimarães, and T. Zylkin (2020): "Fast Poisson Estimation with High-Dimensional Fixed Effects," *The Stata Journal*, 20(1), 95–115.

CTPP (2016): Census Transportation Planning Products, American Association of State Highway and Transportation Officials. https://ctpp.transportation.org/ctpp-data-set-information/. Accessed September 2020.

Davis, M. A., A. C. Ghent, and J. M. Gregory (2021): "The Work-at-Home Technology Boon and its Consequences," Working Paper 28461, National Bureau of Economic Research.

Davis, M. A., and F. Ortalo-Magné (2011): "Household Expenditures, Wages, Rents," *Review of Economic Dynamics*, 14(2), 248 – 261.

De Fraja, G., J. Matheson, and J. Rockey (2021): "Zoomshock: The geography and local labour market consequences of working from home," Working paper.

Delventhal, M. J., E. Kwon, and A. Parkhomenko (2021): "JUE Insight: How do cities change when we work from home?," *Journal of Urban Economics*, p. 103331.

Dingel, J. I., and B. Neiman (2020): "How Many Jobs Can Be Done at Home?," *Journal of Public Economics*, 189, 104235.

Dingel, J. I., and F. Tintelnot (2020): "Spatial Economics for Granular Settings," Working Paper.

Eeckhout, J., R. Pinheiro, and K. Schmidheiny (2014): "Spatial Sorting," *Journal of Political Economy*, 122(3), 554 – 620.

Gaspar, J., and E. Glaeser (1998): "Information Technology and the Future of Cities," *Journal of Urban Economics*, 43(1), 136–156.

Glaeser, E., and G. Ponzetto (2007): "Did the Death of Distance Hurt Detroit and Help New York?," NBER Working Papers 13710, National Bureau of Economic Research, Inc.

Graham, M. R., M. J. Kutzbach, and B. McKenzie (2014): "Design Comparison of LODES and ACS Commuting Data Products," Discussion Paper 14-38, U.S. Census Bureau Working Paper.

Gupta, A., J. Peeters, V. Mittal, and S. Van Nieuwerburgh (2021): "Flattening the Curve: Pandemic-Induced Revaluation of Urban Real Estate," Working paper.

Haslag, P. H., and D. Weagley (2021): "From L.A. to Boise: How Migration Has Changed During the COVID-19 Pandemic," Working paper.

Heblich, S., S. J. Redding, and D. M. Sturm (2020): "The Making of the Modern Metropolis: Evidence from London," *Quarterly Journal of Economics*, 135(4), 2059–2133.

Kyriakopoulou, E., and P. M. Picard (2021): "The Zoom City: Working From Home and Urban Land Structure," Working paper.

Larson, W., and W. Zhao (2017): "Telework: Urban form, energy consumption, and greenhouse gas implications," *Economic Inquiry*, 55(2), 714–735.

Lee, E. (2020): "Trade, inequality, and the endogenous sorting ofheterogeneous workers," *Journal of International Economics*, 125, 103310.

Lennox, J. (2020): "More working from home will change the shape and size of cities," Working Paper.

Li, W., and Y. Su (2021): "The Great Reshuffle: Residential Sorting During the COVID-19 Pandemic and Its Welfare Implications," Working paper.

Liu, S., and Y. Su (2021): "The impact of the COVID-19 pandemic on the demand for density: Evidence from the U.S. housing market," *Economics Letters*, 207, 110010.

LODES (2016): Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics, U.S. Census Bureau. https://lehd.ces.census.gov/data/. Accessed September 2020.

Mas, A., and A. Pallais (2020): "Alternative Work Arrangements," *Annual Review of Economics*.

Mongey, S., L. Pilossoph, and A. Weinberg (2020): "Which Workers Bear the Burden of Social Distancing?," Working Paper 27085, National Bureau of Economic Research.

Monte, F., S. J. Redding, and E. Rossi-Hansberg (2018): "Commuting, Migration, and Local Employment Elasticities," *American Economic Review*, 108(12), 3855–90.

NHTS (2017): National Household Transportation Survey, Federal Highway Administration, U.S. Department of Transportation. https://nhts.ornl.gov/ Accessed May 2021.

Ozimek, A. (2020): "Remote Workers on the Move," Upwork Economist Report.

Rhee, H.-J. (2008): "Home-based telecommuting and commuting behavior," *Journal of Urban Economics*, 63(1), 198–216.

Rosenthal, S. S., W. C. Strange, and J. A. Urrego (2021): "JUE insight: Are city centers losing their appeal? Commercial real estate, urban spatial structure, and COVID-19," *Journal of Urban Economics*, p. 103381.

Safirova, E. (2003): "Telecommuting, traffic congestion, and agglomeration: a general equilibrium model," *Journal of Urban Economics*, 52(1), 26–52.

Saiz, A. (2010): "The Geographic Determinants of Housing Supply*," *The Quarterly Journal of Economics*, 125(3), 1253–1296.

SIPP (2018): Survey of Income and Program Participation, U.S. Census Bureau. https://www.census.gov/programs-surveys/sipp/data/datasets/2018-data/2018.html. Accessed September 2020.

Spear, B. D. (2011): *NCHRP 08-36, Task 098 Improving Employment Data for Transportation Planning*. American Association of State Highway and Transportation Officials.

Stanton, C. T., and P. Tiwari (2021): "Housing Consumption and the Cost of Remote Work," Working Paper 28483, National Bureau of Economic Research.

Tsivanidis, N. (2019): "The Aggregate and Distributional Effects of Urban Transit Infrastructure: Evidence from Bogotá's TransMilenio," Working Paper.

Valentinyi, A., and B. Herrendorf (2008): "Measuring factor income shares at the sectoral level," *Review of Economic Dynamics*, 11(4), 820–835.

Zhu, P. (2012): "Are telecommuting and personal travel complements or substitutes?," *The Annals of Regional Science*, 48(2), 619–639.

A Existence and Uniqueness of an Equilibrium

Consider a simplified version of our model with fixed floorspace supply, single industry, and no heterogeneity in education or occupation. Without telework, this model corresponds to a version of Ahlfeldt, Redding, Sturm, and Wolf (2015) for which Allen, Arkolakis, and Li (2020) derive sufficient conditions for existence and uniqueness.

The simplified model's equilibrium can be written as a system of $I \times 3$ equations in floorspace prices, supply of on-site work days, and productivity as

$$q_i^{1+\gamma\epsilon} = \sum_{j \in \mathcal{I}} \frac{\gamma}{\bar{H}_{Ri}} \Phi^{-1/\epsilon} B_{ij}^{\epsilon} \tilde{\mathbb{Q}}_{ij}^{-\epsilon} \mathbb{Q}_{ij}^{\frac{1+\epsilon(1+\alpha(\zeta-1))}{\alpha(\zeta-1)}} \bar{\alpha}^{1+\epsilon} A_j^{\frac{1+\epsilon}{\alpha}}, \tag{A.1}$$

$$N_{WCi} = \sum_{j \in \mathcal{I}} q_i^{-(1-\alpha)(\zeta-1)} q_j^{-\gamma\epsilon} \Phi^{-1/\epsilon} B_{ji}^{\epsilon} \tilde{\mathbb{Q}}_{ji}^{-\epsilon} \mathbb{Q}_{ji}^{\frac{\epsilon+\alpha(\epsilon-1)(\zeta-1)}{\alpha(\zeta-1)}} \bar{\alpha}^{\epsilon} A_i^{\frac{\epsilon}{\alpha}}, \tag{A.2}$$

$$A_i = a_i \left(\frac{N_{WCi}}{\Lambda_i} \right)^{\lambda}, \tag{A.3}$$

where $\bar{H}_{Ri}$ is the exogenous supply of residential floorspace and $\Phi^{1/\epsilon}$ is expected utility. Let $\mathbb{Q}_{ij}^1 \equiv q_j^{-(1-\alpha)(\zeta-1)}$, $\tilde{\mathbb{Q}}_{ij}^1 \equiv \mathbb{Q}_{ij}^1 e^{\kappa t_{ij}}$, and $\mathbb{Q}_{ij}^2 = \nu^{\zeta-1} q_i^{-(1-\alpha)(\zeta-1)} e^{\kappa t_{ij}(1+\alpha(\zeta-1))}$, as well as $\mathbb{Q}_{ij} \equiv \mathbb{Q}_{ij}^1 + \mathbb{Q}_{ij}^2$ and $\tilde{\mathbb{Q}}_{ij} \equiv \tilde{\mathbb{Q}}_{ij}^1 + \mathbb{Q}_{ij}^2$.

Note that the system (A.1)–(A.3) has the form of system (1) in Allen, Arkolakis, and Li (2020) and can be written as $\mathcal{X}_{ih} = \sum_{j \in \mathcal{I}} \mathcal{F}_{ijh} \left(\mathcal{X}_{j1}, \ldots, \mathcal{X}_{jH} \right)$, where h refers to an interaction of a particular type. In our case, there are 3 interactions with $\mathcal{X}_{j1} = q_j$, $\mathcal{X}_{j2} = N_{WCj}$, and $\mathcal{X}_{j3} = A_j$. Let $\mathcal{E}_{ij} \left(\mathcal{X}_h \mathcal{X}_{h'} \right) \equiv \partial \ln \mathcal{F}_{ijh} / \partial \ln \mathcal{X}_{jh'}$. Using results from Allen, Arkolakis, and Li (2020), we can study existence and uniqueness by studying the properties of the 3×3 matrix where each component is given by $\max_{i,j} \left\{ \left| \mathcal{E}_{ij} \left(\mathcal{X}_h \mathcal{X}_{h'} \right) \right| \right\}$.

Because effective effort and commuting costs include additive terms, two out of nine cross-elasticities that form the above-mentioned matrix are location-specific:

$$\mathcal{E}_{ij}(q,q) = \tfrac{1-\alpha}{1+\gamma\epsilon} \left[\epsilon(\zeta-1) \frac{\tilde{\mathbb{Q}}_{ij}^1}{\tilde{\mathbb{Q}}_{ij}} - \tfrac{1+\epsilon(1+\alpha(\zeta-1))}{\alpha} \frac{\mathbb{Q}_{ij}^1}{\mathbb{Q}_{ij}} \right], \tag{A.4}$$

$$\mathcal{E}_{ij}(N_{WC},q) = \begin{cases} \tfrac{1-\alpha}{1+\gamma\epsilon} \left[\epsilon(\zeta-1) \frac{\mathbb{Q}_{ji}^2}{\tilde{\mathbb{Q}}_{ji}} - \tfrac{\epsilon+\alpha(\epsilon-1)(\zeta-1)}{\alpha} \frac{\mathbb{Q}_{ji}^2}{\mathbb{Q}_{ji}} \right] - \tfrac{\gamma\epsilon}{1+\gamma\epsilon} & \text{if } j \neq i, \\ \tfrac{1-\alpha}{1+\gamma\epsilon} \left[\epsilon(\zeta-1) \frac{\tilde{\mathbb{Q}}_{ji}^1}{\tilde{\mathbb{Q}}_{ji}} - \tfrac{\epsilon+\alpha(\epsilon-1)(\zeta-1)}{\alpha} \frac{\mathbb{Q}_{ji}^1}{\mathbb{Q}_{ji}} \right] - \tfrac{\gamma\epsilon+(1-\alpha)(\zeta-1)}{1+\gamma\epsilon} & \text{if } j = i. \end{cases} \tag{A.5}$$

Even though existence and uniqueness may depend on location-specific outcomes, we can check the domain of $\left\{ \tilde{\mathbb{Q}}_{ij}^1 / \tilde{\mathbb{Q}}_{ij}, \mathbb{Q}_{ij}^1 / \mathbb{Q}_{ij}, \mathbb{Q}_{ji}^2 / \tilde{\mathbb{Q}}_{ji}, \mathbb{Q}_{ji}^2 / \mathbb{Q}_{ji} \right\}$ to obtain maximum absolute values of (A.4) and (A.5), given values of α, γ, ϵ, ζ, λ, κ, and ν from our calibrated model (see

Tables 3 and 5).[41] We do so by noticing that $t_{ij} \in [0,\infty)$ and $q_i \in (0,\infty)$. Thus, the matrix of cross-elasticites $\max_{i,j}\left\{\left|\mathcal{E}_{ij}\left(\mathcal{X}_h \mathcal{X}_{h'}\right)\right|\right\}$ for $h \in \{q, N_{WC}, A\}$ is

$$\mathcal{A} \equiv \begin{bmatrix} \frac{1-\alpha}{1+\gamma\epsilon}\frac{1}{1+\nu^{\zeta-1}}\left[\frac{1+\epsilon(1+\alpha(\zeta-1))}{\alpha} - \epsilon(\zeta-1)\right] & 0 & \frac{1+\epsilon}{\alpha} \\ \frac{1-\alpha}{1+\gamma\epsilon}\frac{1}{1+\nu^{\zeta-1}}\left[\frac{\epsilon+\alpha(\epsilon-1)(\zeta-1)}{\alpha} - \epsilon(\zeta-1)\right] + \frac{\gamma\epsilon+(1-\alpha)(\zeta-1)}{1+\gamma\epsilon} & 0 & \frac{\epsilon}{\alpha} \\ 0 & \lambda & 0 \end{bmatrix} \tag{A.6}$$

Existence and uniqueness. According to Theorem 1 in Allen, Arkolakis, and Li (2020), if $\mathcal{A}$ has a spectral radius less than 1, then the equilibrium exists and is unique. For the parameter values in our calibrated model, the spectral radius of $\mathcal{A}$ is 1.13. That is, in the simplified version of our model the equilibrium is not guaranteed to exist and, if it does, multiple equilibria exist.

How does this finding compare to the result of Allen, Arkolakis, and Li (2020) for a model without telework? They find that, as long as the productive externality is weak enough, $\lambda < \min\left\{1-\alpha, \frac{\alpha}{1+\epsilon}\right\}$, the equilibrium is unique. In our model, $\lambda = 0.086$ and $\min\left\{1-\alpha, \frac{\alpha}{1+\epsilon}\right\} = 0.162$. That is, if our simplified model did not have work from home, the externality would be weak enough to yield uniqueness.

Why does the introduction of the ability to substitute on-site and remote work result in multiple equilibria? In a standard model, the extent to which a location with high exogenous productivity attracts workers is amplified via agglomeration externalities but, in turn, is dampened as the number of workers willing to commute there daily is limited. Work from home expands the firm market access (or "catchment area") in such locations so they can attract more workers because they do not have to commute daily. As a result, even modest values of λ can lead to multiple equilibria.

To confirm this reasoning, we found that when $\lambda < 0.056$, the spectral radius of $\mathcal{A}$ is less than 1. We also shut down the ability to telecommute by setting $\zeta = 0$ and $\nu = 0$. In this case, even with $\lambda = 0.086$, the spectral radius is 0.89, and there exists a unique equilibrium. Since in the data only 34% of workers can work remotely, the latter result is highly relevant and, all else equal, makes the multiplicity less likely.

[41]Our calibrated model has multiple values of ν depending on education and industry. We use ν_S^L; however, elasticities $\mathcal{E}_{ij}(q,q)$ and $\mathcal{E}_{ij}(q,N_{WC})$ are relatively insensitive to the value of ν.

B Welfare Changes

Overall welfare. Our measure of worker's welfare is V^{so}, given by (3.7). As v^{so}_{mij} is proportional to optimal composite consumption, $\tilde{w}^{so}_{mij}p_i^{-\beta}q_i^{-\gamma}$, the percentage change in consumption-equivalent welfare is equal to the percentage change in V^{so}. To find the economy-wide change in welfare, we simply compute the percentage change in the weighted-average of V^{so}, i.e., $V \equiv \sum_s \sum_o l^{so} V^{so}$. In our calculations, we adjust the counterfactual disutility of commuting, d^{so}_{mij}, to reflect changes in commuting frequencies but not in ς^s_m, the aversion to work from home.

Sources of welfare gains. We are also interested in the relative roles of changes in consumption, commuting costs, and amenities. To this end, we compute changes in weighted-average indirect utilities and isolate each of these sources. To measure the part from *consumption only*, we compute

$$V^{so}_{\mathrm{C}} = \sum_m \sum_i \sum_j \pi^{so}_{mij}\tilde{w}^{so}_{mij}p_i^{-\beta}q_i^{-\gamma}. \tag{B.1}$$

The part from *consumption and commuting costs* is computed as

$$V^{so}_{\mathrm{CC}} = \sum_m \sum_i \sum_j \pi^{so}_{mij}\left(1/d^{so}_{mij}\right)\tilde{w}^{so}_{mij}p_i^{-\beta}q_i^{-\gamma}. \tag{B.2}$$

Finally, the contribution of *consumption, commuting costs, and amenities* to welfare is computed as

$$V^{so}_{\mathrm{CCA}} = \sum_m \sum_i \sum_j \pi^{so}_{mij}X^s_{mi}E^s_{mj}\left(1/(g_{ij}d^{so}_{mij})\right)\tilde{w}^{so}_{mij}p_i^{-\beta}q_i^{-\gamma}. \tag{B.3}$$

The effect of amenities comes both from endogenous changes in residential amenities X^s_{mi} and migration to places with different amenities. As in the case of total welfare, we adjust d^{so}_{mij} to reflect changes in commuting frequencies but not in the telework aversion.

Landlord's income. We do not take a stance on the weight of landlords in the social welfare function and compare changes in their income alongside changes in workers' welfare. Landlords' only income source are proceeds from land sales, and their aggregate income is

$$\sum_i \eta_i H_i. \tag{B.4}$$

C Data

C.1 Telecommuting Frequencies

To study the frequency of working from home for individuals in various industries and education levels, we use the data from the 2018 Survey of Income and Program Participation (SIPP). The survey asks how many full paid work days a survey respondent worked in a reference week. We focus our analysis on full-time workers 16 years or older who are not self-employed. Our estimates are based on a final sample of 261,757 observations.

C.2 Local Wage Indices

Our sources of wage data is the Census Transportation Planning Products (CTPP), aggregated at the Census tract level, and microdata from the American Community Survey (ACS). We use the data reported for the 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.[42]

We calculate mean labor earnings for tract k as $\bar{w}_k = \left(\sum_b N_{b,k}\bar{w}_b\right) / \sum_b N_{b,k}$, where $N_{b,k}$ is the number of workers in bin b in tract k, and $\bar{w}_b$ 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 estimate

$$\bar{w}_k = \alpha + \beta_1 age_k + \beta_2 sexratio_k + \sum_r \beta_{2,r} race_{r,k} + \sum_d \beta_{3,d} ind_{d,k} + \sum_o \beta_{4,o} occ_{o,k} + \epsilon_k, \tag{C.1}$$

where age_k is the average age of workers; $sexratio_k$ is the proportion of males to females in the labor force; $race_{r,j}$ is the share of race $r \in \{Asian, Black, Hispanic, White\}$; $ind_{d,k}$ is the share of jobs in industry d; and $occ_{o,k}$ is share of jobs in occupation o in tract k.[43] The

[42]The 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 $\geq \$100,000$.

[43]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.

estimated tract-level wage index is the sum of the estimated constant and the tract fixed effect: $\hat{w}^0_k \equiv \hat{\alpha} + \hat{\epsilon}_k$. We then construct wage indices for each model location j, $\hat{w}^0_j$ as the employment-weighted average of the values of $\hat{w}^0_k$ for each tract k that pertains to location j.

Then, using microdata from the American Community Survey (ACS), we calculate average wage premia for college over non-college workers, and tradable industry over non-tradable industry workers, separately at the place-of work public-use microdata area (POWPUMA) level, and assume that they are uniform across all model locations belonging to a single POWPUMA.[44] Let the college wage premium for model location j be designated ϕ^H_j, and for the sake of concision of presentation let us also define a non-college wage "premium" $\phi^L_j = 1$ that is normalized to 1. Let the tradable industry premium for model location j be defined as ρ^G_j, while the non-tradable premium $\rho^S_j = 1$ is normalized to 1.

For each location j, we need the two sets of conditions to hold. First, the relationships between the wages paid to different education and industry categories implied by the "premia" we have just defined: $\hat{w}^s_{mj}/\hat{w}^{s'}_{m'j} = \left(\phi^s_j \rho^m_j\right) / \left(\phi^{s'}_j \rho^{m'}_j\right)$ for $s, s' \in \{H, L\}$ and $m, m' \in \{G, S\}$. Second, we need the average wage to match the one derived from the data, given the relative prevalence of each type of worker: $\sum_s \sum_m \hat{w}^s_{mj} \pi^s_{mj} = \hat{w}^0_j$, where conditional choice probabilities $\pi^s_{mj} \equiv \sum_i \sum_o \pi^{so}_{mij}$, reflecting the total number of workers of each education level and industry with jobs in j, from all residence locations and occupations, are constructed as follows: we observe $\pi_{mj} \equiv \sum_s \sum_i \sum_o \pi^{so}_{mij}$ for each location, and observe $\pi^s_{m0} \equiv \sum_i \sum_j \sum_o \pi^{so}_{mij}$ at the economy-wide level, and assume that the educational composition of industry does not vary by location: $\pi^s_{mj} = \pi_{mj} \pi^s_{m0}$.

Manipulating these two sets of conditions, we can calculate $\hat{w}^s_{mj}$ in the following way. First, the average wage for college-educated tradable workers, as a function of $\hat{w}^0_j$:

$$\hat{w}^H_{Gj} = \frac{\hat{w}^0_j}{\sum_s \sum_m \frac{\phi^s_j \rho^m_j}{\phi^H_j \rho^G_j} \sum_i \sum_o \pi^{so}_{mij}}. \tag{C.2}$$

Then, wages for each category $s \in \{H, L\}$ and $m \in \{G, S\}$ are given by $\hat{w}^s_{mj} = \frac{\phi^s_j \rho^m_j}{\phi^H_j \rho^G_j} \hat{w}^H_{Gj}$. These are then translated into wages in the model w^s_{mj}, according to the following equation:

$$w^s_{mj} = \frac{\left(\hat{w}^s_{mj}\right)^\alpha}{\alpha^\alpha (1-\alpha)^{1-\alpha}} \left(\frac{\sum_i \sum_o \pi^{so}_{mij}}{\sum_i \sum_o \pi^{so}_{mij} \Omega^{so}_{mij}} \right)^\alpha. \tag{C.3}$$

[44] POWPUMAs are larger than PUMAs and even in dense urban areas often correspond to counties.

C.3 Work-from-Home Wage Premia

We estimate differences between the wages of telecommuters and non-telecommuters from the 2012–2016 ACS. We identify those who work from home full time as individuals who responded to the question about means of transportation to work as "worked at home." For workers with telecommutable occupations only, for each industry/education category separately, we regress log wages on a dummy variable for working from home full time, controlling for age, sex, race, industry, occupation, and PUMA of residence. Our sample includes a total of 4.7 million observations.

C.4 Telecommuters' Distance to Job Sites

To study the relationship between the propensity to work at home and the distance between home and job site, we use data from the 2017 National Household Transportation Survey (NHTS). We focus on full time workers in the 48 contiguous United States and Washington, D.C. Bins for each commuting frequency are constructed as follows: 5 days per week telecommuters reported working from home more than 90% of the days in a 21.67-day average work month; 4 days–between 90% and 70%, 3 days–between 70% and 50%, etc. Sample sizes for each bin are as follows. 0 days: 75,607 observations, representing 92,488,935 workers (90.64% of the overall sample); 1 day: 4,691 obs., 5,775,808 workers (5.66%); 2 days: 1,789 obs., 2,058,022 workers (2.02%); 3 days: 773 obs., 886,423 workers (0.87%); 4 days: 105 obs., 137,542 workers (0.13%); 5 days at home: 547 obs., representing 695,002 workers (0.68%). The distance between home and job site is great circle distance as reported in the database. Those who reported working from home over 22 days a month are excluded.

C.5 Local Rent Indices

We measure local rents by constructing hedonic rent indices at the level of PUMAs as in Eeckhout, Pinheiro, and Schmidheiny (2014). In cases when a PUMA contains more than one model location we assign the same index to all. We use the 2016 5-year ACS sample tabulated by the IPUMS (ACS, 2016).[45] To construct local rent indices, we use self-reported rents and estimate the following regression,

$$\ln \mathbf{q}_{\iota,it} = \beta_0 + \boldsymbol{\beta}_1 X_{\iota,it} + \varphi_i + \varphi_t + \varepsilon_{\iota,it}, \tag{C.4}$$

[45]We keep only household heads to ensure that the analysis is at the level of a residential unit. We exclude observations who live in group quarters; live in farm houses, mobile homes, trailers, boats, tents, etc.; are younger than 18 years old; and live in a dwelling that has no information on the year of construction.

where $\mathbf{q}_{\iota,it}$ is the rent reported by household ι in PUMA i and year t, while $\mathcal{X}_{\iota,it}$ is a vector of controls that includes the number of rooms in the dwelling, the number of units in the structure (e.g., single-family detached, 2-family building), and the year of construction. Parameters φ_i and φ_t are PUMA and year fixed effects, respectively, and $\varepsilon_{\iota,it}$ is the error term. The rent index, $\mathbf{Q}_i$, represents the rent after controlling for the observable characteristics listed before and idiosyncratic effects, and is given by $\mathbf{Q}_i \equiv \exp(\beta_0 + \varphi_i)$.

C.6 Estimation of 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 American Community Survey (ACS) data.[46] Travel times are reported for a little over 4 million trajectories, 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 them. We process this data in the following steps.

First, we calculate average travel time between each pair of locations as the average of all tract-to-tract times with an origin inside one location and a destination in the other. We throw out the calculation for any pair for which less than 10% of all possible tract-to-tract times is reported by CTPP. We also exclude times that imply a speed of more than 100 km/hour or less than 5 km/hour. We perform this same calculation for average distance of each location *from itself*, obtaining data-based estimates of internal travel time for each location.

Second, 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 any are missing, we project a one using estimated coefficients of a regression of average location-to-location travel times on average great circle distance and an indicator of origin = destination. This procedure adds ≈10,000 additional links, out of 20,268,004 possible location-to-location trajectories.

Finally, we take the ≈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.

[46] The 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.

C.7 Safegraph Location Data

Safegraph tracks and collects information from approximately 20 million of mobile devices in the US, and uses this information to construct geographical location data. Home locations are determined based on where mobile devices are detected at nighttime. In order to obtain an estimate of the change in the residence patterns during the 18 months beginning in February 2020, we take the number of devices resident in each Census Block Group in both February 2020 and August 2021. We aggregate these counts up to the level of model locations, and calculate the share of devices found in each location. Finally we calculate the percentage point change in these shares for each location over time.

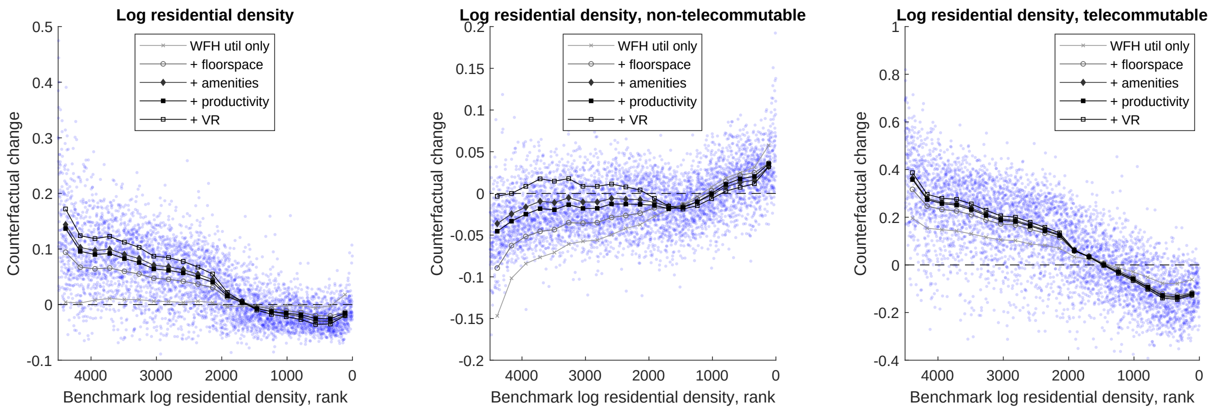
D Further Discussion of Alternative Counterfactuals

Figure D.1 plots reallocations of residents across counterfactuals (2) through (6). Obviously, in the first counterfactual, there is no reallocation of residents. Panel (a) shows the overall reallocation. Here, we see that each step accentuates the initial pattern–a net movement of residents from denser to less dense locations. Panels (b) and (c) break this down by occupation type, and reveal a heterogeneous pattern. For workers who can work from home in panel (c), things look similar to the overall average–each successive step accentuates reallocation from center to periphery. For workers who cannot work from home, in panel (b), the opposite happens–the reallocation from periphery to center is strongest in the second and third counterfactuals. In the fourth and fifth counterfactuals the reallocation into the city is smaller, as the telecommuting workers end up carrying a part of the city's amenities out with them. Finally, in the sixth counterfactual, increased productivity in the periphery draws additional non-telecommutable workers out. In this scenario, non-telecommutable workers move out of medium-density locations, into both peripheral and central locations.

Figure D.2 plots reallocations of jobs across the second through sixth counterfactuals. As with residents, each successive step accentuates the main pattern of reallocation towards less dense locations. Glancing at panel (b), it is clear this is mostly driven by non-tradable sector jobs following the movement of residents. Looking at panel (c), it is interesting to note that the variations between counterfactuals (2), (3), (4), and (5) have very little effect on the reallocation of tradable jobs. Reallocations of labor in the tradable sector are driven by the broadening of the labor market which is already fully operative by counterfactual (2). In counterfactual (6), however, less-dense locations see a significant jump in competitiveness, as remote workers begin contributing to local TFP.

Figure D.1: Change in residents, counterfactuals (2)–(6)

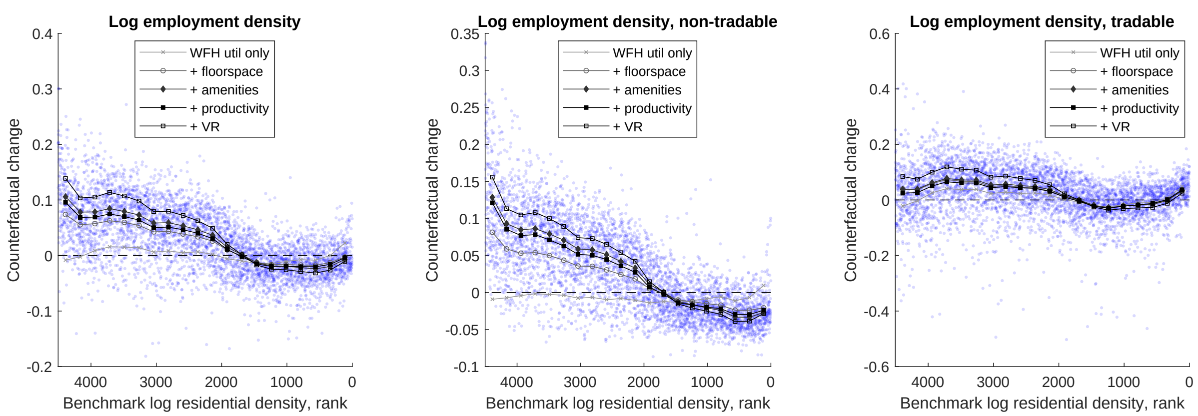
Panel (a): all workers | Panel (b): non-telecommutable | Panel (c): telecommutable



Note: This figure shows the relationship between residential density rank of model locations and counterfactual change in resident density for all residents (panel a), non-telecommutable residents (panel b), and telecommutable residents (panel c). The scatterplot in blue shows individual datapoints, and black and gray markers plot averages by ventile: i.e. below the 5th percentile, from the 5th to the 10th, and so on.

Figure D.2: Change in jobs, counterfactuals (2)–(6)

Panel (a): all workers | Panel (b): non-tradable | Panel (c): tradable



Note: This figure shows the relationship between residential density rank of model locations and counterfactual change in job density for all jobs (panel a), non-tradable jobs (panel b), and tradable jobs (panel c). The scatterplot in blue shows individual datapoints, and black and gray markers plot averages by ventile: i.e. below the 5th percentile, from the 5th to the 10th, and so on.

E Counterfactual: Increased Productivity of Remote Work

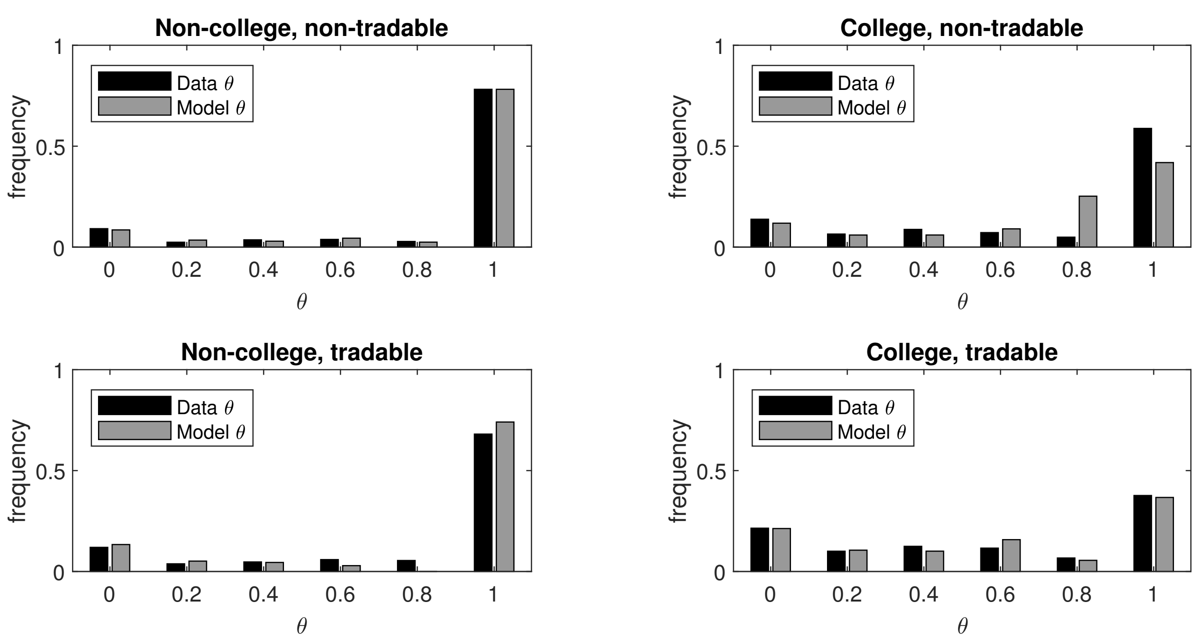
In this section we consider a counterfactual in which increased working from home is due solely to increased productivity, rather than solely to changes in preferences as in the baseline counterfactual. While many of the patterns are similar to those seen in the baseline, it produces unrealistic increases in the wages of telecommuters, and performs poorly in predicting where people have actually moved since February 2020. Table E.1 reports the changes in productivity of work from home required to attain the predicted increase in work from home frequency. The productivity of remote work must go up by about 90% for non-college and by about 53% for college workers in both sectors.

Table E.1: Relative productivity of remote work, baseline vs. counterfactual

Description	Variable	Benchmark	Conterfactual	% change
non-college, non-tradable	ν_S^L	0.9752	1.8817	92.96%
non-college, tradable	ν_G^L	1.1014	2.0817	89.01%
college, non-tradable	ν_S^S	1.0193	1.5660	53.63%
college, tradable	ν_G^S	1.1356	1.7396	53.18%

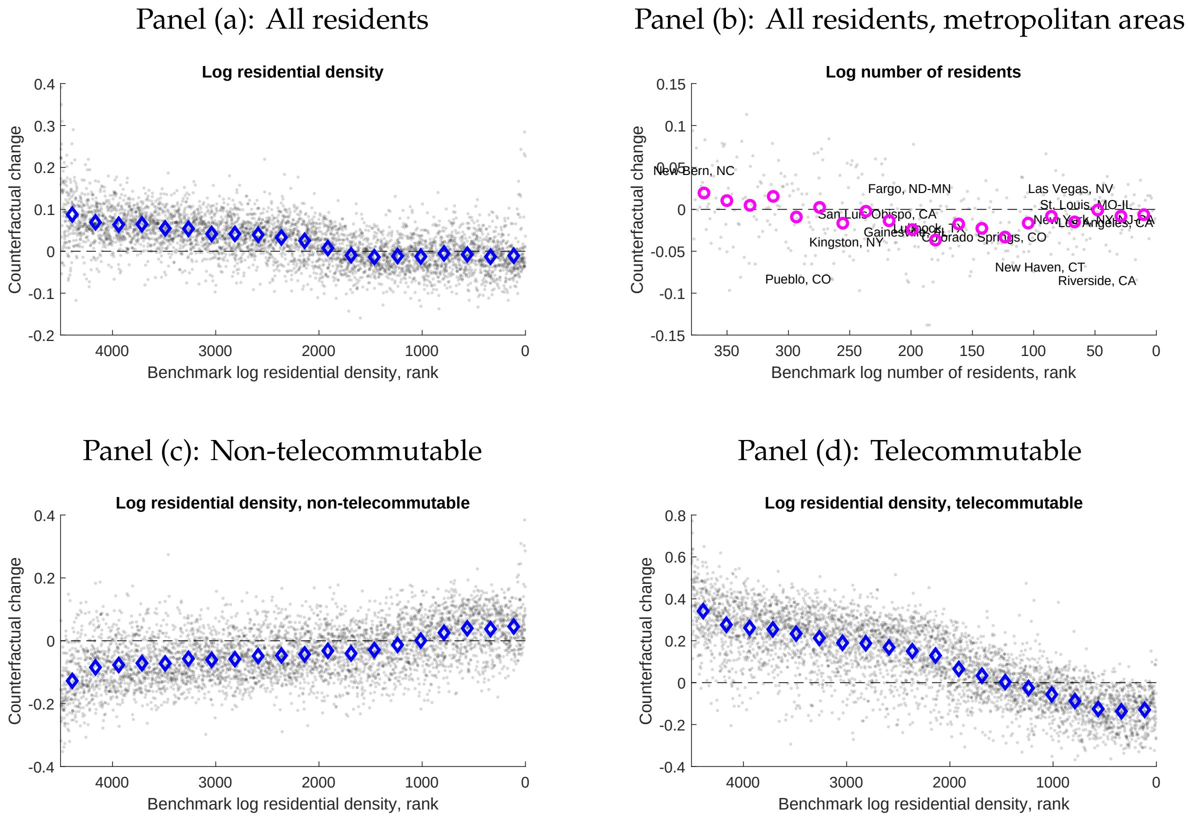
Note: The table shows calibrated values of the relative productivity of remote work.

Figure E.1: Telecommute frequency, survey prediction vs. counterfactual model



Note: "Data" reflects averages calculated from the survey by Barrero, Bloom, and Davis (2021) on work from home expectations after Covid-19. "Model" shows values predicted by the calibrated counterfactual model.

Figure E.2: Change in Residents



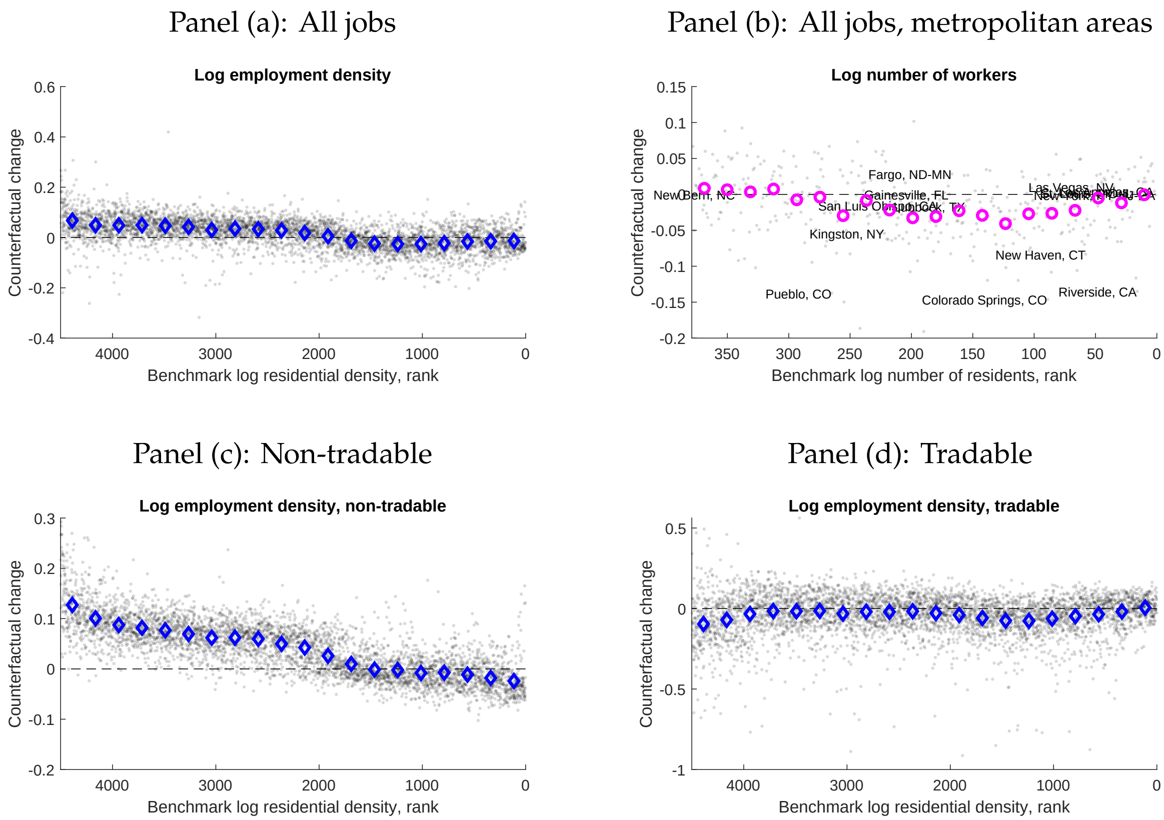
Note: Panel (a) shows the relationship between residential density rank for model locations and counterfactual change in log residential density. Panel (b) shows the relationship between total resident rank for metro areas and the counterfactual change in log total residents. Panel (c) repeats the exercise for non-telecommutable residents by model location, while panel (d) does the same for telecommutable residents. Scatterplots in gray show individual model locations or MSAs, while diamonds or circles represent averages by ventile: i.e. below the 5th percentile, from the 5th to the 10th, etc.

Distribution of telecommuting frequency. Figure E.1 compares the distributions of commuting frequency indicated by the Barrero, Bloom, and Davis (2021) survey with those predicted in the counterfactual. These distributions are similar to those in the baseline counterfactual (see Figure 6).

Distributions of residents and jobs. Comparing Figure E.2 with Figure 7, we can see that the overall patterns are similar, except that the pattern of decentralization of residents among the densest locations and largest metro areas is more mixed. Next, comparing Figure E.3 with Figure 8, we can see that as with residents, the overall patterns of job reallocation are similar between this and the baseline counterfactual. The main driving force for the shifts in residents and jobs is greater attractiveness of work from home, whether due to lower aversion to it or due to its higher productivity.

Aggregate results and welfare effects. Table E.2 reports aggregate results from this

Figure E.3: Change in Employment



Note: Panel (a) shows the relationship between residential density rank for model locations and counterfactual change in log job density. Panel (b) shows the relationship between total resident rank for metro areas and the counterfactual change in log total jobs. Panel (c) repeats the exercise for non-tradable jobs by model location, while panel (d) does the same for tradable jobs. Scatterplots in gray show individual model locations or MSAs, while diamonds or circles represent averages by ventile: i.e. below the 5^{th} percentile, from the 5^{th} to the 10^{th}, etc.

counterfactual. Comparing with Table 7, we can see that changes in aggregate commuting behavior are similar. This is not surprising, as the same changes in average telecommuting frequencies are targeted in the calibration. However, the predictions for changes in income are very different. An average worker earns nearly 24% more, with the increase driven entirely by telecommutable workers. Among these, college workers earn 42% more, while non-college workers earn over 90% more. We find it hard to call the prediction of such increases in the wages of telecommutable professions, due solely to technological changes in the year or so after March 2020, anything but very unrealistic.

Evidence during Covid-19. Finally, we compare this counterfactual's predictions about reallocations of residents with observed migration in 2020 and 2021, as we did in Section 5.4. Comparing Table E.3 with Table 9, we can see that when it is assumed that increased work from home is driven only by productivity, the model is a much poorer predictor of shifts in residential population since February 2020. Once initial density is controlled for, in fact, model projections are uncorrelated with actual changes. This is in contrast to the baseline counterfactual, which is a significant predictor of actual changes, even after density controls.

Table E.2: Aggregate results

		non-college			college		
	all workers	all	non-tel.	tel.	all	non-tel.	tel.
Income, % chg	23.8	22.8	-0.8	90.7	25.5	-3.8	42.3
Average time to work, % chg	33.6	30.3	-1.1	96.3	40.9	-1.5	59.2
Time spent commuting, % chg	-17.6	-14.6	-1.1	-69.1	-25.7	-1.5	-45.5
Average WFH days/week, chg	0.8	0.6	–	2.7	1.1	–	2.8
Floorspace prices, % chg	14.9	15.1	15.9	12.6	14.4	15.6	13.6
Non-tradables prices, % chg	5.6	5.7	5.7	5.7	5.5	5.5	5.5
Welfare, % chg							
consumption only	15.5	14.5	-7.9	78.4	17.3	-10.5	33.0
+ commuting	15.1	14.1	-7.6	78.3	16.8	-10.0	32.6
+ amenities	15.6	14.6	-5.1	73.0	17.3	-5.9	31.2
total welfare	15.7	8.9	-6.8	133.8	43.8	-8.8	60.9

Note: The table shows results of the counterfactual exercise in which the rise of telecommuting is driven by an increase in the productivity of work from home, as described in the text. "tel." refers to telecommutable workers, and "non-tel." to non-telecommutable workers. Price changes refer to the change in the average price faced by a member of the indicated group of workers.

Table E.3: Change in population during Covid-19, model vs. data

Dependent variable: $\Delta \ln N_{Ri}$, Feb'20–Nov'21	(1)	(2)
$\Delta \ln N_{Ri}$, model	0.8362	-0.0467
	(0.0472)	(0.0517)
ln density		-0.0356
		(0.0011)
Observations	4,502	4,502
R^2	0.0651	0.226

Note: The table shows estimates from the regressions of log change in residents between Feb. 2020 and Nov. 2021 from the Safegraph data on the log change in residents in the counterfactual experiment and log residential density in 2012–2016 (panel b). Standard errors are in parentheses.

F In focus: New York Metropolitan Area

In Section 5.2 of the main paper, we discussed how the reduction in the work-from-home aversion affects the largest metropolitan area in the country–New York. Here we provide a more in-depth discussion of spatial changes in the New York metro area.

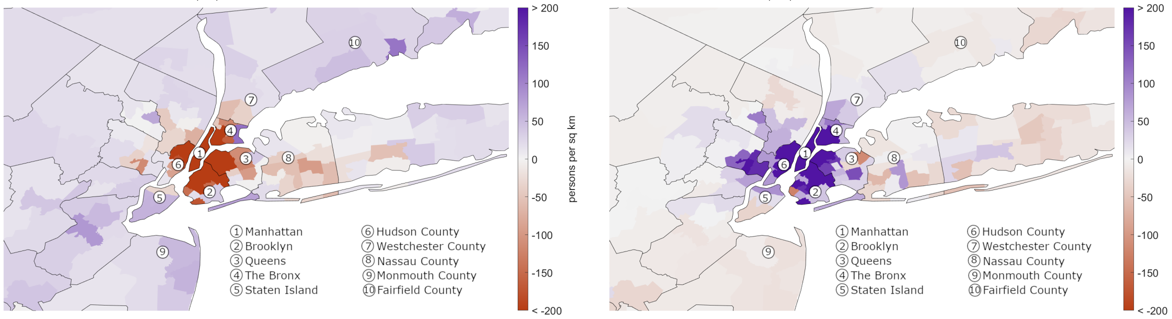
Figure 9 showed reallocation patters for all residents and all jobs. Let us now take a look at the breakdown of movements of residents. As panel (a) of Figure F.1 makes clear, workers with telecommutable occupations overwhelmingly leave central areas and move to peripheral areas–the same pattern we see countrywide. In panel (b), we see workers with non-telecommutable occupations move downtown in signficiant numbers, off-setting much of the telecommutable exodus.

Panel (a) of Figure F.2, we see a heavy exodus of tradable industry jobs from nearly all locations near the center of the city. At the same time, panel (b) shows strong tradable industry job gains for downtown, with some losses in peripheral suburbs.

Panel (a) in Figure F.3 maps changes in floorspace prices, which are most strongly negative in downtown Manhattan, and positive in many outlying areas. Panel (b) maps changes in the price of non-tradables. In outlying areas they mostly increase, which can be interpreted as indicating that rising demand from more residents overwhelms the cost-lowering effect of lower floorspace prices. In some of the most central locations the price of non-tradables falls, indicating that the effect of lower floorspace prices dominates.

Figure F.1: New York metro area, predicted resident movements by occupation

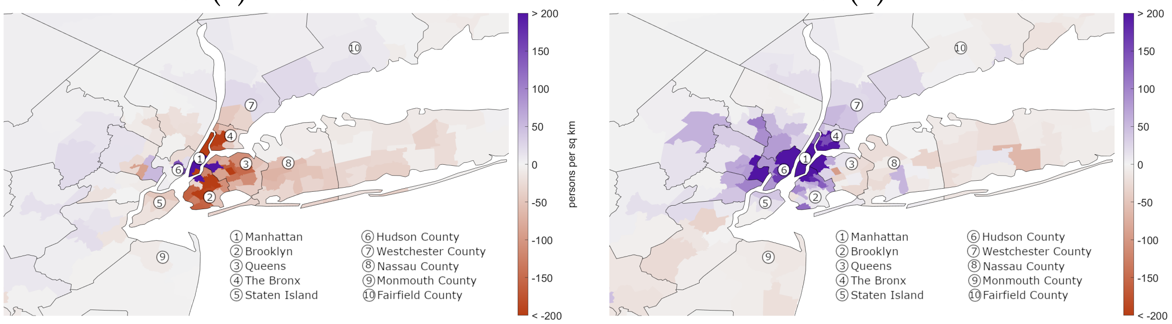
Panel (a): Telecommutable Panel (b): Non-telecommutable



Note: The maps show absolute changes in the number of telecommutable residents (panel a) and non-telecommutable residents (panel b) per square kilometer in the main counterfactual exercise.

Figure F.2: New York metro area, predicted job movements by industry

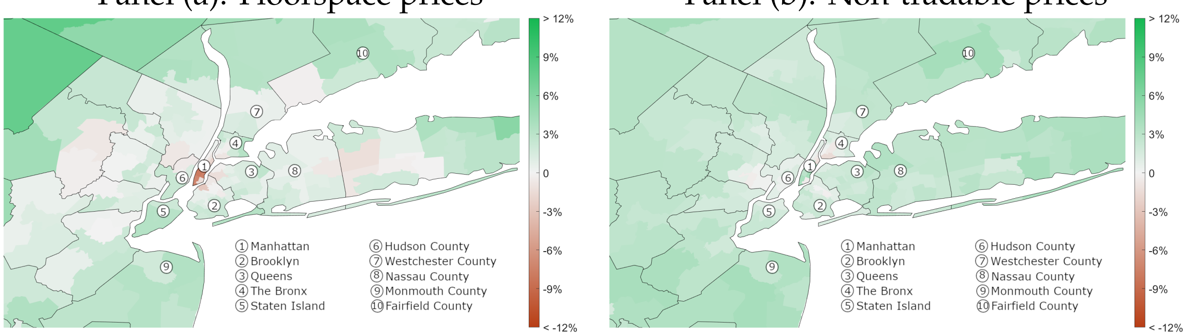
Panel (a): Non-tradable Panel (b): Tradable



Note: The maps show absolute changes in the number of non-tradable jobs (panel a) and tradable jobs (panel b) per square kilometer in the main counterfactual exercise.

Figure F.3: New York metro area, predicted price changes

Panel (a): Floorspace prices Panel (b): Non-tradable prices



Note: The maps show percentage changes in floorspace prices (panel a) and non-tradable goods prices (panel b) in the main counterfactual exercise.

G Robustness

G.1 No Penalty for Living Far from Job Site

One of the innovations of our framework is the penalty for living far from the job site that applies regardless of the frequency of commuting, g_{ij}. How different would our results be if we excluded g_{ij} from the location choice problem?

To answer this question, we recalibrate our model by imposing $\tau = 0$ which implies that $g_{ij} = 1$ for all location pairs. Without the penalty, those workers who commute very infrequently are almost completely untethered from their job sites and can live virtually anywhere, contrary to the evidence on the locations of telecommuters that constitutes *stylized fact* #4 in Section 2. Column 2 of Table G.1 shows that all changes that we observed in our main counterfactual exercise (column 1) are greatly amplified: telecommutable workers relocate farther from job sites and their welfare gains are much more pronounced.

G.2 Equal Reduction in Work-from-Home Aversion

In our main counterfactual, we found that non-college workers experience somewhat larger reductions in their aversion to remote work. This gives boost to counterfactual welfare gains experienced by non-college workers, even though their welfare still increases by only 2.5%, compared to 16.5% for college workers. How sensitive are our results to the differences in calibrated changes in dislike for telework?

We recalibrate the post-COVID economy so that the aggregate reduction in work-from-home aversion is the same for all workers in all industries by targeting the overall, not education-industry specific, increase in work from home. The calibrated fall in the aversion parameter, ς_m^s is 41% for all types of workers. Column 3 of Table G.1 compares the results of this counterfactual to the main counterfactual (column 1). The welfare gap between college and non-college workers becomes even wider–now the welfare of college graduates jumps by over 20%, while the welfare of non-college workers goes up by merely 1.9%.

G.3 Equal Floorspace Supply Elasticities

In our quantitative model, we use estimates of floorspace supply elasticities from Baum-Snow and Han (2021). To our knowledge, these are the only estimates at a sufficiently high level of resolution (Census tracts) that can be applied to our model locations (see the map of elasticities in Figure I.5). At the same time, these elasticities are significantly lower than those estimated in prior literature (see discussion in Section 4.2.1).

To evaluate the sensitivity of our results to these elasticities, we re-calibrate the model by assigning the elasticity of 1.75 (this corresponds to $\eta_i = 0.36$), as found in Saiz (2010), to all model locations. Column 4 of of Table G.1 compares the results of this counterfactual to the main counterfactual (column 1). All results are quite close to the main counterfactual, which suggests that our predictions are robust to our choice of housing supply elasticities.

Table G.1: Aggregate results, robustness counterfactuals

	(1) Main CF	(2) $\tau = 0$	(3) Same chg ς_m^s	(4) Same η_i
Income, % chg				
all workers	1.2	1.0	1.5	1.2
non-telecommutable	-0.7	0.5	-0.6	-0.7
telecommutable	4.2	1.8	4.8	4.0
Floorspace prices, % chg	-0.3	-1.7	-0.2	-0.9
Non-tradable goods prices, % chg	2.1	3.5	2.4	1.8
Average time to work, % chg	29.7	185.1	29.4	30.7
Time spent commuting, all workers, % chg	-17.7	-20.0	-17.8	-17.5
Time spent commuting, commuters ($\theta = 1$), % chg	-0.3	-0.2	-0.3	0.1
Distance traveled, all workers, % chg	-18.1	-21.2	-17.9	-17.4
Average WFH days/week, chg	0.8	0.9	0.8	0.8
Welfare, % chg				
all workers	5.2	29.5	5.5	5.3
non-college	2.5	20.7	1.9	2.6
college	16.5	52.8	20.2	16.3
non-telecommutable	-1.5	-1.5	-1.6	-1.4
telecommutable	26.6	79.2	28.1	26.8
Landlord income, % chg	0.8	-0.1	1.1	1.3
due to change in demand	1.4	1.3	1.7	1.3
due to reallocation to low η_i	-0.6	-1.3	-0.6	0.0

Note: Results of several alternative counterfactuals described in the text, as compared to the main counterfactual.

H Model Inversion and Calibration

H.1 Inversion and Calibration Algorithm

In order to obtain the values of location-specific fundamentals $\tilde{a}_{mi} \equiv a_{mi}\Lambda_i^{-\lambda}$, $\tilde{x}^s_{mi} \equiv x^s_{mi}\Lambda_i^{-\chi}$, $\tilde{\phi}_i \equiv \phi_i\Lambda_i$, X_{mi}, X^s_i, E_{mj}, E^s_j, and ω_{mj}, as well as economy-wide parameters ν^s_m for $m \in \{S, G\}$ and $s \in \{H, L\}$, ς^s_m for $m \in \{S, G\}$ and $s \in \{H, L\}$, τ, and β, we invert the model using the following sequence of steps.

1. Guess the values of X_{mi}, X^s_i, E_{mj}, E^s_j, ν^s_m, ς^s_m, τ, and β.

2. Perform the following sequence:

   (a) Solve for industry and location choice probabilities, π^{so}_{mij}, using equation (3.3) and compute residential population and employment by education and industry as follows: $N_{Rmi} = \sum_s \sum_o \sum_j \pi^{so}_{mij}$, $N^s_{Ri} = \sum_o \sum_m \sum_j \pi^{so}_{mij}$, $N_{Wmj} = \sum_s \sum_o \sum_i \pi^{so}_{mij}$, and $N^s_{Wj} = \sum_o \sum_m \sum_i \pi^{so}_{mij}$.

   (b) Solve for optimal commuting frequency, θ^{so}_{mij}, using equation (3.13) and find the average for each (m, s) type: $\bar{\theta}^s_m \equiv \left(\sum_o \sum_i \sum_j \pi^{so}_{mij}\theta^{so}_{mij}\right) / \left(\sum_o \sum_i \sum_j \pi^{so}_{mij}\right)$.

   (c) Compute the average distance between residence and job site for "commuters" ($\theta > 0.9$) and "telecommuters" ($\theta \leq 0.9$), and then calculate the ratio of the two numbers, as in equation (4.2).

   (d) Solve for optimal effort Ω^{so}_{mij} and commuting costs, as a function of optimal commuting frequency, d^{so}_{mij}, using equations (3.11) and (3.2), respectively.

   (e) Solve for wages and disposable income: (i) convert wages observed in the tradable sector in the data to the measure of wages used in the model using equation (C.3); (ii) find disposable income using equation (3.12).[47]

   (f) Combine equations (3.16) and (3.19) to find ω_{mj}:

$$\omega_{mj} = \left[1 + \left(\frac{w^H_{mj}}{w^L_{mj}}\right)^{\frac{1+\alpha(\xi-1)}{\alpha\xi}} \left(\frac{\sum\limits_o \sum\limits_i \pi^{Lo}_{mij}\Omega^{Lo}_{mij}}{\sum\limits_o \sum\limits_i \pi^{Ho}_{mij}\Omega^{Ho}_{mij}}\right)^{\frac{1}{\xi}}\right]^{-1} \tag{H.1}$$

   (g) Solve for labor productivity in the non-tradable sector using the data on prices of non-tradables and equation (3.22).

[47] As discussed in Section H.2, our model is overidentified because employment amenities determine both local employment by industry and education and the college wage premium in the non-tradable sector. Thus, we take wages in the tradable sector directly from the data, while wages in the non-tradable sector are determined within the model.

(h) Compute the ratio between mean wages in tradable/non-tradable sectors, as in equation (4.3).

(i) Compute for each industry/education pair the ratio between mean wages for telecommutable workers with $\theta > .9$, and those with $\theta < .1$.

(j) Update $\bar{X}_{mi}$, $\bar{X}^s_i$, $\bar{E}_{mj}$, $\bar{E}^s_j$: increase $\bar{X}_{mi}$ if the value of N_{Rmi} in the model is lower than in the data, reduce it otherwise; increase $\bar{X}^s_i$ if the value of N^s_{Ri} in the model is lower than in the data, reduce it otherwise; increase $\bar{E}_{mj}$ if the value of N_{Wmj} in the model is lower than in the data, reduce it otherwise; increase $\bar{E}^s_j$ if the value of N^s_{Wj} in the model is lower than in the data, reduce it otherwise.

(k) Update the WFH aversion ς^s_m: increase ς^s_m if the average θ of type (m, s) in the data is greater than the value of $\bar{\theta}^s_m$; reduce ν^s_m otherwise.

(l) Update the WFH productivity ν^s_m: increase ν^s_m if the wage ratio between telecommutable workers with $\theta < 0.1$ to those with $\theta > 0.9$ is lower than the wage gap between those who work from home full-time to those who commute full time in the data; reduce ν^s_m otherwise.

(m) Update τ: increase τ if the ratio of average distance between residence and job site for "commuters" to "telecommuters" is higher in the model than its data counterpart; reduce τ otherwise.

(n) Update the non-tradables expenditure share β: increase β if the ratio between mean wages in tradable/non-tradable sectors is lower in the model than in the data; decrease β otherwise.

(o) Return to step (2a) and repeat the sequence, unless moments computed in steps (2a), (2b), (2c), and (2h) in the model are equal to their counterparts in the data within a tolerance limit.

3. Construct education-industry amenities as $X^s_{mi} = X_{mi}X^s_i$ and $E^s_{mj} = E_{mj}E^s_j$.

4. Compute the exogenous part of amenities, $\tilde{x}^s_{mi} \equiv x^s_{mi}\Lambda_i^{-\chi}$, using equation (3.27) as follows: $\tilde{x}^s_{mi} = X^s_{mi}/\left(N_{Ri}\right)^{\chi}$, where N_{Ri} and N_{WTj} are constructed using probabilities computed in step (2a).

5. Compute the exogenous part of productivity, $\tilde{a}_{mi} \equiv a_{mi}\Lambda_i^{-\lambda}$, using equation (3.26) as follows: $\tilde{a}_{mi} = A_{mj}/\left(N_{WCj} + \psi N_{WTj}\right)^{\lambda}$, where N_{WCj} and N_{WTj} are constructed from choice probabilities computed in step (2a), and commuting frequencies computed in step (2b). Figure I.6 shows calibrated values of A_{mj} on a map.

6. Compute floorspace demand H_i and then compute construction sector productivities, $\tilde{\phi}_i \equiv \phi_i\Lambda_i$, using equations (3.24) and (3.25) as follows: $\tilde{\phi}_i = H_i q_i^{-\frac{1}{\eta_i}}(1-\eta_i)^{-\frac{1-\eta_i}{\eta_i}}$.

H.2 Proof of Proposition 1: Existence and Uniqueness of Model Inversion

In what follows we prove that there exists a unique set of parameters consistent with the data being an equilibrium of the model.[48] These parameters are $\tilde{a}_{mi} \equiv a_{mi}\Lambda_i^{-\lambda}$, $\tilde{x}^s_{mi} \equiv x^s_{mi}\Lambda_i^{-\chi}$, $\tilde{\phi}_i \equiv \phi_i\Lambda_i$, X_{mi}, X^s_i, E_{mj}, E^s_j, and ω_{mj}.

Existence and uniqueness of employment amenities. Recall that we assume that employment amenities can be split into an education- and an industry-specific component as $E^s_{mj} = E_{mj}E^s_j$. Note that once the markets for non-college and college labor, as well as labor in the non-tradable industry clear, the market for labor in the tradable industry will clear as well. Thus, we can normalize $E_{Gj} = 1$ for all j. Define composite employment amenities as a function of amenities per se and wages:

$$\hat{E}_{mj}\hat{E}^s_j = E_{mj}E^s_j w^s_{mj}. \tag{H.2}$$

In equilibrium, these three labor market clearing conditions must hold in each location:

$$D^L_{Wj}\left(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right) \equiv N^L_{Wj} - \sum_i N^L_{Ri} \sum_o \left[\frac{\left(\hat{E}_{Sj}\hat{E}^L_j\Phi^{Lo}_{Sij}\right)^\epsilon}{\sum_{j'}\left(\hat{E}_{Sj'}\hat{E}^L_{j'}\Phi^{Lo}_{Sij'}\right)^\epsilon} n^{Lo}_{RSi} + \frac{\left(\hat{E}^L_j\Phi^{Lo}_{Gij}\right)^\epsilon}{\sum_{j'}\left(\hat{E}^L_{j'}\Phi^{Lo}_{Gij'}\right)^\epsilon} n^{Lo}_{RGi}\right] = 0, \tag{H.3}$$

$$D^H_{Wj}\left(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right) \equiv N^H_{Wj} - \sum_i N^H_{Ri} \sum_o \left[\frac{\left(\hat{E}_{Sj}\hat{E}^H_j\Phi^{Ho}_{Sij}\right)^\epsilon}{\sum_{j'}\left(\hat{E}_{Sj'}\hat{E}^H_{j'}\Phi^{Ho}_{Sij'}\right)^\epsilon} n^{Ho}_{RSi} + \frac{\left(\hat{E}^H_j\Phi^{Ho}_{Gij}\right)^\epsilon}{\sum_{j'}\left(\hat{E}^H_{j'}\Phi^{Ho}_{Gij'}\right)^\epsilon} n^{Ho}_{RGi}\right] = 0, \tag{H.4}$$

$$D_{WSj}\left(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right) \equiv N_{WSj} - \sum_i N_{RSi} \sum_o \left[\frac{\left(\hat{E}_{Sj}\hat{E}^L_j\Phi^{Lo}_{Sij}\right)^\epsilon}{\sum_{j'}\left(\hat{E}_{Sj'}\hat{E}^L_{j'}\Phi^{Lo}_{Sij'}\right)^\epsilon} n^{Lo}_{RSi} + \frac{\left(\hat{E}_{Sj}\hat{E}^H_j\Phi^{Ho}_{Sij}\right)^\epsilon}{\sum_{j'}\left(\hat{E}_{Sj'}\hat{E}^H_{j'}\Phi^{Ho}_{Sij'}\right)^\epsilon} n^{Ho}_{RSi}\right] = 0, \tag{H.5}$$

where $\Phi^{so}_{mij} \equiv \frac{1}{g_{ij}d^{so}_{mij}}\frac{\Omega^{so}_{mij}}{p_i^\beta q_i^\gamma}$ and $n^{so}_{Rmi} \equiv N^{so}_{Rmi}/N_{Rmi}$.[49] Note that d^{so}_{mij} and Ω^{so}_{mij} are functions of observed floorspace prices and the productivity of telework. Each of these conditions are of the form of the market clearing condition (S.43) in Ahlfeldt, Redding, Sturm, and Wolf (2015). Thus, using the same steps as in their Lemma S.6, we can show that function

[48] The proof follows closely Ahlfeldt, Redding, Sturm, and Wolf (2015) (see Propositions S.3 and S.4 in their appendix) but requires extra steps due to the nature of our model and data. When appropriate, we refer to lemmas and equations in their proof.

[49] Even though employment shares n^{so}_{Rmi} are unobserved, their presence does not change the properties of market clearing conditions that are required for the set of employment amenities to exist and be unique.

$D^s_{Wj}\left(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right)$ is continuous, homogeneous of degree zero, and exhibits gross substitution in $\hat{\mathbf{E}}^s$ for all $s \in \{L, H\}$. Similarly, function $D_{WSj}\left(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right)$ is continuous, homogeneous of degree zero, and exhibits gross substitution in $\hat{\mathbf{E}}^S$. Moreover, $\sum_j D^s_{Wj}\left(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right) = 0$ and $\sum_j D_{WSj}\left(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right) = 0$ for all $s \in \{L, H\}$, $j \in \mathcal{I}$, and $\left\{\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right\} \in \mathbb{R}^I_+ \times \mathbb{R}^I_+ \times \mathbb{R}^I_+$.

Next, using the same steps as in Lemma S.7 in Ahlfeldt, Redding, Sturm, and Wolf (2015), we can demonstrate that, given the parameters $\{\epsilon, \kappa, \tau, \alpha, \zeta, \nu^s_m\}$ and observables $\{\mathbf{N}_{Wm}, \mathbf{N}_{Rm}, \mathbf{q}, \mathbf{p}, \mathbf{t}\}$: (1) conditional on $\hat{\mathbf{E}}_S$, there exists a unique vector $\hat{\mathbf{E}}^L$ that solves (H.3) for all j; (2) conditional on $\hat{\mathbf{E}}_S$, there exists a unique vector $\hat{\mathbf{E}}^H$ that solves (H.4) for all j; and (3) conditional on $\left\{\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H\right\}$, there exists a unique vector $\hat{\mathbf{E}}_S$ that solves (H.5) for all j. However, uniqueness of each vector of employment amenities conditional on another vector does not imply that the set of vectors $\left\{\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right\}$ consistent with labor market clearing is unique. In order to show that it is indeed unique, we employ a strategy similar to the first part of the proof of Lemma S.7 in Ahlfeldt, Redding, Sturm, and Wolf (2015).

Lemma H.1. Given the parameters $\{\epsilon, \kappa, \tau, \alpha, \zeta, \nu^s_m, \varsigma^s_m\}$ observables $\{\mathbf{N}_{Wm}, \mathbf{N}_{Rm}, \mathbf{q}, \mathbf{p}, \mathbf{t}\}$, there exist a unique set of vectors $\left\{\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right\}$ such that conditions (H.3), (H.4), and (H.5) hold for all j.

Proof. The existence of $\left\{\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right\}$ is guaranteed by the existence of each separate vector $\hat{\mathbf{E}}^L$, $\hat{\mathbf{E}}^H$, and $\hat{\mathbf{E}}_S$ that solves equations (H.3), (H.4), and (H.5), respectively, that we established above. Below we show that this set is also unique.

Denote by $D_W\left(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right)$ a stacked $3I \times 1$ vector that is composed of $D^L_{Wj}\left(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right)$, $D^H_{Wj}\left(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right)$, and $D_{WSj}\left(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right)$ for all j. Suppose that there exist two sets $\left\{\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right\}$ and $\left\{\tilde{\mathbf{E}}^L, \tilde{\mathbf{E}}^H, \tilde{\mathbf{E}}_S\right\}$ such that $\left\{\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right\} \neq \left\{\tilde{\mathbf{E}}^L, \tilde{\mathbf{E}}^H, \tilde{\mathbf{E}}_S\right\}$, while $D_W\left(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right) = D_W\left(\tilde{\mathbf{E}}^L, \tilde{\mathbf{E}}^H, \tilde{\mathbf{E}}_S\right) = \mathbf{0}$. By homogeneity of degree zero, we can rescale each of $\tilde{\mathbf{E}}^L$, $\tilde{\mathbf{E}}^H$, and $\tilde{\mathbf{E}}_S$ such that $\tilde{E}^L_j \geq \hat{E}^L_j$, $\tilde{E}^H_j \geq \hat{E}^H_j$, and $\tilde{E}_{Sj} \geq \hat{E}_{Sj}$ for all j, whereas $\tilde{E}^L_i = \hat{E}^L_i$, $\tilde{E}^H_i = \hat{E}^H_i$, and $\tilde{E}_{Si} = \hat{E}_{Si}$ for some i. Next, consider adjusting $\left\{\tilde{\mathbf{E}}^L, \tilde{\mathbf{E}}^H, \tilde{\mathbf{E}}_S\right\}$ to $\left\{\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right\}$ in $I-1$ steps. By gross substitution, the excess labor demand in location i cannot decrease in any step and must increase in at least one step. Therefore, $D^L_{Wi}\left(\tilde{\mathbf{E}}^L, \tilde{\mathbf{E}}^H, \tilde{\mathbf{E}}_S\right) > D^L_{Wi}\left(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right)$, $D^H_{Wi}\left(\tilde{\mathbf{E}}^L, \tilde{\mathbf{E}}^H, \tilde{\mathbf{E}}_S\right) > D^H_{Wi}\left(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right)$, and $D_{WSi}\left(\tilde{\mathbf{E}}^L, \tilde{\mathbf{E}}^H, \tilde{\mathbf{E}}_S\right) > D_{WSi}\left(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right)$, a contradiction. Thus, there exists a unique set of vectors $\left\{\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right\}$ such that $D_W\left(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right) = \mathbf{0}$. □

Existence and uniqueness of residential amenities. We can also define the following labor market clearing conditions in terms of the number of residents:

$$D_{Rj}^{L}\left(\mathbf{X}^{L},\mathbf{X}^{H},\mathbf{X}_{S}\right)\equiv N_{Rj}^{L}-\sum_{j}N_{Wj}^{L}\sum_{o}\left[\frac{\left(X_{Si}X_{i}^{L}\Phi_{Sij}^{Lo}\right)^{\epsilon}}{\sum_{i'}\left(X_{Si'}X_{i'}^{L}\Phi_{Si'j}^{Lo}\right)^{\epsilon}}n_{WSj}^{Lo}+\frac{\left(X_{i}^{L}\Phi_{Gij}^{Lo}\right)^{\epsilon}}{\sum_{i'}\left(X_{i'}^{L}\Phi_{Gi'j}^{Lo}\right)^{\epsilon}}n_{WGj}^{Lo}\right]=0, \tag{H.6}$$

$$D_{Rj}^{H}\left(\mathbf{X}^{L},\mathbf{X}^{H},\mathbf{X}_{S}\right)\equiv N_{Rj}^{H}-\sum_{j}N_{Wj}^{H}\sum_{o}\left[\frac{\left(X_{Si}X_{i}^{H}\Phi_{Sij}^{Ho}\right)^{\epsilon}}{\sum_{i'}\left(X_{Si'}X_{i'}^{H}\Phi_{Si'j}^{Ho}\right)^{\epsilon}}n_{WSj}^{Ho}+\frac{\left(X_{i}^{H}\Phi_{Gij}^{Ho}\right)^{\epsilon}}{\sum_{i'}\left(X_{i'}^{H}\Phi_{Gi'j}^{Ho}\right)^{\epsilon}}n_{WGj}^{Ho}\right]=0, \tag{H.7}$$

$$D_{RSj}\left(\mathbf{X}^{L},\mathbf{X}^{H},\mathbf{X}_{S}\right)\equiv N_{RSj}-\sum_{j}N_{WSj}\sum_{o}\left[\frac{\left(X_{Si}X_{i}^{L}\Phi_{Sij}^{Lo}\right)^{\epsilon}}{\sum_{i'}\left(X_{Si'}X_{i'}^{L}\Phi_{Si'j}^{Lo}\right)^{\epsilon}}n_{WSj}^{Lo}+\frac{\left(X_{Sj}X_{i}^{H}\Phi_{Sij}^{Ho}\right)^{\epsilon}}{\sum_{i'}\left(X_{Si'}X_{i'}^{H}\Phi_{Si'j}^{Ho}\right)^{\epsilon}}n_{WSj}^{Ho}\right]=0. \tag{H.8}$$

Then we could proceed exactly as above to show that there exists a unique set $\{\mathbf{X}^L,\mathbf{X}^H,\mathbf{X}_S\}$ consistent with those market clearing conditions.

Lemma H.2. Given the parameters $\{\epsilon,\kappa,\tau,\alpha,\zeta,\nu_m^s,\varsigma_m^s\}$ and observables $\{\mathbf{N}_{Wm},\mathbf{N}_{Rm},\mathbf{q},\mathbf{p},\mathbf{t}\}$, there exists a unique set of vectors $\{\mathbf{X}^L,\mathbf{X}^H,\mathbf{X}_S\}$ such that conditions (H.6), (H.7), and (H.8) hold for all j.

Proof. The proof is identical to the proof of Lemma H.1. □

Decomposition of wages and employment amenities. We have shown the uniqueness of composite employment amenities that incorporate wages (equation H.2). Given that we observe wages by education and industry for each model location, we can now decompose the amenities in the tradable sector $\hat{\mathbf{E}}_G^s$ into a non-wage component $\mathbf{E}_G^s$ and wages. We can also determine the college premium, w_{Sj}^H/w_{Sj}^L, but not wage levels, in the non-tradable sector.

Lemma H.3. Given the parameters $\{\epsilon,\kappa,\tau,\alpha,\zeta,\nu_m^s,\varsigma_m^s\}$ observables $\left\{\mathbf{N}_{Wm},\mathbf{N}_{Rm},\mathbf{q},\mathbf{p},\mathbf{t},\hat{\mathbf{w}}_G^s\right\}$, there exists a unique vector $\mathbf{E}_G^s$ for each $s\in\{L,H\}$ and a unique college wage premium in the non-tradable sector.

Proof. Note, by inspection of the indirect utility function (3.1) and choice probability (3.3), that uniqueness of $\left\{\hat{\mathbf{E}}^L,\hat{\mathbf{E}}^H,\hat{\mathbf{E}}_S\right\}$ and $\mathbf{X}_m^s$ implies that choice probabilities are also unique, conditional on observables. Here each element of $\mathbf{X}_m^s$ is $X_{mi}^s=X_i^sX_{mi}$ This means that there is a unique mapping between education-industry-specific wages in the tradable sector observed in the data, $\hat{w}_{Gj}^s$, and their model counterpart, w_{Gj}^s, as given by equation (C.3). Once wages are known, we can solve for $E_j^s=\hat{E}_j^s/w_{Gj}^s$, where we used the fact that $\hat{E}_{Gj}=1$.

Next, observe that in the non-tradable sector, $\hat{E}^s_j \hat{E}_{Sj} = E^s_j E_{Sj} w^H_{sj}$. Though we cannot separately identify amenities from wages, we can determine the college wage premium as

$$\frac{w^H_{Sj}}{w^L_{Sj}} = \frac{\hat{E}^H_j \hat{E}_{Sj}}{\hat{E}^L_j \hat{E}_{Sj}} \frac{\hat{E}^L_j}{\hat{E}^H_j}, \tag{H.9}$$

since both ratios on the right-hand side are identified. □

Existence and uniqueness of local productivities. The following result demonstrates that there are unique vectors of parameters that determine local productivity in tradable sector, non-tradable sector, and construction that are consistent with observed data and unobserved skill and occupation shares.

Lemma H.4. Given the parameters $\{\epsilon, \kappa, \tau, \alpha, \zeta, \nu^s_m, \varsigma^s_m\}$, observables $\left\{\mathbf{N}_{Wm}, \mathbf{N}_{Rm}, \mathbf{q}, \mathbf{p}, \mathbf{t}, \hat{\mathbf{w}}^s_G\right\}$, employment amenities in the tradable sector $\mathbf{E}^s_G$, college wage premium in the non-tradable sector w^H_{Sj}/w^L_{Sj}, and residential amenities $\mathbf{X}^s_m$, there exist unique vectors $\omega_m \in \mathbb{R}^I_{++}$ and $\mathbf{A}_m \in \mathbb{R}^I_{++}$ for each $m \in \{G, S\}$, and a unique vector $\tilde{\phi} \in \mathbb{R}^I_{++}$.

Proof. There is sufficient information to construct a unique matrix of choice probabilities. Thus, the results follow immediately from equation (H.1), the zero-profit condition (3.21), and the land and floorspace market clearing conditions, (3.24) and (3.25). □

Wages in the non-tradable sector. Note that our model is overidentified because employment amenities determine both local employment by industry and education and, as shown in equation (H.9), the college wage premium in the non-tradable sector. Thus, while our quantitative model takes wages in the tradable sector directly from the data, wages in the non-tradable sector are determined within the model. To identify wages in the non-tradable sector, we use the values of $\mathbf{A}_m$ and ω_m, and equation (3.15).

Existence and uniqueness of exogenous components of amenities and productivity. The last result demonstrates that there are unique vectors of parameters that determine local amenities that are consistent with observed data and unobserved skill and occupation shares.

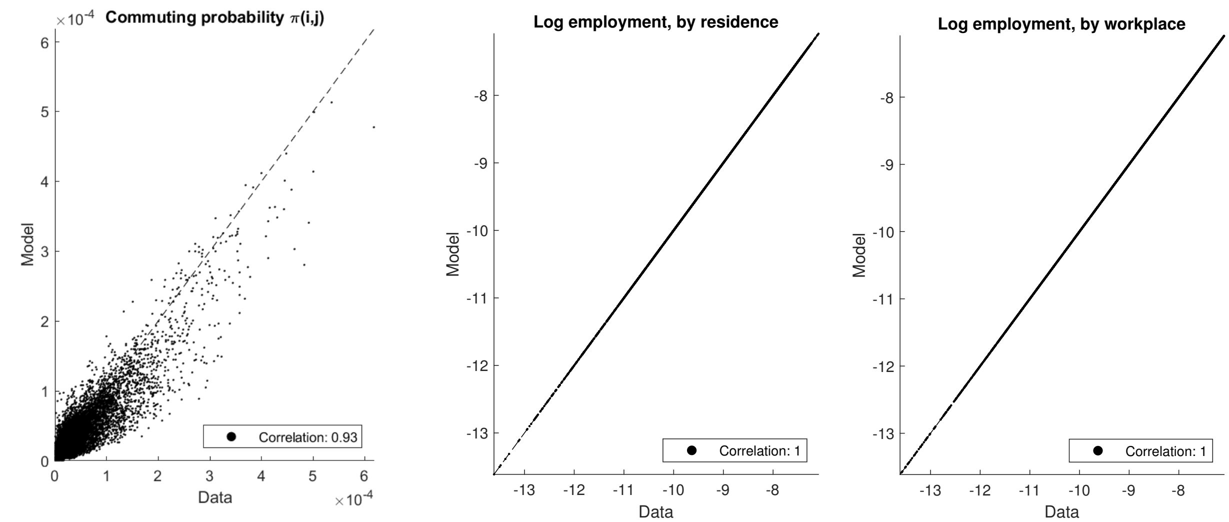
Lemma H.5. Given the parameters $\{\epsilon, \kappa, \tau, \alpha, \zeta, \nu^s_m, \varsigma^s_m\}$, observables $\left\{\mathbf{N}_{Wm}, \mathbf{N}_{Rm}, \mathbf{q}, \mathbf{p}, \mathbf{t}, \hat{\mathbf{w}}^s_G\right\}$, employment amenities in the tradable sector $\mathbf{E}^s_G$, college wage premium in the non-tradable sector w^H_{Sj}/w^L_{Sj}, residential amenities $\mathbf{X}^s_m$, and productivities $\mathbf{A}_m$ there exist unique vectors a_m and x^s_m.

Proof. The results follow immediately from equations that determine local productivity and amenities, (3.26) and (3.27). □

I Additional Figures, Tables, and Maps

Figure I.1: Commuting flows and employment, model vs data

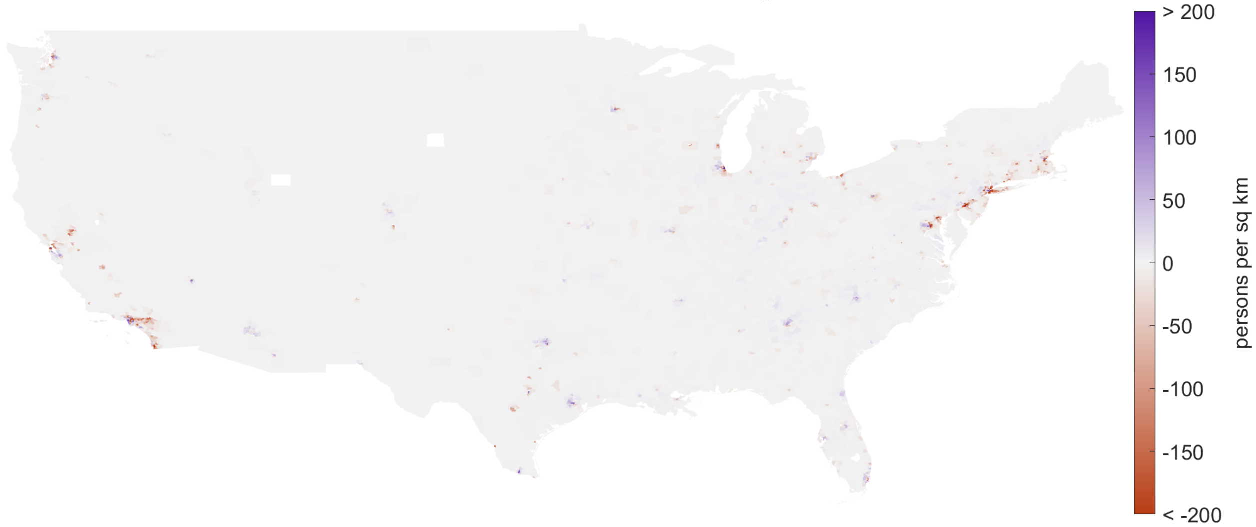
Panel (a) Panel (b) Panel (c)



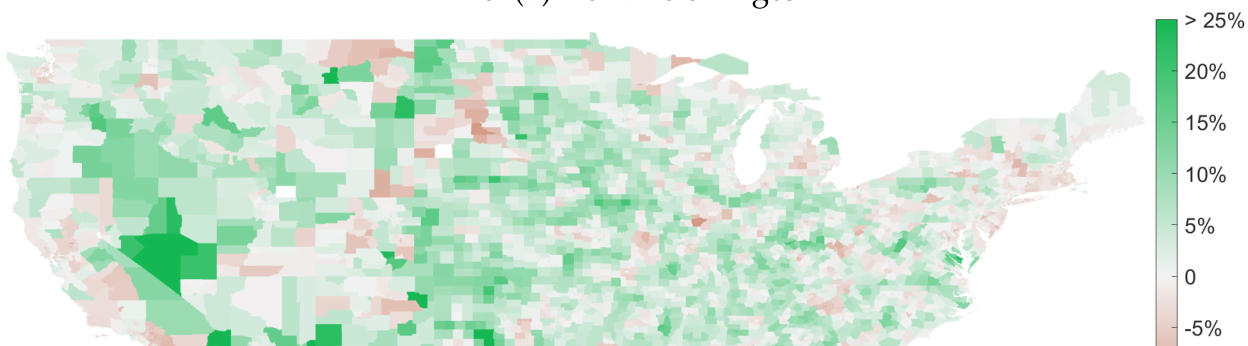
Note: These scatterplots show the relationship between commuting flows (panel a), log residents (panel b), and log jobs (panel c) in the LODES data and their counterparts in the model. The dashed line is the 45-degree line. Since over 98% of location pairs in the data have zero commuters, the logarithmic version of panel (a) is not feasible.

Figure I.2: Density of residents

Panel (a): absolute changes



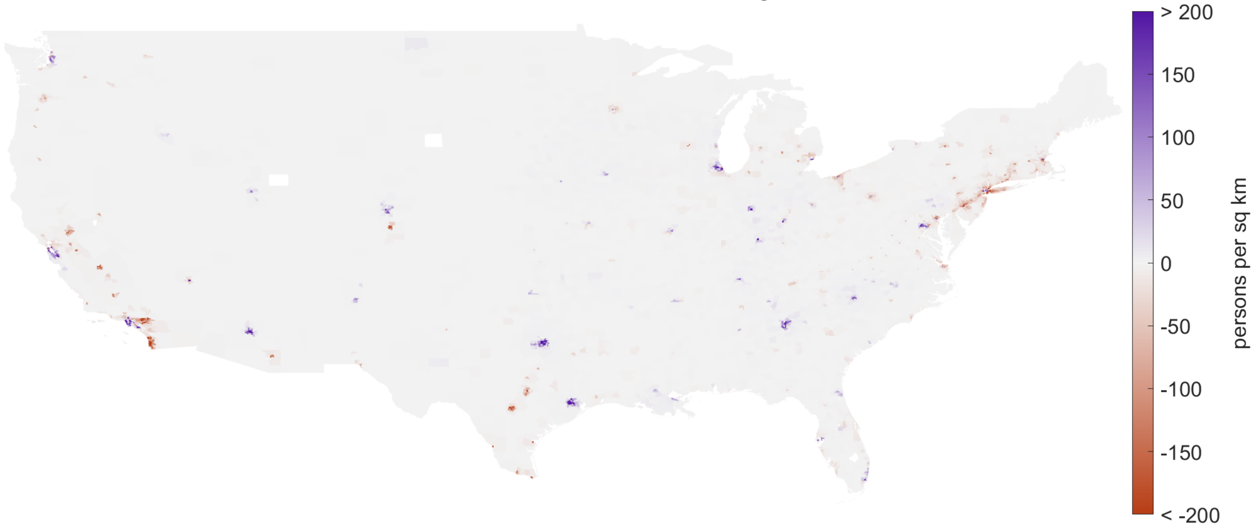
Panel (b): relative changes



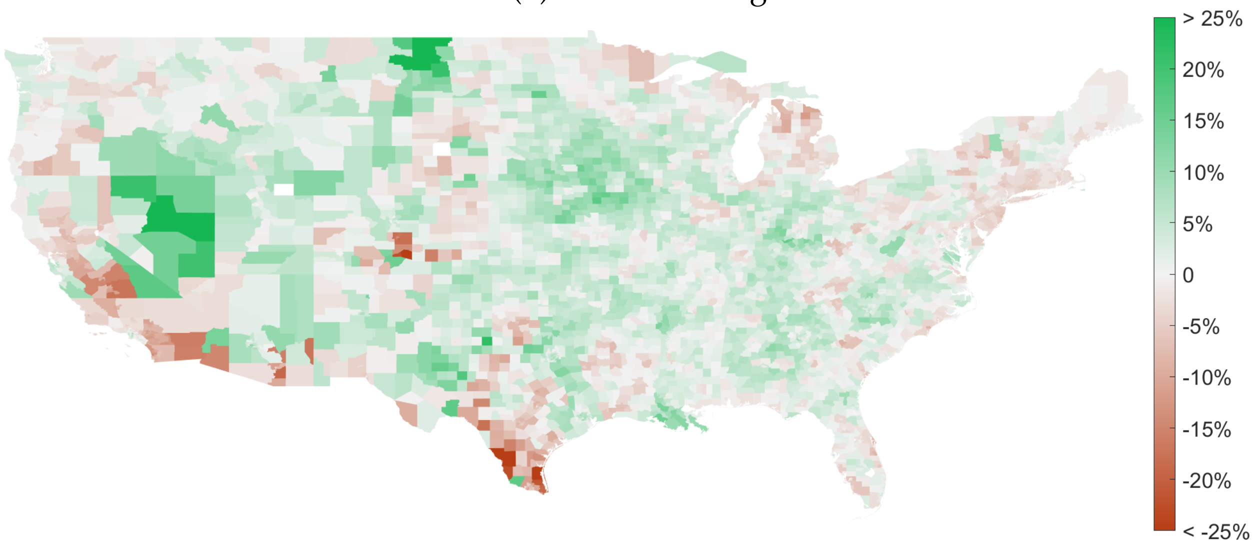
Note: Panel (a) shows absolute changes in the number of residents per square kilometer in each model location in the main counterfactual where the aversion for work from home falls and all endogenous variables adjust. Panel (b) shows percentage changes.

Figure I.3: Density of jobs

Panel (a): absolute changes

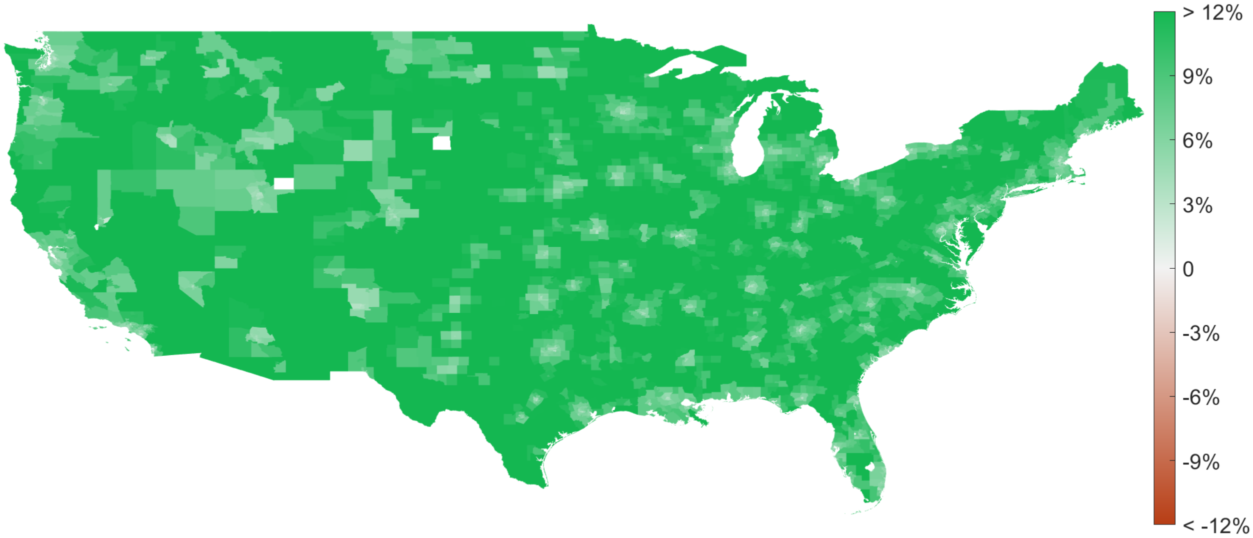


Panel (b): relative changes



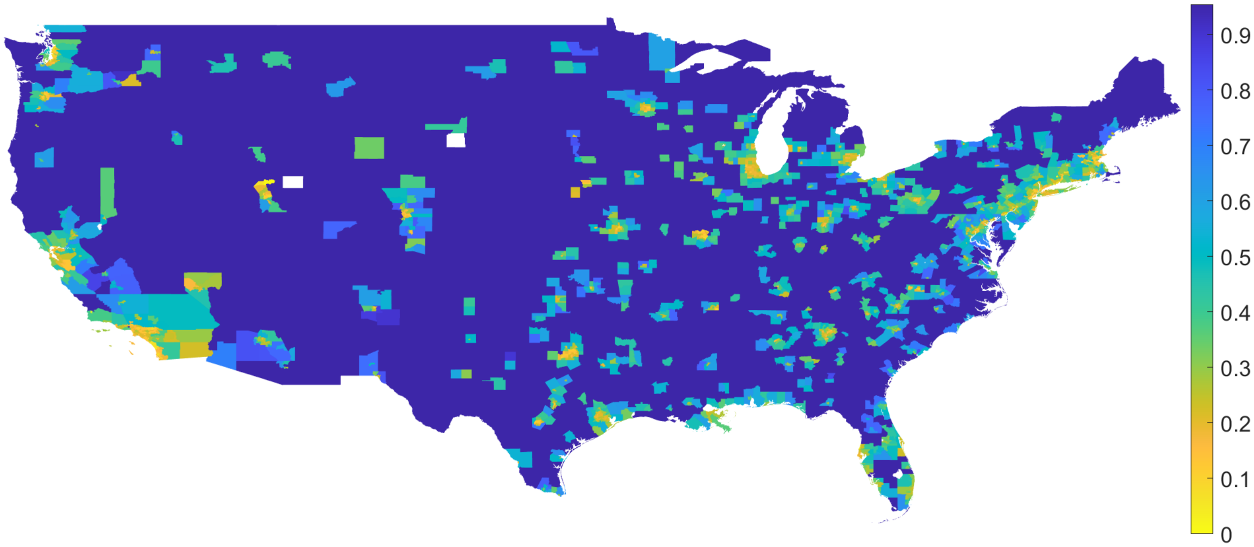
Note: Panel (a) shows absolute changes in the number of jobs per square kilometer in each model location in the main counterfactual where the aversion for work from home falls and all endogenous variables adjust. Panel (b) shows percentage changes.

Figure I.4: Floorspace prices, percentage changes



Note: The map shows percentage changes in the price of floorspace in the main counterfactual where the aversion for work from home falls and all endogenous variables adjust.

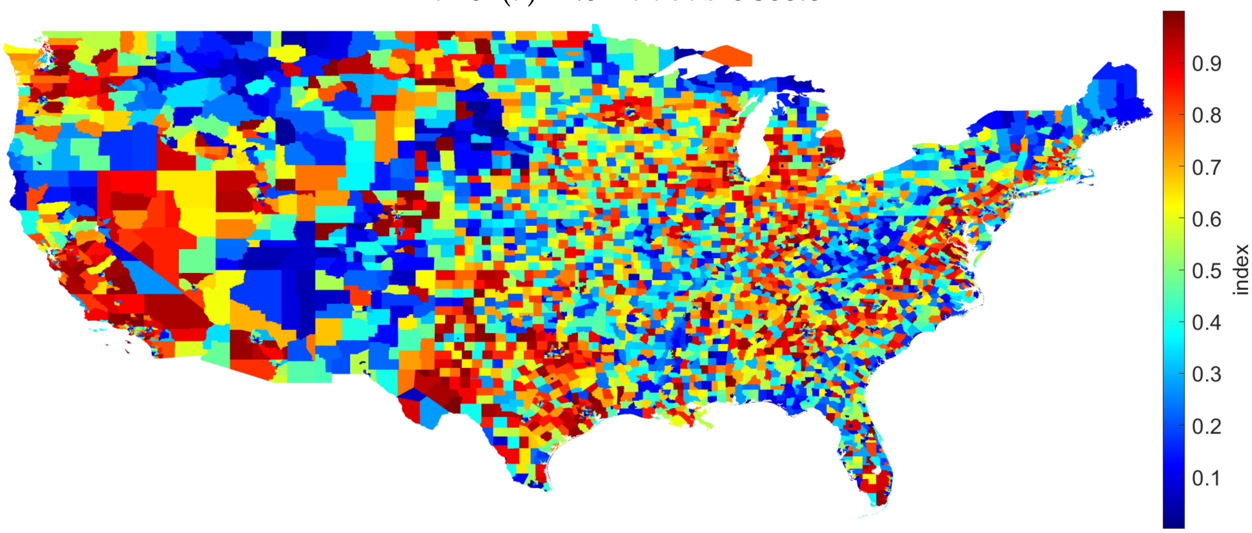
Figure I.5: Elasticities of floorspace supply



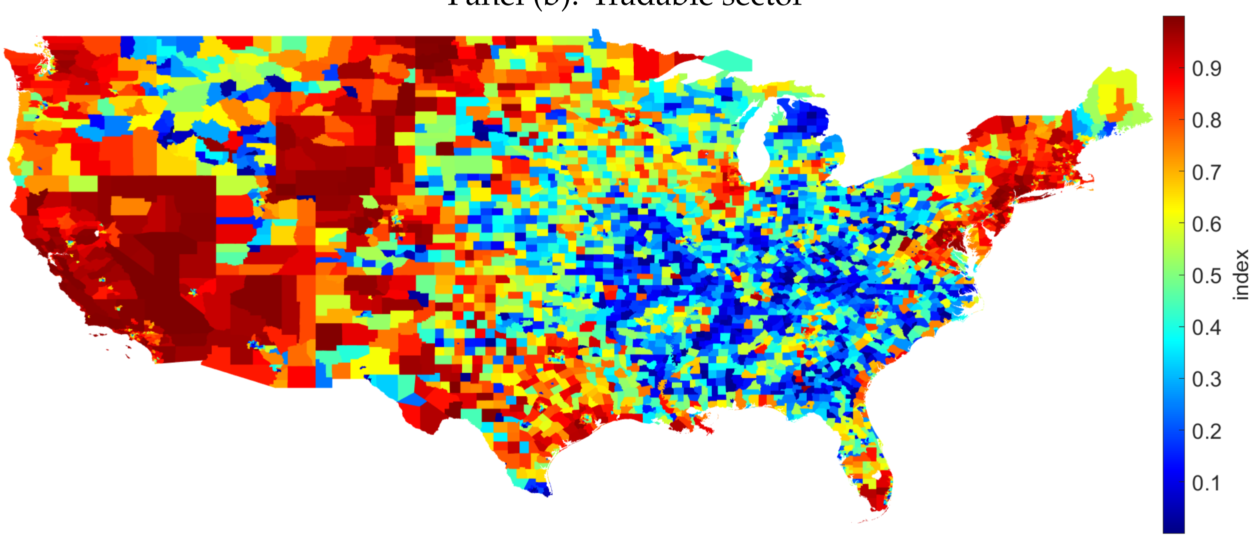
Note: This map shows the floorspace supply elasticities from Baum-Snow and Han (2021), aggregated to the level of our model locations.

Figure I.6: Location-specific productivity, quantiles

Panel (a): Non-tradable sector



Panel (b): Tradable sector



Note: Panel (a) shows quantiles of calibrated non-tradable sector location-specific productivities, A_{Sj}. Panel (b) shows quantiles of tradable sector location-specific productivities, A_{Gj}.

Table I.1: Changes in residents in 40 largest MSAs

MSA	all residents		non-coll.	coll.	non-trad.	trad.	non-telec.	telec.	on-site	remote
	%	'000	'000	'000	'000	'000	'000	'000	'000	'000
New York-Newark-Jersey City, NY-NJ-PA	1.0	92	71	21	26	66	98	-6	-1419	2665
Los Angeles-Long Beach-Anaheim, CA	-2.0	-113	-53	-60	-110	-2	76	-189	-827	1420
Chicago-Naperville-Elgin, IL-IN-WI	0.0	1	8	-7	-15	16	75	-74	-668	1232
Dallas-Fort Worth-Arlington, TX	-2.0	-64	-35	-29	-56	-8	80	-144	-430	755
Houston-The Woodlands-Sugar Land, TX	-2.0	-57	-35	-22	-60	4	54	-110	-386	662
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	0.2	5	1	4	8	-3	-20	25	-486	840
Atlanta-Sandy Springs-Alpharetta, GA	-0.3	-8	-0	-8	-22	14	30	-38	-357	643
Boston-Cambridge-Newton, MA-NH	-1.8	-43	-19	-24	-31	-12	20	-62	-386	698
Miami-Fort Lauderdale-Pompano Beach, FL	-4.0	-96	-58	-39	-66	-30	38	-134	-326	518
San Francisco-Oakland-Berkeley, CA	-2.7	-57	-31	-26	-59	2	17	-74	-339	594
Washington-Arlington-Alexandria, DC-VA-MD-WV	0.6	12	12	-0	-3	15	22	-10	-314	592
Detroit-Warren-Dearborn, MI	-1.9	-36	-13	-23	-14	-22	19	-55	-282	490
Phoenix-Mesa-Chandler, AZ	-3.9	-72	-46	-26	-62	-9	40	-112	-240	399
Minneapolis-St. Paul-Bloomington, MN-WI	-3.0	-56	-29	-27	-26	-30	18	-74	-273	469
Seattle-Tacoma-Bellevue, WA	-4.1	-70	-36	-34	-52	-18	37	-107	-245	423
Riverside-San Bernardino-Ontario, CA	0.8	13	0	12	7	5	-47	59	-298	467
San Diego-Chula Vista-Carlsbad, CA	-3.9	-54	-33	-21	-14	-40	-5	-49	-224	348
Denver-Aurora-Lakewood, CO	-4.2	-56	-30	-26	-46	-10	29	-85	-180	312
St. Louis, MO-IL	-1.6	-22	-12	-9	-15	-7	20	-42	-185	320
Baltimore-Columbia-Towson, MD	-0.7	-9	-7	-2	-14	4	-7	-2	-220	370
Tampa-St. Petersburg-Clearwater, FL	-2.8	-35	-24	-10	-19	-15	12	-47	-174	290
Pittsburgh, PA	-1.4	-16	-11	-5	-6	-10	-1	-15	-178	298
Charlotte-Concord-Gastonia, NC-SC	0.4	4	5	-1	2	2	15	-11	-153	283
Portland-Vancouver-Hillsboro, OR-WA	-3.5	-38	-21	-17	-20	-19	12	-50	-160	268
Orlando-Kissimmee-Sanford, FL	-2.2	-23	-17	-6	-9	-14	9	-33	-149	249
Cincinnati, OH-KY-IN	0.1	1	2	-1	-3	4	5	-4	-153	278
Kansas City, MO-KS	-2.5	-26	-14	-12	-15	-11	11	-37	-143	243
Cleveland-Elyria, OH	-1.9	-19	-11	-8	-6	-13	-7	-12	-153	251
San Antonio-New Braunfels, TX	-2.6	-25	-19	-7	-15	-10	-2	-23	-145	219
Indianapolis-Carmel-Anderson, IN	-1.7	-16	-10	-6	-18	2	-0	-16	-142	235
Columbus, OH	-1.0	-9	-3	-6	-4	-5	3	-12	-144	252
Sacramento-Roseville-Folsom, CA	-3.3	-31	-24	-7	-22	-9	-17	-13	-160	244
San Jose-Sunnyvale-Santa Clara, CA	-2.5	-23	-10	-12	-18	-4	20	-42	-133	250
Austin-Round Rock-Georgetown, TX	-2.3	-21	-11	-10	-10	-11	4	-24	-137	229
Las Vegas-Henderson-Paradise, NV	-4.7	-42	-25	-17	-29	-13	20	-62	-107	181
Nashville-Davidson–Murfreesboro–Franklin, TN	-1.7	-14	-7	-7	-14	-0	4	-18	-125	209
Milwaukee-Waukesha, WI	-2.8	-22	-15	-7	-15	-7	2	-24	-116	187
Providence-Warwick, RI-MA	-1.7	-13	-10	-3	-15	1	-5	-8	-132	212
Virginia Beach-Norfolk-Newport News, VA-NC	-2.1	-14	-12	-1	-4	-10	-4	-10	-101	163
Jacksonville, FL	-2.7	-17	-11	-6	-9	-8	7	-24	-85	146

Note: The table shows counterfactual results for changes in residents aggregated to the metropolitan statistical area (MSA) level for the largest 40 MSAs, ranked according to number of residents 2012–2016. The first two columns show percentage and absolute overall changes. The next two show absolute changes by education level. The next two show absolute changes by industry. The next two show absolute changes by occupation. The last two columns show absolute changes in the total number of days worked on-site ("on-site") or at home ("remote"), measured in resident-equivalent units (e.g., someone who works 4 days/week on site and 1 day/week at home contributes 0.8 to the on-site person count and 0.2 to the remote person count).

Table I.2: Changes in jobs in 40 largest MSAs

MSA	all jobs		non-coll.	coll.	non-trad.	trad.	non-telec.	telec.	on-site	remote
	%	’000	’000	’000	’000	’000	’000	’000	’000	’000
New York-Newark-Jersey City, NY-NJ-PA	2.2	194	89	105	41	154	96	98	-1454	2806
Los Angeles-Long Beach-Anaheim, CA	0.7	43	31	12	-57	100	65	-21	-895	1672
Chicago-Naperville-Elgin, IL-IN-WI	2.0	91	63	28	-2	92	77	14	-680	1332
Dallas-Fort Worth-Arlington, TX	1.4	46	42	4	-30	76	83	-37	-447	889
Houston-The Woodlands-Sugar Land, TX	1.1	33	32	1	-29	62	54	-21	-397	765
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	-0.4	-10	-12	1	-0	-10	-16	6	-487	819
Atlanta-Sandy Springs-Alpharetta, GA	1.8	45	35	11	-6	52	32	13	-372	712
Boston-Cambridge-Newton, MA-NH	-0.3	-7	-4	-3	-18	11	22	-29	-430	790
Miami-Fort Lauderdale-Pompano Beach, FL	-3.0	-75	-51	-24	-64	-11	35	-110	-337	554
San Francisco-Oakland-Berkeley, CA	1.4	32	21	10	-19	51	11	21	-363	708
Washington-Arlington-Alexandria, DC-VA-MD-WV	2.7	57	32	25	20	38	23	34	-338	676
Detroit-Warren-Dearborn, MI	-1.6	-31	-19	-12	-24	-7	17	-48	-284	493
Phoenix-Mesa-Chandler, AZ	-1.4	-26	-10	-16	-38	12	39	-65	-248	454
Minneapolis-St. Paul-Bloomington, MN-WI	-3.4	-64	-35	-29	-38	-26	21	-85	-284	472
Seattle-Tacoma-Bellevue, WA	-1.7	-31	-13	-18	-35	4	39	-70	-265	490
Riverside-San Bernardino-Ontario, CA	-5.1	-68	-54	-14	-19	-49	-36	-32	-241	309
San Diego-Chula Vista-Carlsbad, CA	-8.7	-117	-74	-43	-37	-81	-6	-112	-228	289
Denver-Aurora-Lakewood, CO	-1.5	-21	-7	-13	-32	11	28	-49	-185	355
St. Louis, MO-IL	-1.3	-18	-10	-8	-16	-2	20	-38	-190	329
Baltimore-Columbia-Towson, MD	-0.1	-1	-2	1	-7	6	-7	6	-217	376
Tampa-St. Petersburg-Clearwater, FL	-2.5	-31	-20	-11	-23	-8	12	-43	-179	299
Pittsburgh, PA	-1.6	-19	-13	-6	-8	-11	0	-20	-185	302
Charlotte-Concord-Gastonia, NC-SC	1.8	20	16	5	-2	22	17	3	-162	309
Portland-Vancouver-Hillsboro, OR-WA	-4.0	-45	-26	-19	-23	-21	14	-59	-167	270
Orlando-Kissimmee-Sanford, FL	-2.9	-34	-23	-10	-14	-20	11	-45	-171	272
Cincinnati, OH-KY-IN	0.7	7	6	1	-3	10	8	-1	-154	282
Kansas City, MO-KS	-2.7	-28	-17	-11	-19	-9	12	-40	-149	246
Cleveland-Elyria, OH	-2.6	-27	-18	-9	-13	-14	-4	-23	-165	260
San Antonio-New Braunfels, TX	-5.3	-50	-38	-12	-18	-32	-2	-48	-141	189
Indianapolis-Carmel-Anderson, IN	1.8	19	14	5	-1	20	2	17	-154	285
Columbus, OH	-0.4	-4	-1	-2	-4	0	5	-9	-156	273
Sacramento-Roseville-Folsom, CA	-4.6	-42	-27	-15	-15	-28	-15	-27	-161	236
San Jose-Sunnyvale-Santa Clara, CA	0.1	1	4	-3	-12	12	22	-21	-154	307
Austin-Round Rock-Georgetown, TX	-4.0	-38	-24	-14	-8	-30	3	-40	-149	225
Las Vegas-Henderson-Paradise, NV	-5.4	-49	-32	-17	-29	-21	19	-68	-112	179
Nashville-Davidson–Murfreesboro–Franklin, TN	0.2	2	3	-1	-5	7	5	-3	-137	240
Milwaukee-Waukesha, WI	-1.3	-11	-8	-4	-11	0	5	-16	-130	217
Providence-Warwick, RI-MA	-1.7	-12	-8	-3	-12	0	-9	-2	-115	191
Virginia Beach-Norfolk-Newport News, VA-NC	-4.1	-27	-19	-8	-10	-16	-4	-22	-102	151
Jacksonville, FL	-2.2	-14	-9	-5	-11	-3	8	-22	-91	155

Note: The table shows counterfactual results for changes in jobs aggregated to the metropolitan statistical area (MSA) level for the largest 40 MSAs, ranked according to number of residents 2012–2016. The first two columns show percentage and absolute overall changes. The next two show absolute changes by education level. The next two show absolute changes by industry. The next two show absolute changes by occupation. The last two columns show absolute changes in the total number of days worked on-site (“on-site”) or at home (“remote”), measured in job-equivalent units (e.g., someone who works 4 days/week on site and 1 day/week at home contributes 0.8 to the on-site person count and 0.2 to the remote person count).