Spatial Implications of Telecommuting*

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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. We quantify our framework to match the distribution of jobs and residents across 4,502 U.S. locations. Then we simulate permanent increases in the attractiveness and productivity of telework that lead to greater adoption of hybrid and fully remote work. To validate our model, we show that our results are positively correlated with local changes in residents and housing costs observed 2019–2023. The rise of telework results in a rich non-monotonic pattern of reallocations of residents and jobs within and across cities. Workers who can telecommute experience welfare gains, and those who cannot suffer losses. Broader access to jobs reduces wage inequality across residential locations, and heralds a partial reversal in the spatial concentration of talent and spending power known as the "Great Divergence."

Key Words: urban, work from home, commuting, spatial equilibrium
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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 over one-half of American workers to telecommute. What started as an emergency response has for many become a new norm: in late 2024, nearly five years after the initial shock, work from home still accounted for over one quarter of all full paid days of work.

This matters because the daily commute has been one of the primary sinews stitching commercial and residential areas together within the urban landscape. If this tie is loosened, workers with remote or "hybrid" jobs nominally located in a city center may choose to live beyond the bounds of its administratively-defined commuting zone–and perhaps on the other side of the country entirely. This is a new type of worker mobility which previous urban economic models–which allow movement *either* within cities *or* between them–are not equipped to cope with. Beyond shuffling workers and jobs between neighborhoods and cities, it may also have macro-level implications–for example, either accelerating or reversing the trend of spatially concentrating talent and income known as the "Great Divergence."

In this paper, we aim to update the spatial modeling toolbox to allow remote and hybrid employment, and develop a quantitative framework capable of analyzing the full range of likely reallocations, both within and across cities. We divide the continental United States into 4,502 locations, and allow each worker to choose any pair of residence and job sites. Some workers are able to substitute on-site effort with work done from home. Being able to produce output at home saves them from costly commuting, and may induce them to choose a more distant residence location. On the other hand, when working remotely, they have a different level of productivity and have to procure floorspace for a home office. Their choice of how often to work on site versus at home also depends on a preference shifter we label *work-from-home aversion*, representing tastes, norms, and institutional policies regarding remote work. We show that, because telework allows firms to hire workers from a broader "catchment area," the range of parameter values for which a unique equilibrium is guaranteed is narrower than in a conventional quantitative spatial model.

We calibrate our model to be consistent with key facts about pre-2020 telecommuting. Both the opportunity to telecommute, and commuting choices of remote-capable workers, are allowed to differ for college and non-college educated workers, and for workers in tradable and non-tradable industries, consistent with the data. Our framework is also consistent with the observed distribution of commuting frequencies, and the observed spatial distribution of remote worker residences relative to their sites of employment. We calibrate the elasticity of substitution between remote and on-site work, the relative productivity of remote work, and the work from home aversion, separately for each sector and education level.

We simulate a permanent increase in remote work by increasing work from home productivity and lowering work from home aversion, guided by survey evidence from Barrero, Bloom, and Davis (2021). This results in a greater adoption of hybrid and fully remote work arrangements. We predict a net reallocation of jobs and residences across model locations equivalent to 4.5% of the population.

Workers who can work from home experience a fall in the cost of choosing residence locations far from jobs. This causes many of them to decentralize, moving to less densely-populated areas, and allows them to be more selective in choosing locations with low housing costs and better amenities. This movement creates some opportunities for those who cannot work remotely. In response to falling housing prices in locations with convenient commutes, they centralize, moving towards denser locations in larger metro areas. This fall in the cost of a short commute also induces them to substitute away from amenities, leaving more high-amenity locations for the telecommuters.

Jobs in the non-tradable sector follow the movement of telecommuters out to suburbs and smaller cities. Jobs in the tradable sector move in both directions. Some firms take advantage of low real estate costs in low-density areas that can now pull from a larger pool of remote workers. Others increase their operations in the highly-productive centers of the largest cities, enjoying not only an expanded worker pool but also a decline in the high cost of office space.

In aggregate, the average worker lives 47% farther from their place of work, but spends 25% less time commuting, pointing to potential reductions in traffic congestion and vehicle use. The share of workers living in one commuting zone (CZ) and working in another increases from 22% to nearly 32%, which may have major impacts on travel patterns and call into question the current administrative definitions of CZs.

As model validation, we show that our counterfactual results are positively correlated with observed changes in population and housing rents between 2019 and 2023.

We leverage our disaggregated and quantitative approach to explore the consequences of remote work for a complex of recent trends across and within cities known as "The Great Divergence" (Moretti, 2012). Our model predicts significant re-convergence: a fall in skill sorting both within and across CZs, a fall in residential income inequality, and a fall in spatial house price inequality both within and across CZs. We review available data for 2019–2023, and find trends broadly consistent with our model predictions.

Our framework builds on quantitative spatial models of joint job and residence choice, such as Ahlfeldt, Redding, Sturm, and Wolf (2015). 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 as inter-city, adjustments. We contribute to this literature by extending the toolbox to include a full-fledged model of working from home.

Several other recent papers also use spatial equilibrium models to study the effects of remote work on cities. Behrens, Kichko, and Thisse (2021), Brueckner, Kahn, and Lin (2023), Davis, Ghent, and Gregory (2024), Kyriakopoulou and Picard (2021), Monte, Porcher, and Rossi-Hansberg (2023), Brueckner (2024), and Richard (2024) develop stylized spatial 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. Our framework has three main advantages relative to these more stylized approaches. First, by including a large number of locations, our framework can predict *how far* new telecommuters will move from their jobs, a crucial variable if we want to understand the impact on, e.g., real estate markets and commuting patterns. Second, closely related to the first, our framework can also represent changes in the distribution of workers across different work-from-home frequencies–crucial as "hybrid" work has emerged as a popular option. Third, our model predicts how the location of jobs will also change–a question with important implications for, e.g., the impact on city centers. We also model telecommuting as an endogenous choice, a feature shared only with Davis, Ghent, and Gregory (2024), Monte, Porcher, and Rossi-Hansberg (2023), and Richard (2024) from the list above, which allows us to speak to the motivations and contributing factors of the shift towards remote work.

Delventhal, Kwon, and Parkhomenko (2022) build a quantitative spatial model limited to a single urban area–Los Angeles. Unlike in this paper, workers are homogeneous, work from home behavior is exogenous, and there is no heterogeneity in the number of days worked remotely among those who can work from home. Moreover, relocations across metro areas are not allowed and non-tradable local goods are not considered. All of these features are both conceptually and quantitatively essential.

Our paper also follows an earlier literature studying the impact of communication technologies and telework, which includes contributions from Gaspar and Glaeser (1998), Ellen and Hempstead (2002), Safirova (2003), Walls, Safirova, and Jiang (2006), Glaeser and Ponzetto (2007), Rhee (2008), and Larson and Zhao (2017).

Yet another strand of recent research empirically studies the role of work from home in movement of residents, changes in real estate prices, and supply of amenities during the pandemic, e.g., Althoff, Eckert, Ganapati, and Walsh (2022), Brueckner, Kahn, and Lin (2023), Haslag and Weagley (2024), Li and Su (2021), Gupta, Mittal, Peeters, and Van Nieuwerburgh (2022), Liu and Su (2021), Rosenthal, Strange, and Urrego (2021), De Fraja, Matheson, and Rockey (2021), Dalton, Dey, and Loewenstein (2022), Veuger, Hoxie, and Brooks (2023), Duranton and Handbury (2023), and Bick, Blandin, Mertens, and Rubinton (2024), among others. A few recent papers also study the effects of telework on residential and commercial real estate values using structural models, e.g., Mondragon and Wieland (2022), Howard, Liebersohn, and Ozimek (2022), Gamber, Graham, and Yadav (2023), and Gupta, Mittal, and Van Nieuwerburgh (2022), among others. Recent research on remote work and its effects on migration and real estate prices is summarized in Van Nieuwerburgh (2023).

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 simulations where work from home increases permanently. In Section 6 we explore the consequences of remote work for the "Great Divergence" in economic outcomes across U.S. cities. Section 7 concludes.

2 Remote Work: Past and Present

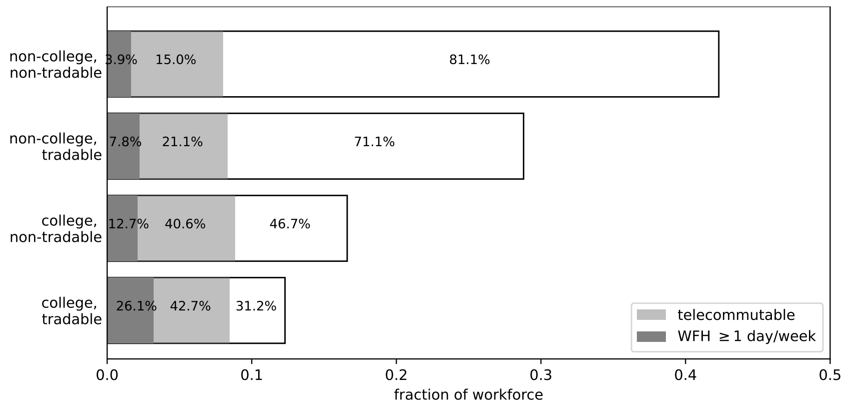
In this section we establish facts about telecommuting prior to 2020 and its trajectory during the Covid-19 pandemic. This will motivate the way we build the model as well as how we approach the counterfactual exercise.

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? Third, *where* do telecommuters live?

To address the first question, we divide the workforce by education level and industry. *College* workers have obtained a four-year degree or more, and *non-college* have not. *Tradable*

Figure 1: Telecommutability and uptake



Note: 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 from SIPP. Light-gray represents those with telecommutable professions who do not work remotely. White areas represent those in non-telecommutable occupations. Numbers in each color area report the fraction with each commuting status.

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.[1] Using data on full-time workers in the 48 contiguous 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.

Who can telecommute? To measure *telecommutability*, i.e., the ability to telecommute, we combine 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.[2]

Who does telecommute? 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 A.1 for more details. Focusing

[1]We use the BEA 2012 NAICS categories and divide them as follows. *Tradable:* 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.

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

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.

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%.[3] We dub these gaps by education and industry *Stylized Fact #2*.

How frequent is telecommuting? Using the data from SIPP, we investigate how often remote workers dial it in from home. As Table 1 shows, a notable feature of the distribution for each worker category is *bi-modality*: most are full-time on-site or full-time at home.[4] We call this *Stylized Fact #3*. The bimodality is less pronounced for college-educated workers in tradable industries. For them, hybrid work (i.e., one to four days per week) accounts for over 11% of paid workdays.

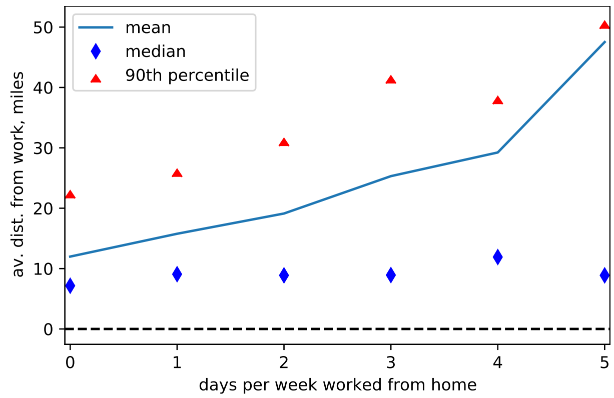
Where do telecommuters live? Using data from the 2017 National Household Transportation Survey (NHTS), we find a positive relationship between work-from-home frequency and distance to job site, as shown in Figure 2; see Appendix Section A.3 for more details on the data.[5] We shall refer to this relationship as *Stylized Fact #4*. It is consistent

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

[4]An advantage of the SIPP data is that it allows us to calculate numbers for each frequency from a single data source applying a consistent methodology. Mas and Pallais (2020) also report some numbers related to work from home frequency, but the variance in definitions across the patchwork of data sources obscures the bimodality that we find here. Another advantage of SIPP is that it counts full *paid* days worked from home and that the sample sizes are large enough for us to focus on full-time workers. Furthermore, SIPP allows us to observe the exact number of days per week that an individual works from home, while other data sources, such as the Leave and Job Flexibility model of the American Time Use Survey (ATUS) and the General Social Survey (GSS), only report intervals: i.e., "1 to 2 days a week" or "more than once a week." At the same time, SIPP may oversample low-income workers and this could understate the amount of hybrid work in the data. ATUS and GSS appear to report more common hybrid work than SIPP (Davis, Ghent, and Gregory, 2024), but sample sizes are small, and the definition of home work is different: ATUS and GSS count any day when work was done from home, regardless of whether that work was paid or not. We believe that these differences are why GSS suggests somewhat different patterns than what we report here, which can be seen, for example, in Table 3 of the related Bureau of Labor Statistics news release: https://www.bls.gov/news.release/flex2.t03.htm#cps_jf_table3.f.1.

[5]Zhu (2012) also found that telecommuters live at a farther distance from work than commuters.

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.

with telework being a way of reducing the effective commuting cost.

2.2 Covid-19: A Telework Shock

In 2018, no more than 8% of paid full workdays were remote, based on data from SIPP. When the Covid-19 pandemic began in early 2020, lockdowns and distancing moved over one third of the workforce from offices to their homes, as shown in Figure 3.

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 that between one-quarter and one-third of paid workdays will be remote even after the pandemic.[6]

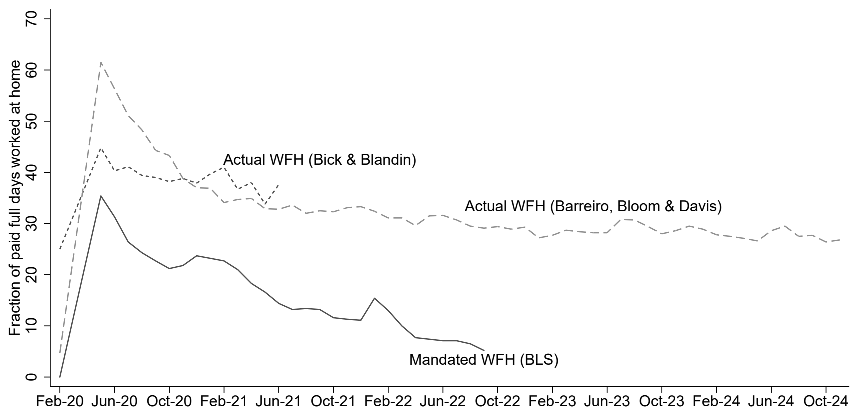
There are at least four hypotheses as to what the Covid-19 telework shock really was.[7] None are mutually exclusive, though some may be more important than others. And the implications of each for the future of remote work are quite distinct.

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, norms and institutional policies* around working from home, driven by a combination of new information and the facts on the ground created by forced remote work

[6] Other surveys indicated 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.

[7] Van Nieuwerburgh (2023) describes the debate between different explanations for the rise in remote work.

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).

during the pandemic. Barrero, Bloom, and Davis (2021) take the position that working from home was always great but social norms and stigma–combined with downstream corporate policies–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, sizable investments in remote-complementary physical capital were made, and individuals and organizations did a great deal of learning by doing. 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 trends shown in Figure 3. The share of *mandated* remote work has fallen from 35% in May 2020 to 5% in mid-2022. At the same time, *actual* working from home, as measured in a survey by Barrero, Bloom, and Davis (2021), has stabilized at around 25–30%. We therefore believe it is highly likely that some combination the latter three hypotheses are playing a role. Our theoretical model described in Section 3 and counterfacgtual simulations in Section 5 incorporate both preference and technology shocks. Nonetheless, in Section 5.8 we will argue 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 role of workplace coordination as a potential topic of future research.

3 Model

The economy 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 workers without college education ($s = L$) 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 some are Non-telecommutable ($o = N$) and must be performed on-site.[8] The four types that are the product of $\{H, L\}$ and $\{T, N\}$ are 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 $\ell^{HN} + \ell^{LN} + \ell^{HT} + \ell^{LT} = 1$.

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.[9] Floorspace ($m = F$) 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 at-home work relative to on-site work, the elasticity of substitution between the two work modes, 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, 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

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

[9]Tradable output is indexed $m = G$ as in our data it consists largely (though not entirely) of Goods, while non-tradable is indexed $m = S$ for Services, for the same reason.

in the office and working at home. The first three types of choices are not unusual in a quantitative spatial model and are discussed immediately below. The choice of how often to work from home is described later in Section 3.1.1.

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; $\mu_{m,\iota}$ is the idiosyncratic preference shock over industry, drawn from a Fréchet distribution $\Phi_{\text{ind}}(\mu) = \exp(-\mu^{-\sigma})$; and $\xi_{ij,\iota}$ is the idiosyncratic preference shock over residence-workplace pairs, also drawn from a Fréchet distribution $\Phi_{\text{loc}}(\xi) = \exp\left(-\xi^{-\epsilon}\right)$. The common component of indirect utility is

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

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 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 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. The worker only experiences the part of disutility which comes from commuting on the days she commutes: the first term of equation (3.2) ranges from 0 when $\theta = 0$, to $e^{\kappa t_{ij}}$ when $\theta = 1$. The latter case is a standard functional form for commuting costs in urban models without telecommuting. 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 $\theta = 0$. This functional form of the disutility of commuting highlights the role of telecommuting in reducing the importance of distance to work.[10]

[10]A related study by Lennox (2020) builds a quantitative spatial model of Australia and studies a fall in

In what follows, we will refer to ς_m^s as the "aversion to telecommuting." Assuming that ς_m^s takes a value greater than 1 (as it does for all worker categories in our calibration), it lends itself to a range of interpretations, not all of which fall within the realm of worker "preferences" or average tastes per se. For example, they could also reflect 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.[11]

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. In Appendix Section H.1 we recalibrate the model and repeat our main counterfactual assuming that $g_{ij} = 1$ so the whole cost of distance is loaded onto commuting. This results in much larger relocations and welfare gains.

Let us designate the optimal choice of θ, discussed later, as θ_{mij}^{so}; and the associated indirect utility, disposable income, and disutility of commuting as v_{mij}^{so}, $\tilde{w}_{mij}^{so}$, and d_{mij}^{so}. 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

$$\pi_{mij}^{so} = \mathrm{l}^{so} \pi_m^{so} \pi_{ij|m}^{so}, \tag{3.3}$$

where π_m^{so} is the probability that a worker with education level s and occupation o chooses industry m, and $\pi_{ij|m}^{so}$ is the probability that such a worker chooses the location pair (i, j),

transport costs as a proxy for an increase in remote work.

[11]To put it another way: Does $\varsigma_m^s > 1$ mean that workers "hate" remote work? Certainly not! As we have just mentioned, there are many other well-known non-pecuniary barriers to telecommuting. If we take at the evidence from Mas and Pallais (2020) and He, Neumark, and Weng (2021) that the average worker values remote flexibility, calibrated values of $\varsigma_m^s > 1$ imply that these other impediments turn out to be large enough to dominate workers' positive taste for remote work.

[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.

conditional on having chosen industry m. These two probabilities are given by

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

Choice probabilities π_{mij}^{so} 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

$$N_{Ri}^{so} = \sum_m \sum_j \pi_{mij}^{so}. \tag{3.5}$$

Summing $\pi_{ij|m}^{so}$ over j, we obtain the probability that a worker chooses to live in location i: $\pi_{i|m}^{so} = (\sum_{i'} \sum_{j'} (v_{mi'j'}^{so})^{\epsilon})^{-1} X_{mi}^{s} p_i^{-\beta} q_i^{-\gamma} CMA_{i|m}^{so}$. Summing $\pi_{ij|m}^{so}$ over i, we obtain the probability that a worker in chooses to work in location j: $\pi_{j|m}^{so} = (\sum_{i'} \sum_{j'} (v_{mi'j'}^{so})^{\epsilon})^{-1} E_{mj}^{s} FMA_{j|m}^{so}$. In these two expressions, $CMA_{i|m}^{so}$ and $FMA_{j|m}^{so}$ are commuter market access (CMA) and firm market access (FMA). These two variables are measures of the access to jobs from residential location i and the access to workers from workplace location j, and are defined as:

$$CMA_{i|m}^{so} \equiv \sum_j \frac{E_{mj}^{s} \tilde{w}_{mij}^{so}}{d_{mij}^{so} g_{ij}} \qquad \text{and} \qquad FMA_{j|m}^{so} \equiv \sum_i \frac{X_{mi}^{s} \tilde{w}_{mij}^{so}}{p_i^{\beta} q_i^{\gamma} d_{mij}^{so} g_{ij}}. \tag{3.6}$$

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

$$N_{WCj}^{s} = \sum_m \sum_i \left[\theta_{mij}^{sT} \pi_{mij}^{sT} + \pi_{mij}^{sN}\right] \qquad \text{and} \qquad N_{WTj}^{s} = \sum_m \sum_i (1 - \theta_{mij}^{sT}) \pi_{mij}^{sT}. \tag{3.7}$$

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

$$V^{so} = \Gamma\left(\frac{\epsilon - 1}{\epsilon}\right) \Gamma\left(\frac{\sigma - 1}{\sigma}\right) \left[\sum_m \left[\sum_i \sum_j \left(v_{mij}^{so}\right)^{\epsilon}\right]^{\frac{\sigma}{\epsilon}}\right]^{\frac{1}{\sigma}}, \tag{3.8}$$

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. 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: $n^{\alpha}h^{1-\alpha}$.[14]

Tasks done at home may be different from those done at the job site. Reflecting this, overall effective labor supply is a constant elasticity of substitution combination of labor on-site and at home, with the elasticity of substitution for each education level and industry $\zeta^s_m > 1$:

$$z^{so}_m(\theta, h_C, h_T) = \left[\left(\theta^{\alpha}h^{1-\alpha}_{WC}\right)^{\frac{\zeta^s_m-1}{\zeta^s_m}} + \left(\nu^s_m(1-\theta)^{\alpha}h^{1-\alpha}_{WT}\right)^{\frac{\zeta^s_m-1}{\zeta^s_m}}\right]^{\frac{\zeta^s_m}{\zeta^s_m-1}}. \tag{3.9}$$

Parameter $\nu^s_m > 0$ 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.[15] A worker of education level s in industry m takes as given that they will be paid a wage w^s_{mj} 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,

$$\tilde{w}^{so}_{mij}(\theta) \equiv w^s_{mj}z^s_m(\theta, h_{WC}, h_{WT}) - q_j h_{WC} - q_i h_{WT}.$$

Income-maximizing floorspace choices of a worker who commutes to the job site with frequency θ yield optimal effective labor supply $z^{so}_{mij}(\theta) = \left((1-\alpha)w^s_{mj}\right)^{(1-\alpha)/\alpha}\Omega^{so}_{mij}(\theta)$, and disposable income

$$\tilde{w}^{so}_{mij}(\theta) = \alpha\,(1-\alpha)^{\frac{1-\alpha}{\alpha}}\,(w^s_{mj})^{\frac{1}{\alpha}}\Omega^{so}_{mij}(\theta), \tag{3.10}$$

where

$$\Omega^{so}_{mij}(\theta) \equiv \left[\left(\theta^{\alpha}q_j^{-(1-\alpha)}\right)^{\frac{\zeta^s_m-1}{1+\alpha(\zeta^s_m-1)}} + \left(\nu^s_m(1-\theta)^{\alpha}q_i^{-(1-\alpha)}\right)^{\frac{\zeta^s_m-1}{1+\alpha(\zeta^s_m-1)}}\right]^{\frac{1}{\alpha}\frac{1+\alpha(\zeta^s_m-1)}{\zeta^s_m-1}}. \tag{3.11}$$

Finally, 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. Maximizing the part of indirect utility (3.1) that depends on commuting frequency, $\tilde{w}^{so}_{mij}(\theta)/d_{ij}(\theta)$, with respect

[14]The need to use floorspace to produce output from home is consistent with Stanton and Tiwari's (2021) finding that, conditional on location, income, and family structure, telecommuters own larger houses.

[15]For simplicity of exposition, floorspace choice is done by the worker; firms' payments to workers compensate both labor and floorspace. There is an isomorphic specification in which firms rent floorspace directly.

to θ, we obtain

$$\theta_{mij}^{sT} = \left[1 + \left(\nu_m^s \left(\frac{q_j}{q_i} \right)^{1-\alpha} \right)^{\zeta_m^s - 1} \left(\frac{e^{\kappa t_{ij}}}{\varsigma_m^s} \right)^{1+\alpha\left(\zeta_m^s - 1\right)} \right]^{-1}. \tag{3.12}$$

Thus, a worker chooses to work remotely more often, i.e., chooses lower θ, when telework is relatively productive (large ν_m^s), floorspace at home is relatively cheap (large q_j/q_i), the aversion to work from home is low (small ς_m^s), and the commuting cost is high (large t_{ij}).

3.1.2 Remote/On-Site Time Complementarity and Corner Time Allocations

Imperfect substitution between on-site and remote work implies that all workers in telecommutable occupations choose an interior θ. At first glance this might seem inconsistent with large numbers of workers making "corner" choices to work nearly full-time in the office or full-time at home. Yet, in Table 1 we see that not only are corner choices common, but *both* opposite corner choices are relatively more frequent than intermediate choices (*stylized fact* #3). More puzzling still, if we skip ahead to peek at Section 4, we see that the model has no trouble replicating this pattern.

What makes this possible is the distribution of job-residence location pairs. From equation (3.12) we can see that workers choosing these pairs with high t_{ij} will choose low θ. Idiosyncratic location preferences ensure there is always some demand for each location pair, and globally there are many more pairs with high t_{ij} than low; it does not seem unlikely at all that this larger mass of high-distance pairs could generate a mode near $\theta = 0$. Location pairs with with low t_{ij} are relatively few, but disproportionately valuable because commuting is costly. Again, it seems perfectly natural that this could generate another mode near $\theta = 1$.

3.2 Firms

In each location there are many perfectly competitive firms producing tradable products, and likewise producing non-tradable products. A firm in industry m and location j produces output

$$Y_{mj} = A_{mj} \left[\omega_{mj} \left(y_{mj}^L \right)^{\frac{\xi-1}{\xi}} + (1 - \omega_{mj}) \left(y_{mj}^H \right)^{\frac{\xi-1}{\xi}} \right]^{\frac{\xi}{\xi-1}}, \tag{3.13}$$

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.[16]

The firm chooses labor inputs y^s_{mj} so as to maximize profit: $p_{mj}Y_{mj} - w^L_{mj}y^L_{mj} - w^H_{mj}y^H_{mj}$. Profit maximization implies the following equilibrium relationship between non-college wages and output prices in each industry,

$$\frac{w^L_{mj}}{p_{mj}} = A_{mj}\omega_{mj}^{\frac{\xi}{\xi-1}}\left[1+\left(\frac{1-\omega_{mj}}{\omega_{mj}}\right)^{\xi}\left(\frac{w^L_{mj}}{w^H_{mj}}\right)^{\xi-1}\right]^{\frac{1}{\xi-1}}. \tag{3.14}$$

Since there are no transport costs for shipping the output of the tradable sector, the price of tradable products is a numeraire: $p_{Gj} = 1$ 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. Meanwhile, optimal use of inputs implies that the college premium has the following relationship to the input levels of each skill type:

$$\frac{w^H_{mj}}{w^L_{mj}} = \frac{1-\omega_{mj}}{\omega_{mj}}\left(\frac{y^L_{mj}}{y^H_{mj}}\right)^{\frac{1}{\xi}}. \tag{3.15}$$

3.3 Developers

Floorspace is demanded by workers both for residential use and as a production input. In each location, there is a large number of perfectly competitive developers which produce floorspace using technology

$$H_i = K_i^{1-\eta_i}\left(\phi_i L_i\right)^{\eta_i}, \tag{3.16}$$

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. Let q_i be the equilibrium price of floorspace. Then the equilibrium

[16] There may be benefits of explicitly modeling firms' preferences over on-site versus at-home work. For example, if there positive externalities associated with on-site work, firms may want to encourage it. At the same time, Brown and Tousey (2023) document that the gap between workers' preferences and managers' plans for the share of remote work has halved between July 2020 and December 2022. This suggests that optimal choices of firms may not be very different from those of workers. See the "Productivity and Welfare Pack" extension to Barrero, Bloom, and Davis (2021) for an example of a model where firms decide on how often employees are allowed to work from home.

supply of floorspace in location i is

$$H_i = \phi_i (1-\eta_i)^{\frac{1-\eta_i}{\eta_i}} q_i^{\frac{1-\eta_i}{\eta_i}} L_i. \tag{3.17}$$

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

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

$$y^s_{mj} = \left((1-\alpha) w^s_{mj}\right)^{\frac{1-\alpha}{\alpha}} \sum_o \sum_i \pi^{so}_{mij} \Omega^{so}_{mij}. \tag{3.18}$$

Applying equation (3.18) to equation (3.15), we obtain the equilibrium college wage premium,

$$\frac{w^H_{mj}}{w^L_{mj}} = \left(\frac{1-\omega_{mj}}{\omega_{mj}}\right)^{\frac{\alpha\xi}{1+\alpha(\xi-1)}} \left(\frac{\sum_o \sum_i \pi^{Lo}_{mij} \Omega^{Lo}_{mij}}{\sum_o \sum_i \pi^{Ho}_{mij} \Omega^{Ho}_{mij}}\right)^{\frac{\alpha}{1+\alpha(\xi-1)}}. \tag{3.19}$$

Wage levels can then be found by plugging in this expression in equation (3.14).

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

$$p_{Sj} Y_{Sj} = \left(p_{Sj} A_{Sj}\right)^{\frac{1}{\alpha}} (1-\alpha)^{\frac{1-\alpha}{\alpha}} \omega_{Sj}^{\frac{\xi}{\alpha(\xi-1)}} \left(\sum_o \sum_i \pi^{Lo}_{Sij} \Omega^{Lo}_{Sij}\right) \left[1 + \left(\frac{1-\omega_{Sj}}{\omega_{Sj}}\right)^{\xi} \left(\frac{w^L_{Sj}}{w^H_{Sj}}\right)^{\xi-1}\right]^{\frac{1+\alpha(\xi-1)}{\alpha(\xi-1)}}. \tag{3.20}$$

Let total disposable income in residential location i be $W_i \equiv \sum_s \sum_o \sum_m \sum_j \pi^{so}_{mij} \tilde{w}^{so}_{mij}$. 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:

$$p_{Sj} A_{Sj} = \frac{(\beta W_i)^{\alpha}}{(1-\alpha)^{1-\alpha} \omega_{Sj}^{\frac{\xi}{\xi-1}} \left(\sum_o \sum_i \pi^{Lo}_{Sij} \Omega^{Lo}_{Sij}\right)^{\alpha}} \left[1 + \left(\frac{1-\omega_{Sj}}{\omega_{Sj}}\right)^{\xi} \left(\frac{w^L_{Sj}}{w^H_{Sj}}\right)^{\xi-1}\right]^{-\frac{1+\alpha(\xi-1)}{\alpha(\xi-1)}}. \tag{3.21}$$

Demand for residential floorspace in location i is $H_{Ri} = \gamma W_i / q_i$. Demand for on-site office space is $H_{WCi} = \sum_s \sum_o \sum_m \sum_j \pi^{so}_{mji} h^{so}_{mji,WC}$, and demand for home office space is $H_{WTi} = \sum_s \sum_m \sum_j \pi^{sT}_{mij} h^{sT}_{mij,WT}$. Then, total local floorspace demand is

$$H_i = H_{Ri} + H_{WCi} + H_{WTi}. \tag{3.22}$$

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, $q_i H_i$. The price per unit of land must then be equal to total earnings divided by the quantity of land:

$$l_i = \frac{\eta_i q_i H_i}{\Lambda_i}. \tag{3.23}$$

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

$$q_i = \frac{1}{\eta_i^{\eta_i}(1-\eta_i)^{1-\eta_i}} \left(\frac{l_i}{\phi_i}\right)^{\eta_i}. \tag{3.24}$$

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 local density of on-site and remote employment:

$$A_{mj} = a_{mj} \left(\frac{N_{WCj} + \psi N_{WTj}}{\Lambda_j}\right)^{\lambda}. \tag{3.25}$$

Parameter $\lambda > 0$ is the elasticity of productivity with respect to employment density, and $\psi \in [0, 1]$ 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 working from home, they may not participate fully in 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:

$$X^s_{mi} = x^s_{mi} \left(\frac{N_{Ri}}{\Lambda_i} \right)^{\chi}, \tag{3.26}$$

where $\chi > 0$ is the elasticity of amenities with respect to the local density of residents.[17] 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.[18]

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, $\mathbb{I}^{so}$; and economy-wide parameters, ν^s_m, ς^s_m, ψ, α, β, γ, ϵ, σ, ζ^s_m, 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), (3.12), (3.25), (3.26), (3.14), (3.19), (3.18), (3.24), (3.17), (3.21), (3.20), and (3.23) are satisfied.

3.6.1 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 B, we evaluate equilibrium properties of a simplified model with exogenous floorspace supply, single industry, and no heterogeneity in education or occupation, but with remote work.

We show that the introduction of telecommuting narrows the range of parameter values for which a unique equilibrium is guaranteed. In a standard model, the extent to which a highly productive location attracts employment is amplified via agglomeration externalities but is dampened as the number of workers willing to commute to this location daily is limited. This is because commuting costs combined with idiosyncratic location preferences constitute a congestion force. In a model with work from home, productive

[17]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.

[18]We assume that all residents contribute equally to amenity externalities, although it is also possible that telecommuters contribute more by spending more time in the area of their residence. Another important channel of amenity adjustments are local services financed by state or municipal taxes. Agrawal and Brueckner (2022) study how work from home and resulting shifts in residents and jobs may affect local tax revenues.

locations have a greater access to potential workers because 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 from 2012–2016.[19] We define a model location as the intersection of a Census Public Use Microdata Area (PUMA) and a county.[20] Defining locations this way and dropping two locations with missing wage data, we end up with 4,502 model locations. Then we must populate them with relevant data.

4.1 Data

Residents, jobs, and commuting. The total number of workers by education level is calculated from the ACS data as described in Section 2. To obtain information on resident population, jobs, and commuting flows, we turn to the LEHD Origin-Destination Employment Statistics (LODES) database, taking averages across 2012–2016. LODES provides workplace and residence job counts separately by education level or by industry at the Census block level, which we aggregate to the level of model locations. We define industry and education as described in Section 2.

Wages. We use the Census Transportation Planning Products (CTPP) database and the American Community Survey (ACS) microdata for 2012–2016 to obtain estimates of average wage by industry m and education s for each location j: $\hat{w}^s_{mj}$. In our model, firms pay workers for their labor as well as for floorspace expenses. We convert observed wages $\hat{w}^s_{mj}$ into their model counterpart w^s_{mj} by applying floorspace expenditures predicted by the model. More details can be found in Appendix Section A.2.

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

[19] 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.

[20] PUMA is the smallest geography for which individual-level data is publicly available. The Census Bureau designs PUMAs to have between 100,000 and 200,000 residents. 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 geographically-detailed data and study patterns within metro areas. In rural areas, where there may be several counties in a single PUMA, each county is a model location.

output prices. We use the 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.

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 A.4 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 A.5.

Work from home. To infer values of some work from home parameters, we use data from the Survey of Working Arrangements and Attitudes (SWAA) conducted by Barrero, Bloom, and Davis (2021) on a monthly basis since May 2020. The survey is representative of the U.S. labor force.

4.2 Parameterization

4.2.1 Work from Home Parameters

The distribution of worker types by education and ability to telecommute is constructed as follows. First, we use the fractions of college and non-college workers we calculated in Section 2. Then, we calculate the average answer to the question *"Are you able to do your job from home (at least partially)?"* for each of the two education types from the SWAA. We find that nearly 50% of all workers in our model can work remotely.[21] In particular, 40.6% of non-college and 72.7% of college workers can work from home. Table 2 shows the distribution of worker types implied by these numbers.[22]

The relative productivities of remote work for each type of a worker, ν_m^s, are calibrated as follows. The SWAA asked respondents about their productivity of working from home. We first calculate the average response to the question *"How efficient are you WFH during COVID, relative to on business premises before COVID? (%)"* for each type of worker. We interpret answers to this question as a self-assessed productivity of remote versus on-site

[21]Some respondents who answered "yes" during the pandemic might have responded "no" before the pandemic, even if their job did not change. We view a "yes" response as an indication that it is technologically possible to perform at least some job tasks at home. Given that communication technology used for remote work during the pandemic largely existed before 2020 and given that changes in the occupational composition of the economy since 2019 have been minimal, we view the average responses to this question as a measure of the fraction of jobs that can be performed at home. This number is higher than the 37% estimated by Dingel and Neiman (2020). However, we believe this to be an underestimate, given that, according to Barrero, Bloom, and Davis (2021), 30% of all paid work days are worked from home.

[22]While the levels are different, these numbers are consistent with the evidence reported in Figure 1.

work during the pandemic, and we will use these numbers to calibrate the post-pandemic economy in Section 5. Then, we calculate the average response to the question "*Relative to expectations before COVID, how productive are you WFH during COVID? (%)*" for each type of worker. We interpret answers to this question as a self-assessed improvement in remote work productivity during the pandemic relative to the pre-pandemic period. Finally, we divide the average response to the first question by one plus the average response to the second question, and obtain an estimate of the pre-pandemic work from home productivity. These numbers are reported in Table 2. We find that remote work is nearly as productive as on-site work with relative productivity ranging from 0.9896 to 0.999.[23] These values are consistent with existing empirical evidence.[24]

The calibrated values of aversion to remote work ς_m^s and the elasticity of substitution between on-site and remote work ζ_m^s are shown in Table 2. While we jointly calibrate these and several other parameters, these two sets of parameters are primarily determined by two sets of targets.

The first set of targets is comprised of 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.

The second set of targets consists of the variance for each group of the choice of on-site work frequency for choices which fall between 1 and 4 days per week, i.e. $0.2 \leq \theta \leq 0.8$.[25] These variances are calculated from the SIPP data, as described in Section 2. The variances are primarily used to calibrate the elasticity of substitution between on-site and remote work: the more substitutable the two modes are, the more likely is a worker to choose a θ close to 0 or 1, and the larger will be the variance of θ's in the quantitative model.

The calibrated elasticities of substitution between remote and on-site work are higher

[23]Davis, Ghent, and Gregory (2024) calibrate pre-pandemic relative productivities of remote work to be approximately 0.35 for both high and low-skilled workers. Combined with worker-type-specific TFP estimates, this implies that pre-2020, a full-time remote worker would only earn slightly over one third of the wage of an otherwise identical non-remote worker. This same paper estimates a single elasticity of substitution for all worker categories, finding a value of 3.5, squarely in the middle of our calibrated values. Using a different specification, the aforementioned study also estimates work from home preference parameters. They find a positive preference for having the option of working from home, which helps rationalize pre-Covid existence of remote work in spite of its low (estimated) productivity.

[24]Work from home productivity is the subject of active current research. A randomized study conducted during the pandemic by Bloom, Han, and Liang (2022) finds no differences in promotions and performance evaluations, lower quit rates, and less frequent sick leaves, suggesting that work from home is at least as productive as work in the office. Other studies that find that remote and/or hybrid work are at least as productive as in-person work include Bloom, Liang, Roberts, and Ying (2015) and Choudhury, Khanna, Makridis, and Schirmann (2022), among others. Studies that find productivity losses include Emanuel, Harrington, and Pallais (2022) and Gibbs, Mengel, and Siemroth (2022).

[25]We target this middle range so that the moment is more distinct from the average freqency, which is heavily influenced by the masses of workers with $\theta < 0.2$ and $\theta > 0.8$.

Table 2: Work from home parameters

Parameter	Description	Value	Source or Target
	Distribution of worker types:		
ι^{LN}	non-college, non-telecom.	0.4225	ACS and Barrero, Bloom, and Davis (2021)
ι^{LT}	non-college, telecommutable	0.2884	—
ι^{HN}	college, non-telecommutable	0.0790	—
ι^{HT}	college, telecommutable	0.2101	—
	Productivity of remote work:		
ν_S^L	non-college, non-tradable	0.9929	Barrero, Bloom, and Davis (2021)
ν_G^L	non-college, tradable	0.9961	—
ν_S^H	college, non-tradable	0.9896	—
ν_G^H	college, tradable	0.9990	—
	Aversion to work from home:		Average commuting frequency:
ς_S^L	non-college, non-tradable	3.3599	$\bar{\theta}_S^L = 0.970$
ς_G^L	non-college, tradable	2.7522	$\bar{\theta}_G^L = 0.939$
ς_S^H	college, non-tradable	2.8196	$\bar{\theta}_S^H = 0.913$
ς_G^H	college, tradable	2.3985	$\bar{\theta}_G^H = 0.817$
	Elasticity of substitution between on-site and remote work:		Variance of WFH frequency:
ζ_S^L	non-college, non-tradable	4.1884	$\text{Var}(\theta_S^L \mid \theta \in [0.2, 0.8]) = 0.0356$
ζ_G^L	non-college, tradable	3.8924	$\text{Var}(\theta_G^L \mid \theta \in [0.2, 0.8]) = 0.0367$
ζ_S^H	college, non-tradable	4.3548	$\text{Var}(\theta_S^H \mid \theta \in [0.2, 0.8]) = 0.0351$
ζ_G^H	college, tradable	3.0330	$\text{Var}(\theta_G^H \mid \theta \in [0.2, 0.8]) = 0.0273$
κ	Elasticity of commuting cost to commuting time	0.0086	Ahlfeldt, Redding, Sturm, and Wolf (2015) and Tsivanidis (2019)
τ	Elasticity of distance penalty g_{ij} to commuting time	0.0024	Ratio between non-telecommuters' and telecommuters' distance to work = 0.338
ψ	Contribution of telecommuters to productivity externalities	{0,1}	We run separate counterfactuals with $\psi = 0$ and $\psi = 1$

Note: The table lists model parameters directly related to work from home.

in the non-tradable than in the tradable industry, with values ranging from 3.03 to 4.35. The calibrated aversion parameters range from 2.4 to 3.36, indicating large non-pecuniary barriers to remote work, especially for non-college workers in the non-tradable sector.

College workers in the tradable industry have the smallest aversion to working from home but their at-home and on-site effort is less substitutable. On the one hand, such workers may have enjoyed more flexible working arrangements even before the pandemic. On the other hand, in the knowledge-intensive industries (finance, IT) which make up much of the tradable sector, there may be greater complementarity between individual tasks that are relatively easy to do at home, and knowledge-sharing and coordination which are more efficiently accomplished on-site.

In our model, worker's utility is decreasing in commuting 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 (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.

Then we calibrate 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 the distance penalty g_{ij}. If they can telecommute, the distinction becomes 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 are 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 set τ so that the ratio of average distances, is the same in the model and in the data, and find $\tau = 0.0024$. Finally, we recover $\kappa = 0.011 - \tau = 0.0086$.

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, in our main counterfactual we will assume that remote work does not contribute to productivity at all, i.e., use $\psi = 0$. Then in Section 5.7 we study a scenario in which remote work does not inhibit productive externalities, i.e., $\psi = 1$.

4.2.2 Other Parameters

We set the consumption share of housing, $\gamma = 0.24$, following Davis and Ortalo-Magné (2011). Spending on non-tradable goods is an important determinant of wages in the non-tradable sector. Therefore, we calibrate β, the expenditure share of non-tradable goods, so that the ratio between the mean wages in the tradable and non-tradable sectors, is the same in the model and in the data.

Valentinyi and Herrendorf (2008) estimate that the combined share of land and structures in the U.S. is 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

Table 3: Other parameters

Parameter	Description	Value	Source or Target
γ	Consumption share of housing	0.24	Davis and Ortalo-Magné (2011).
β	Consumption share of non-tradables	0.6978	Ratio between average wages in the tradable and non-tradable sectors = 1.05
α	Labor share in production	0.82	Valentinyi and Herrendorf (2008)
ξ	Elasticity of substitution between college and non-college labor	2	Card (2009)
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)
σ	Fréchet elasticity of industry shock	1.4	Lee (2020)
ϵ	Fréchet elasticity of location shock	4.026	Estimated

Note: The table lists model parameters not directly related to work from home.

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 borrow the values of the elasticities of local productivity and amenities with respect to density from Heblich, Redding, and Sturm (2020), and set $\lambda = 0.086$ and $\chi = 0.172$.[26] To examine the sensitivity of our results to these two values, we run counterfactuals where each of these values is set to zero. Naturally, magnitudes of reallocations are slightly smaller but none of the results change in any major way; see Appendix F for details.

We set the Fréchet elasticity of the distribution of industry preference shocks, σ, equal to 1.4, following Lee (2020). To obtain the value of the Fréchet elasticity of location preference shocks ϵ, we estimate $(\kappa + \tau)\epsilon$ from the relationship between commuting flows and commuting times using Poisson pseudo maximum likelihood (PPML). Our estimate of $(\kappa + \tau)\epsilon$ is 0.0443. Then, to recover ϵ, we use the value $\kappa + \tau = 0.011$, as discussed in Section 4.2.1, and obtain $\epsilon = 0.0443/0.011 = 4.026$. Estimation details are provided in Appendix Section C.1.

4.2.3 Local Parameters

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,

[26] Meta-analysis of estimated density elasticities in Ahlfeldt and Pietrostefani (2019) finds an average productivity elasticity of 0.06 from 15 studies (category 2 from Table 3). The elasticity of amenities depends on the type of amenity, and averaged over 67 studies the estimates vary from −0.04 to 0.24 (categories 5, 6, 8, 9, and 10 from Table 3).

$(1-\eta_i)/\eta_i$, 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.[27] We aggregate these to the level of our model locations using population weights. The advantage of these estimates is their geographic granularity. At the same time, they are significantly lower than previous studies have found.[28] In Appendix Section H.3 we show that the results of our counterfactuals change little if we use higher values of the elasticity.

We also need to quantify several vectors of location-specific fundamentals, and we do this by inverting the model. These fundamentals are land-adjusted exogenous productivity $\tilde{a}_{mi} \equiv a_{mi}\Lambda_i^{-\lambda}$, land-adjusted exogenous amenities $\tilde{x}^s_{mi} \equiv x^s_{mi}\Lambda_i^{-\chi}$, land-adjusted productivity of floorspace developers $\tilde{\phi}_i \equiv \phi_i\Lambda_i$, workplace amenities E^s_{mj}, and education-specific productivity shifters ω_{mj}.[29]

These parameters are pinned down by using the following local data. Labor productivity parameters $\tilde{a}_{mi}$ and ω_{mj} are determined from observed wages by industry and skill.[30] Floorspace productivity parameter $\tilde{\phi}_i$ is determined from observed housing rents. Residential amenities $\tilde{x}^s_{mi}$ are determined from the total population of a location. 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 $x^s_{mi} = x_{mi}x^s_i$ and $E^s_{mj} = E_{mj}E^s_j$. Needless to say, in practice locations differ in many other important ways, e.g., climate, access to transportation, etc. All these differences are implicitly captured by the amenity parameters.

The following result states that, given observed data and economy-wide parameters, there are unique vectors of location-specific fundamentals, consistent with an equilibrium.

Proposition 1. *Given the data, $N_{R,mi}$, $N_{W,mj}$, $N^s_{R,i}$, $N^s_{W,j}$, I^{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, $\tilde{a}_{mi}$, x_{mi}, x^s_i, $\tilde{\phi}_i$, E_{mj}, E^s_j, and ω_{mj}, that is consistent with the data being an*

[27] We take the 2011 total floorspace elasticities estimated with the FMM-IV model (variable *gamma11b_space_FMM*). For locations with missing elasticity data, we impute the elasticities by first regressing available elasticities on a cubic polynomial of population density (the R^2 of this regression is 0.66) and then using the regression prediction in locations where elasticity estimates are not available.

[28] At the level of our model locations, elasticities vary from 0.08 to 1.57, and the population-weighted average is 0.68. For comparison, Saiz (2010) estimates the elasticities to be on average 1.75 at the metro area level, and Baum-Snow and Han (2021) discuss the reasons for this discrepancy. Recall that in our model parameter η_i corresponds to the land share in housing production. The values of elasticities that we use imply that η_i ranges from 0.39 to 0.93 and the average is 0.6. Thus, the average 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 in the U.S.)

[29] Separate identification of land area Λ_i is not required for the model.

[30] In our model, wages include firms' payments for labor and floorspace expenditures. When calibrating $\tilde{a}_{mi}$ and ω_{mj}, we only use the portion of wages that are paid for labor effort.

equilibrium of the model.

Proof. The proof follows closely the proof of a similar result in Ahlfeldt, Redding, Sturm, and Wolf (2015). See Appendix Section C.3 ☐

4.3 Model Fit

Stylized facts about telecommuting. How does our model do in matching the stylized facts laid out in Section 2.2? For *stylized fact #1*, while we match the fraction of telecommutable workers by education and the total number of workers in each industry during our calibration, the model endogenously produces the fraction of telecommutable workers by industry. Figure 1 reported that the share of those who cannot work remotely is 81.1% for non-college workers in the non-tradable sector, 71.1% for non-college workers in the tradable sector, 46.7% for college workers in the non-tradable sector, and 31.2% for college workers in the tradable sector. The corresponding numbers in our model are 59.8%, 58.9%, 28.4%, and 25.7%.[31] Though the ranking is preserved, the industry gap is smaller than in the data. This is not surprising as we do not model the structural links between occupations and industries that almost certainly drive most of the gap in the data.

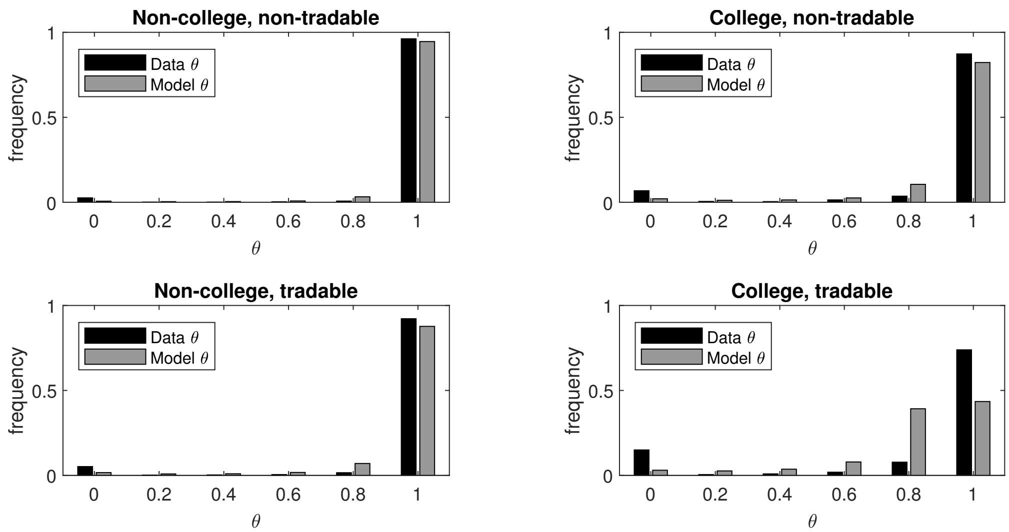
For *stylized fact #2*, our model successfully produces the gap in telecommuting *uptake* for each worker type. Figure 1 showed that the fraction of those who work from home at least one paid full day per week is 3.9% among non-college workers in the non-tradable sector, 7.8% for non-college workers in the tradable sector, 12.7% for college workers in the non-tradable sector, and 26.1% for college workers in the tradable sector. The corresponding numbers in our model are nearly identical: 3.2%, 7.3%, 10.3%, and 27.6%.

The model ably reproduces *stylized fact #3*, as demonstrated in Figure 4. By targeting the mean frequency for each education-industry pair and the variance for the interior of the distribution, $\theta \in [0.2, 0.8]$, we can reproduce the heavy right tail and, to some extent, the bimodality of the distribution. One exception is the distribution for college graduates in tradable industries. Due to the relatively low calibrated elasticity of substitution between on-site and remote work, our model generates a lower number of full-time commuters compared to the data. *Stylized fact #4* 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. Thus

[31] The levels are lower because the data we use to measure the ability to telecommute in the model is different from the data we used in Section 2. See Section 4.2.1 for details.

Figure 4: Telecommute frequency, data vs. benchmark model



Note: "Data" reflects averages from SIPP, as described in Section 2. A bar at a given θ includes values $\theta \pm 0.1$. Values of $\theta > 0.9$ are included with $\theta = 1$; values < 0.1 with $\theta = 0$.

$\pi_{ij} \equiv \sum_s \sum_o \sum_m \pi^{so}_{mij}$ is an untargeted moment that we can use to evaluate our model.[32] We find that the correlation between model and data flows is 0.928.

5 Implications of an Increase in Telecommuting

In this section, we study the long-run impact of the rise in work 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.

5.1 Counterfactual Setup

Our baseline assumption is that the increase in remote work is driven by a combination of an increase in work from home productivity ν^s_m and a fall in the aversion to telecommuting ς^s_m. How do we determine the size of the changes in these parameters? The calibrated changes in work from home productivity were described in Section 4.2.1. We also rely on the SWAA survey data to obtain information about employers' plans for the number of days per week a worker is expected to work remotely in the long run. From these data we calculate a counterfactual mean on-site working frequency for each worker type, and lower the aversion to remote work to match it.[33]

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

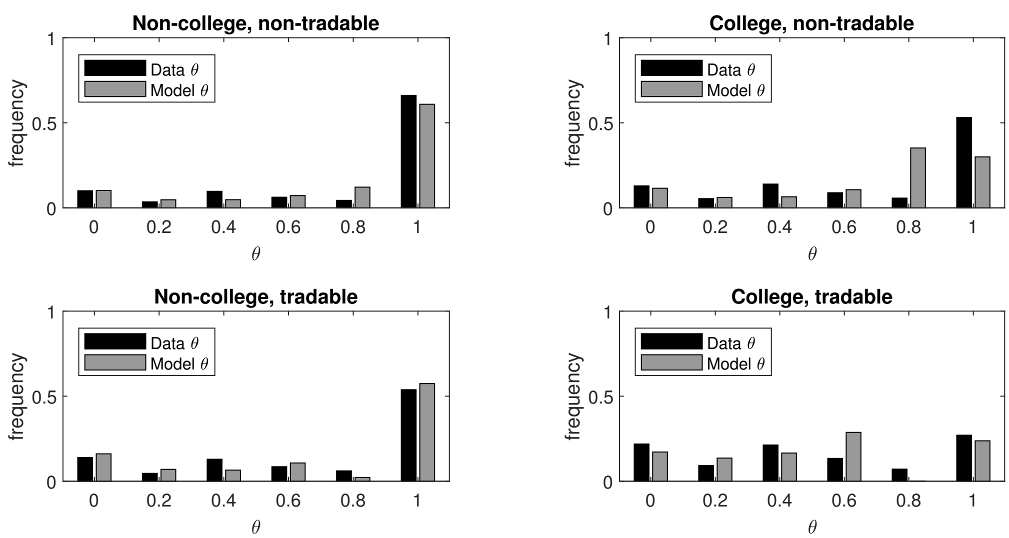
[33] As discussed in Section 3.6, the equilibrium of the model need not be unique. We follow Tsivanidis (2019) in focusing on the counterfactual equilibrium that is computed using the benchmark equilibrium as

Table 4: Work from home productivity and aversion parameters

Parameter	Description	Benchmark	Counterfactual	% change	Target
	Productivity of remote work:				
ν_S^L	non-college, non-tradable	0.9929	1.0718	7.95%	
ν_G^L	non-college, tradable	0.9961	1.0945	9.88%	
ν_S^H	college, non-tradable	0.9896	1.0807	9.21%	
ν_G^H	college, tradable	0.9990	1.0978	9.88%	
	Aversion to work from home:				
ς_S^L	non-college, non-tradable	3.3599	1.7471	-68.3%	$\bar{\theta}_S^L = 0.779$
ς_G^L	non-college, tradable	2.7522	1.5167	-70.5%	$\bar{\theta}_G^L = 0.699$
ς_S^H	college, non-tradable	2.8196	1.5167	-46.5%	$\bar{\theta}_S^H = 0.697$
ς_G^H	college, tradable	2.3985	1.5245	-62.4%	$\bar{\theta}_G^H = 0.512$

Note: The table shows calibrated values of the work from home productivity and aversion parameters in the benchmark and the counterfactual economies. Since $\varsigma_m^s = 1$ corresponds to the absence of work from home aversion, we calculate the percentage change in $\varsigma_m^s - 1$ for each type of worker. The last column lists targeted counterfactual work from home frequencies for each type of worker.

Figure 5: Commuting frequency, survey prediction vs. counterfactual model



Note: "Data" reflects predicted post-pandemic distribution of days per week worked on site from the survey by Barrero, Bloom, and Davis (2021). A bar at a given θ includes values $\theta \pm 0.1$. Values of $\theta > 0.9$ are included with $\theta = 1$, and values of $\theta < 0.1$ with $\theta = 0$.

Table 4 shows the values of work from home productivity and aversion parameters. All types of workers experience similar increases in productivity, between 8% and 10%. Non-college workers in both sectors see somewhat larger drops in their work from home aversion than college workers, and all but non-college workers in the non-tradable sector

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).

end up with similar levels of aversion. One possible interpretation of this result is that even before the pandemic the technological and cultural barriers to telework were lower for college graduates, and they still remain high for non-college workers in the non-tradable sector. In Appendix Section H.2, we study a scenario in which all types of workers experience the same change in work-from-home aversion. This does not change the results in any major way.

Figure 5 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. Compared to the pre-pandemic distribution shown in Figure 4, we see a sizable increase in hybrid and full-time remote work even though most workers still commute to the office every day.

In our baseline counterfactual, we assume that remote workers do not contribute to productive externalities, i.e., we set $\psi = 0$. We study the implications of this assumption in Section 5.7.

5.2 Residents, Jobs and Real Estate Prices

Distribution of residents. As panels A and B in Figure 6 show, residents move away from the densest locations and biggest cities, towards sparser locations and smaller cities.[34] While there is much heterogeneity in the changes not explained by the crude ranking of locations and cities, the *average* trend is monotonic.[35]

While panel D of Figure 6 shows that telecommutable residents take advantage of increased remote work opportunities to move away from density, panel C shows that this is partially counteracted by a smaller movement of non-telecommutable residents back towards dense areas. 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.

Distribution of jobs. In contrast to the reallocation of residents, job movements are not entirely monotonic in residential density. As panel A in Figure 7 shows, jobs increase on average in locations below the median density and decrease in locations which are above the median, while showing no average change in the most-dense locations. A similar pattern is observed at the CZ level, as shown in panel B.[36]

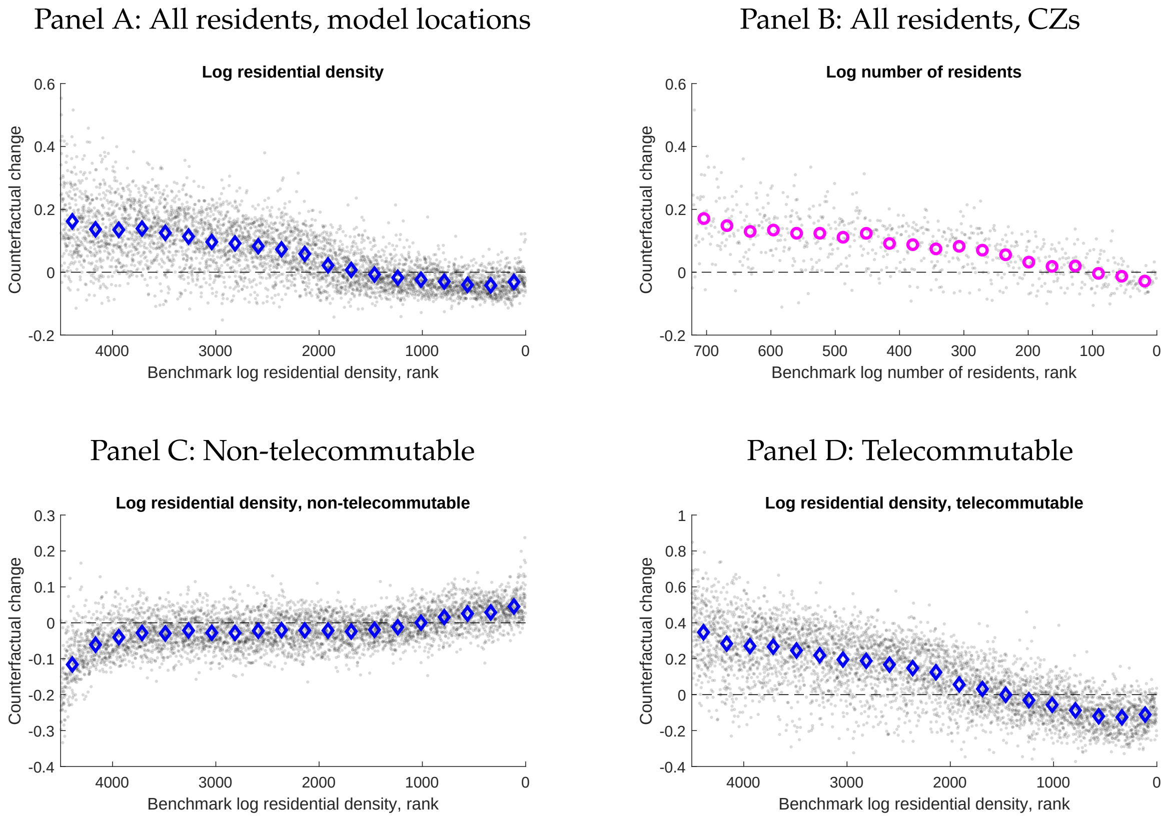
Panel C shows that non-tradable jobs monotonically follow the source of their demand,

[34] Althoff, Eckert, Ganapati, and Walsh (2022) and Haslag and Weagley (2024) documented a reallocation of residents from the densest to the least dense locations during the pandemic.

[35] Appendix Figure J.1 displays predicted changes on a map.

[36] Appendix Figure J.2 maps predicted changes.

Figure 6: Change in Residents



Note: Panel A shows the relationship between residential density rank for model locations and change in log residential density. Panel B shows the relationship between total resident rank for CZs and change in log total residents. Panels C and D repeats the exercise for non-telecommutable and telecommutable residents by model location. Scatterplots in gray show individual model locations or CZs, 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.

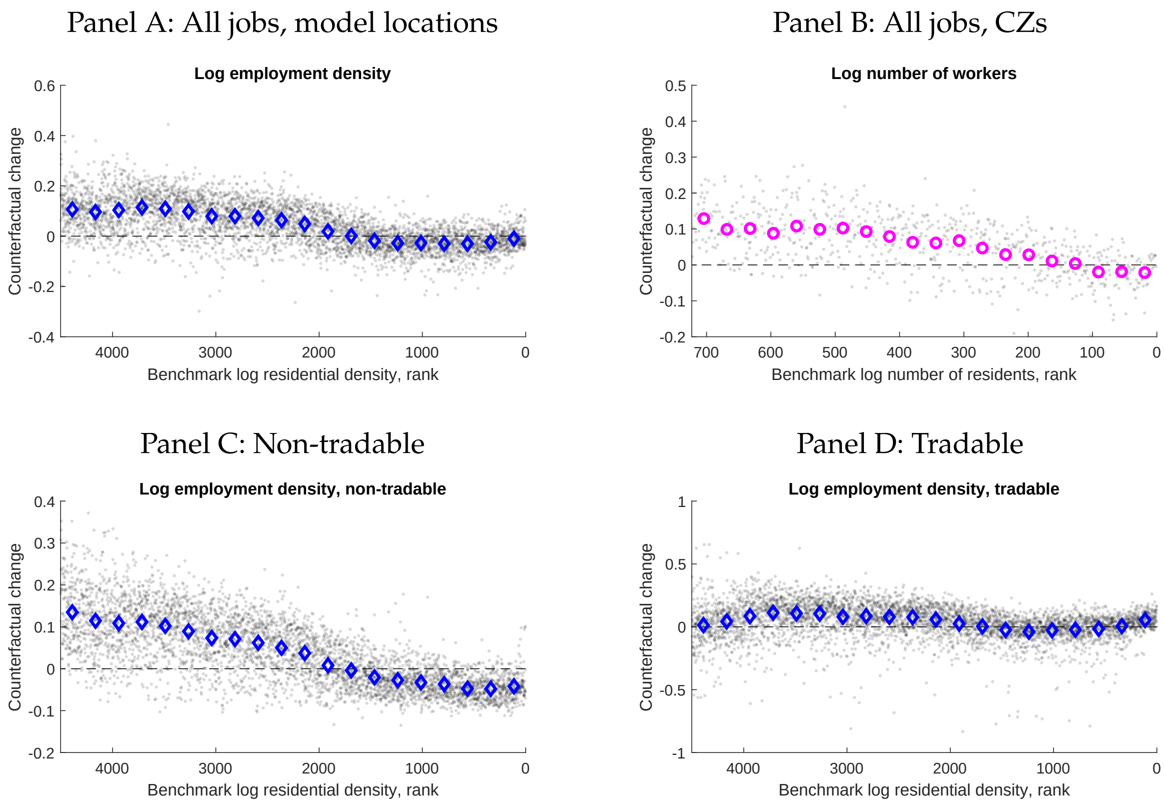
residents, to less dense locations.[37] This means that the mixed pattern shown in panel A must be due to shifts in tradable sector jobs, shown in panel D. Thanks to the weakening of spatial frictions in the labor market, two types of locations win out and add workers to their tradable industries. One type consists of low-density places with low real estate costs. The other consists of the highest-density places with the highest productivity, such as Manhattan, and also the biggest reduction in real estate costs.[38] As a result, the densest 5% of locations see tradable employment go up by an average of over 5%.

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 8. Prices decrease in most top-quartile locations and increase in

[37] Althoff, Eckert, Ganapati, and Walsh (2022) provide empirical evidence for this mechanism during the pandemic.

[38] The correlation between log productivity in the tradable sector and log residents per square km is 0.63.

Figure 7: Change in Employment



Note: Panel A shows the relationship between residential density rank for model locations and the change in log job density. Panel B shows the relationship between total resident rank for CZs and the the change in log total jobs. Panels C and D repeat the exercise for non-tradable and tradable jobs by model location. Scatterplots in gray show individual model locations or CZs, 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.

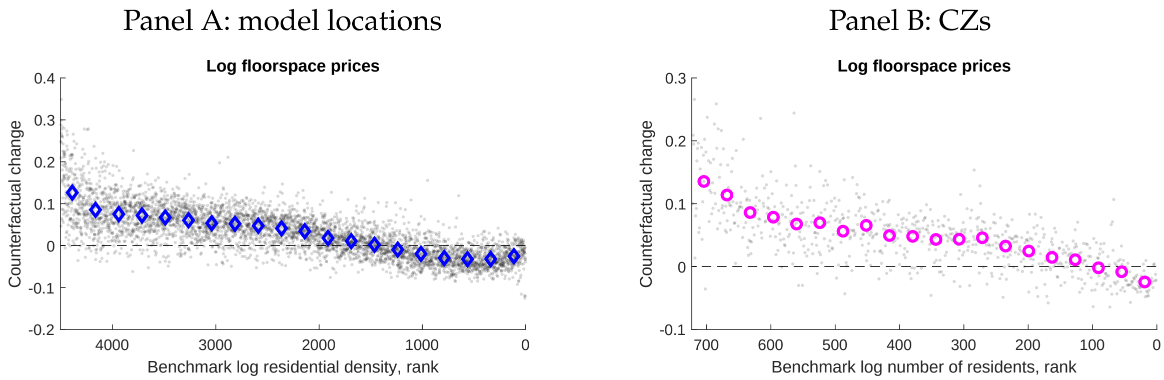
most locations below the top quartile. Both the location-level and CZ-level patterns are consistent with the shift of residents and non-tradable jobs to less dense locations driving up floorspace demand.[39] Appendix Figure J.3 displays predicted price changes on a map.

Changes within cities. In Appendix Figure J.4 we plot the counterfactual change in residents, jobs, and floorspace prices as a function of the distance to the city center for 10 largest CZs. We show that, on average, locations closer to the center lose more residents and see larger reductions in floorspace prices, but at the same time add jobs.

New York case study. In Appendix Section D, we describe shifts in residents, jobs, and floorspace prices in New York to demonstrate an example of patterns that take place within a large urban agglomeration.

[39] Rappaport (2022) investigates the effect of remote work on housing supply.

Figure 8: Floorspace prices



Note: Panel A shows the relationship between residential density rank for model locations and the change in floorspace prices. Panel B shows the relationship between total resident rank for CZs and the change in floorspace prices. Scatterplots in gray show individual model locations or CZs, 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.

5.3 Why do workers move?

In Figure 6 we see telecommutable workers decentralize while non-telecommutable workers centralize. But what accounts for the considerable heterogeneity we observe around this trend? And, more importantly, what motivates these moves?

Four possible motives, corresponding to the four components of workers' utility, are (a) lower house prices, (b) lower non-tradable prices, (c) better amenities, and (d) better job access, as measured by the commuter market access (CMA) defined in equation (3.6). Table 5 reports the best-fit line slopes from bivariate regressions of log changes in residents between the benchmark and the counterfactual on logs of each of these variables, in either the benchmark or counterfactual economy. All among this first set of coefficients go in the same direction as the overall correlation between each variable and density. To gain more insight into sources of heterogeneity and workers' motives, we condition on density by running each regression separately for each density ventile, plotting the best-fit coefficients in Figure 9.

As we saw in Figure 6, *non-telecommutable* workers move towards denser locations, and thus, as in Table 5, towards higher prices, higher amenities, and higher CMA. Conditional on density, all of those correlations reverse, except for CMA. In Figure 9, we see that within each density ventile, non-telecommutable workers move towards lower-priced locations with lower amenties, but towards locations with higher market access. This strongly suggests that the overall trend towards denser locations is motivated by better job market access. There is also a substitution effect at play here: the departure of telecommutable workers from central locations lowers the cost choosing high-CMA locations with shorter

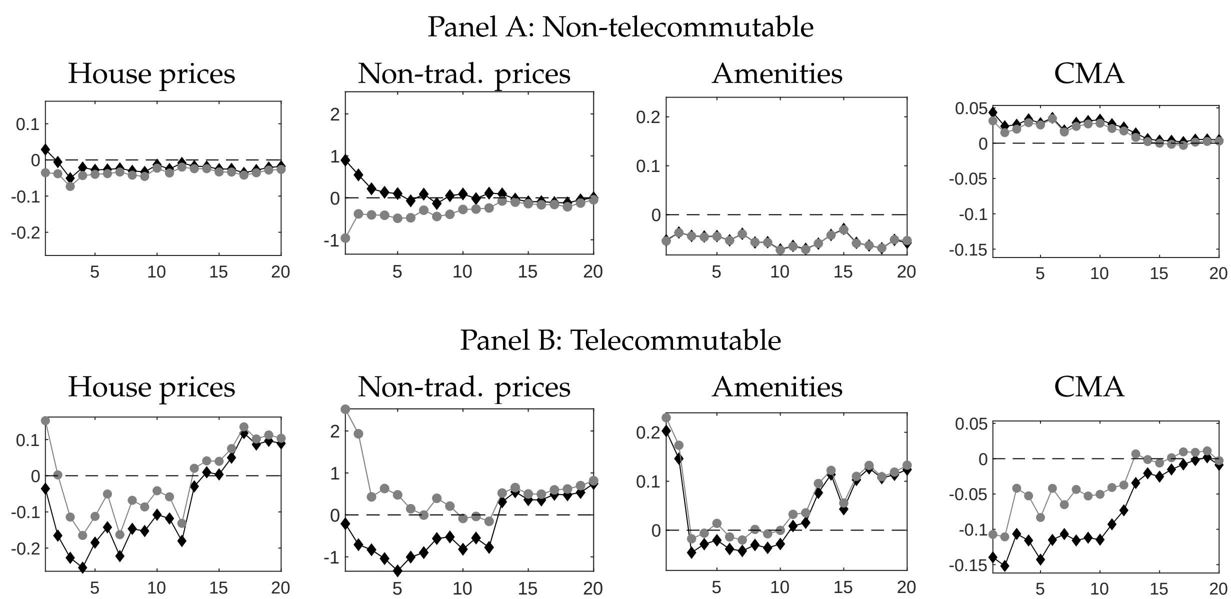
Table 5: Importance of location characteristics for reallocation of workers

Panel A: Model locations

	House prices		Non-trad. prices		Amenities		CMA	
	Coeff.	R^2	Coeff.	R^2	Coeff.	R^2	Coeff.	R^2
Benchmark values								
Non-telecommutable	0.04***	0.07	0.27***	0.10	0.02***	0.02	0.03***	0.29
Telecommutable	-0.28***	0.34	-1.34***	0.19	-0.26***	0.21	-0.12***	0.46
Counterfactual values								
Non-telecommutable	0.03***	0.04	0.03***	0.00	0.02***	0.02	0.03***	0.19
Telecommutable	-0.26***	0.24	-0.71***	0.06	-0.24***	0.17	-0.11***	0.27

Note: This table shows the values of coefficients and R^2 from bivariate regressions of log resident changes on log house prices, non-tradable prices, amenities, and CMA in the benchmark and counterfactual economies. *, **, and *** indicate 10%, 5%, and 1% significance levels.

Figure 9: Importance of location characteristics for reallocation of workers, by density



Note: This figure shows the values of coefficients (on y-axis) from bivariate regressions of log resident changes on log house prices, non-tradable prices, amenities, and CMA in the benchmark (black line with diamonds) and counterfactual (gray line with circles) economies, separately for each ventile of population density (on x-axis) in the benchmark economy.

commute times and higher wages. This induces non-telecommutable workers to substitute towards consumption and short commutes, and away from amenities.

We can analyze the movements of *telecommutable* workers in a similar way. But first, let us note that unlike the substitution effect impacting non-telecommutable workers, remote-capable workers are hit with an income effect–the cost of location choice has gone down, effectively expanding their budget set along all the dimensions of utility (housing, goods, amenities, commute times). Figure 6, shows them moving to less dense locations, producing the expected negative correlations for prices, amenities, and CMA in Table 5. Conditioning on density, we see that telecommutable workers use their improved ability to choose locations differently depending on density. Among the highest- and lowest-density locations, they seek out high amenities, and are willing to pay higher prices for houses and non-tradables to get them. Among medium-density locations, they seek out low house prices and, to a lesser extent, low non-tradable prices, and show indifference to the distribution of amenities. There is a significant gap between the benchmark and counterfactual lines for house and non-tradable prices, because telecommuters drive them up in the places they move to. Telecommutable workers move away from market access because they no longer need it as much, especially in lower-density locations.

The difference in the location choices of telecommutable and non-telecommutable workers resembles the recent tendency of college graduates to increasingly concentrate in high-amenity and high-cost areas (Diamond and Gaubert, 2022). In this case, however, what distinguishes the two groups is not the presence of a college degree but the ability to engage in production from one's home, and thus the freedom to choose where to live based on one's preferences, and less based on where good jobs are.

5.4 Why do jobs move?

We now conduct an exercise similar to the one in Section 5.3, but for jobs. We particularly hope to shine light on the motives of tradable firms, who in Figure 7 appear to have a mixed pattern of relocations.[40] The four main motivating factors for job movements in our model are (a) floorspace rents, (b) workers' wages, (c) productivity, and (d) firm market access (FMA), as defined in equation (3.6). The results are shown in Table 6 and Figure 10.

Non-tradable firms' moves are substantially correlated with lower floorspace rents and, to a lesser extent, with lower FMA because they follow the mass of workers as they decentralize. Little is explained by a correlation with workers' wages or productivity, as these firms' location choices are of necessity driven much more by shifting demand rather than costs.

Tradable firms also generally move towards lower rents. There is non-monotonicity–in both the densest and least dense places, jobs do not move differentially toward lower-rent locations, while in low-to-medium density places they do, strongly. There appears to be a price-productivity trade-off–in the most- and least-dense ventiles, firms seek out the highest productivity locations in the neighborhood, while in medium-density ventiles

[40]See also Appendix Section I, where we examine how the increase in remote work intensifies sectoral specialization of cities.

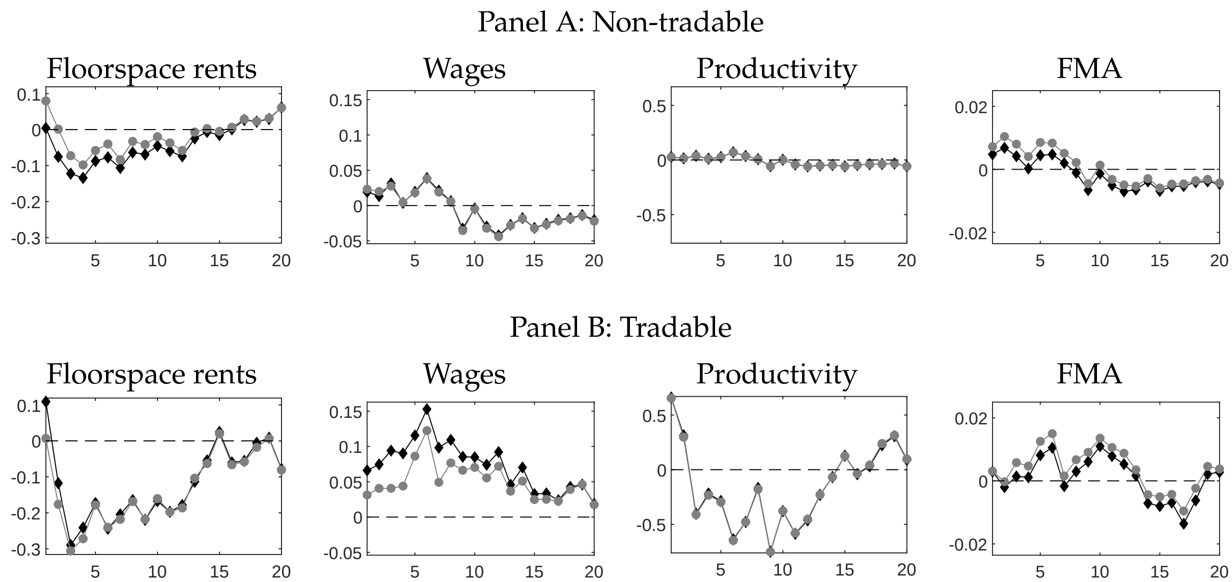
Table 6: Importance of location characteristics for reallocation of jobs

Panel A: Model locations

	Flsp. rents		Wages		Productivity		FMA	
	Coeff.	R^2	Coeff.	R^2	Coeff.	R^2	Coeff.	R^2
Benchmark values								
Non-tradable	-0.12***	0.35	-0.01***	0.00	-0.01	0.00	-0.01***	0.11
Tradable	-0.11***	0.12	0.07***	0.03	-0.29***	0.05	-0.00***	0.00
Counterfactual values								
Non-tradable	-0.11***	0.25	-0.01***	0.00	-0.01	0.00	-0.01***	0.06
Tradable	-0.13***	0.12	0.05***	0.02	-0.29***	0.05	-0.00	0.00

Note: This table shows the values of coefficients and R^2 from bivariate regressions of log job changes on log floorspace rents, wages, productivity, and FMA in the benchmark and counterfactual economies. *, **, and *** indicate 10%, 5%, and 1% significance levels.

Figure 10: Importance of location characteristics for reallocation of jobs, by density



Note: This figure shows the values of coefficients (on y-axis) from bivariate regressions of log job changes on log floorspace rents, wages, productivity, and FMA in the benchmark (black line with diamonds) and counterfactual (gray line with circles) economies, separately for each ventile of population density (on x-axis) in the benchmark economy.

their pursuit of low rents leads them to less productive locations on average. Both of these motives lead them to places that have somewhat higher wages, though the lower magnitudes of the best-fit coefficients suggest that the higher labor cost is more than offset by lower floorspace cost or higher productivity. FMA appears to have little explanatory power.

5.5 Model Validation: Residents and Rents, 2019–2023

Since 2020 there were large changes in the distribution of residents and housing in the United States. These are at best medium-run, and not long-run, changes. They are also influenced by a host of factors, from politics to fear of Covid to monetary and fiscal policy, which we do not model. Nevertheless, if the increase in remote work was one of the important motivations, our model predictions should be correlated with these observed changes. So, are they?

Residents. We find that our model's counterfactual residential relocations are positively correlated with observed migration between 2019 and 2023. We use aggregated ACS data at the PUMA level to measure changes in population counts between 2019 and 2023. We then regress observed migration on model-predicted migration, and report the results in Table 7, panel A.

Column (1) corresponds to a specification with no controls, and shows a positive, statistically significant relationship between model predictions and observed changes.[41] Moreover, this is not merely due to the negative relationship between initial residential density and change in population. As Column (2) shows, even after controlling for density in 2012–2016 model predictions retain positive, significant correlation with the data.

Then we introduce fixed effects for commuting zones (CZ) to evaluate the match between our predictions and observed shifts *within* cities. Column (3) shows that are model predictions are positively correlated with observed changes, albeit weakly so. Results in column (4) emphasize the role of density for migration patterns and show that out model's predictions on migration within cities are not correlated with the data, once density is controlled for. In Columns (5) and (6), we aggregate to the level of CZs, and see that our model is a good predictor of shifts *across* CZs, as well.

Rent prices. Our model's counterfactual changes in floorspace prices are also positively correlated with observed changes in housing costs between December 2019 and December 2023, although mostly within CZs. We use Zillow data to construct a measure of residential rent price changes and regress this on our model's predictions.[42] We use the same sequence

[41] Haslag and Weagley (2024) study interstate migration since 2020 and find that 12% of moves were influenced by the pandemic and that among pandemic-influenced movers, 15% were influenced by remote work. Ozimek (2020) estimates that 2.4% of adults in the U.S. have moved residences because of remote work since 2020. The fact that many moves since 2020 are not motivated by the ability to work from home may explain why the predictions of our model are positively correlated with the data but the R^2's are low.

[42] Here we use Zillow's Observed Rent Index (ZORI) as our measure of housing costs because of the close connection between rents and current housing demand, which also exists in our model. Conducting the same exercise for Zillow's House Value Index (ZHVI), we similarly find a positive and significant relationship with our model predictions for changes 2019–2021, but no relationship for the changes over the entire period from 2019 to 2023. We believe this is due to a lack of alignment between real estate investors' expectations and current market conditions, which is beyond the scope of the current study.

Table 7: Changes from 2019 to 2023, model vs. data

Panel A: Residents

	(1)	(2)	(3)	(4)	(5)	(6)
Log chg residents, model	0.160***	0.186***	0.0874*	-0.0151	0.246***	0.320***
	(0.0257)	(0.0348)	(0.0390)	(0.0520)	(0.0596)	(0.0724)
Level of obs.	ML	ML	ML	ML	CZ	CZ
Density control	no	yes	no	yes	no	yes
CZ fixed effects	no	no	yes	yes	–	–
Observations	4502	4502	4453	4453	723	723
R-squared	0.00850	0.00878	0.384	0.385	0.0230	0.0273

Panel B: House rents

	(1)	(2)	(3)	(4)	(5)	(6)
Log chg prices, model	0.546***	0.131	0.774***	0.729***	-2.984*	-3.097
	(0.110)	(0.126)	(0.111)	(0.146)	(1.279)	(1.573)
Level of obs.	ML	ML	ML	ML	CZ	CZ
Density control	no	yes	no	yes	no	yes
CZ fixed effects	no	no	yes	yes	–	–
Observations	1334	1334	1293	1293	172	172
R-squared	0.0182	0.0475	0.492	0.492	0.0310	0.0311

Note: In panel A, the dependent variable is the log change in residents between 2019 and 2023 constructed from the ACS. In panel B, the dependent variable is the log change in house rents between December 2019 and December 2023 constructed from Zillow. Standard errors are in parentheses. The regressions are estimated at the level of model locations ("ML"), with or without CZ fixed effects, or at the level of CZs ("CZ"). Regressions at the model location level with CZ fixed effects have fewer observations because some CZs correspond to model locations. *, **, and *** indicate 10%, 5%, and 1% significance levels.

of specifications as we did for migration, and report the results in Table 7, panel B.

Column (1) shows a positive, significant relationship between model predictions and with rent price changes across model locations, although as column (2) shows the predictive power of our model largely relies on the relationship between initial density and rents.[43] As shown in columns (3) and (4), the model's within-city predictions line up well with the data, even when controlling for initial density. Columns (5) and (6) show, however, that the changes our model predicts across CZs are poorly correlated with what happened 2019–2023. This could be due to forces outside the model, such as differences in pandemic policies at the state or local levels, which may have had an important influence on real estate demand across cities during those years. Figure 14 below confirms that,

[43]The relationship between initial density and price or rent growth during the pandemic has been previously documented. Gupta, Mittal, Peeters, and Van Nieuwerburgh (2022) and Liu and Su (2021) find a "flattening" of the relationship between prices and distance to the center in major metro areas for residential real estate; Rosenthal, Strange, and Urrego (2021) report a similar relationship for commercial real estate.

while our model predicts a convergence of CZ-level prices in the counterfactual economy, in the data CZs with higher prices in 2019 did not experience lower price growth.

5.6 Commuting and Welfare

Table 8 summarizes aggregate results for the main counterfactual scenario, broken down by worker type. In what follows, we will discuss each row in turn.

Commuting. The average worker lives 47% farther in commuting time from their workplace.[44] Yet they still spend 25% less time commuting, because the average frequency of remote has increased by 1.1 days per week. Moreover, those who cannot work from home reduce their commutes by moving slightly closer to their workplaces. Commutes across metro areas become more common. In the benchmark economy, 22.5% of workers live and work in different CZs. In the counterfactual economy, this number goes up to 31.7% as remote work increases the average distance between residence and workplace.

Income and inequality. Workers' income falls marginally, by 0.4%, averaging sizable gains by those who can work from home and losses by those who cannot. A major reason for this disparity is that, in our calibration, for most workers telework is more productive in the counterfactual economy; therefore, more frequent remote work boosts their incomes.[45]

Among non-telecommutable workers, those without a college degree experience a 6.3% fall in income, while college graduates see a 7.7% drop in income. The fall is larger for college workers because there are more remote-capable workers among the college-educated and, by supplying a greater amount of labor effort due to working from home more often, they complement the labor effort of non-college workers but compete with college workers who cannot telecommute. Averaged together, the incomes of the college-educated increase while the incomes of their non-college counterparts fall, which means that the overall college wage gap widens.

Prices. The average price of floorspace drops by 1.8%, due to the net movement of residents and jobs to peripheral locations with lower building costs and higher housing supply elasticities. Telecommutable workers pay between 2.5 and 3.1% less for housing, as they relocate to more affordable areas. Non-telecommutable workers move to denser locations, and see much smaller reductions in their housing costs.

Non-tradable prices increase by around 2.3%. This can be attributed to a combination of the increase in income, and a movement of demand to less-dense places which tend to

[44]Using matched employer-employee data for the U.S., Akan, Barrero, Bloom, Bowen, Buckman, Davis, Pardue, and Wilke (2024) show that the average distance between employers and employees rose from 10 miles in 2019 to 27 miles in 2023.

[45]This result is consistent with Pabilonia and Vernon (2023) who, using ACS data, find that between 2019 and 2021 real wages grew by 4.4% faster for remote workers than for office-based workers.

Table 8: Aggregate results

	all workers	non-college all	non-college non-tel.	non-college tel.	college all	college non-tel.	college tel.
Average time to work, % chg	46.8	48.2	-0.4	102.6	43.8	-0.6	55.6
Time spent commuting, % chg	-25.4	-23.4	-0.4	-60.0	-30.5	-0.6	-43.6
Average WFH days/week, chg	1.1	1.1	–	2.6	1.3	–	2.6
Income, % chg	-0.4	-0.7	-6.3	6.9	0.2	-7.7	2.8
Floorspace prices, % chg	-1.8	-1.7	-0.7	-3.1	-2.2	-1.3	-2.5
Non-tradables prices, % chg	2.3	2.3	2.4	2.1	2.3	2.4	2.2
Welfare, % chg							
consumption only	-1.6	-2.0	-7.8	5.9	-1.0	-9.1	1.6
+ commuting	0.2	-0.6	-7.6	9.2	1.7	-8.8	5.2
+ amenities	0.3	-0.4	-6.1	7.4	1.5	-6.2	4.1
total welfare	12.7	10.5	-6.9	41.5	19.6	-8.0	22.5

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.

also have lower workplace amenities for the non-tradable sector.[46]

Workers' welfare and landowners' income. In Table 8, we break down welfare gains by incrementally considering the effects of consumption, commuting, and amenities.[47] Combined consumption of housing, tradable, and non-tradables goods goes up for telecommuters and down for non-telecommuters, declining by 1.6% on average. This is the net result of a 0.4% decrease in income and a 3.5% increase in the price of non-tradables, partly offset by the 1.8% fall in floorspace prices. The reduction in time commuting yields small gains for non-telecommutable workers and large gains for the remote-capable.[48] In the next row, we see that non-telecommutable workers enjoy better amenities on average, due to their moving to more central locations, while the peripheral destinations of the telecommutable workers mean they enjoy somewhat poorer amenities than before.

Overall welfare–expected utility prior to the realization of preference shocks–increases by an average of 12.7%. This is the net result of large gains for telecommutable workers and smaller losses for the rest.[49] An important contributor to telecommuters' gains is that less

[46]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.

[47]Welfare decomposition is described in Appendix Section E.

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

[49]Because we do not take a position on whether the calibrated "aversion to telecommuting" parameters, ς_m^s, 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.

frequent commutes leave them free to choose a particular residence location and job site that suit their idiosyncratic preferences, represented by high values of the Fréchet shocks. Overall, college workers gain more than non-college: even though telecommutable non-college workers gain the most, their numbers are small; while telecommutable workers make up a large proportion of the college-educated.

We do not take a stance on the weight of landlords in the social welfare function, and so have omitted them from the preceding calculations and discussion. Overall demand for floorspace falls by a mere 0.1%. This demand is allocated to places with higher supply elasticity (and, therefore, lower land share), and thus floorspace prices decline by 1.8%. Due to the combination of fixed land and roughly unchanged floorspace demand, average land prices, and thus landlord income, experience a smaller decline of about 0.8%.

5.7 The Role of Real Estate Supply, Amenities, and Knowledge Spillovers

To assess the roles of various mechanisms, we run five alternative counterfactuals in which some variables do not adjust. Appendix Section F contains the details.

In one of these scenarios workers are permitted to change jobs and residences, but the supply of real estate, as well as the levels of productivity and amenities are held fixed. This leads to a 16% jump in residential prices and a 15% fall in commercial prices. This mimics the bifurcated shift in real estate values observed during the pandemic years, and highlights the importance of both new construction and conversion of commercial to residential for our baseline long-run prediction of a slight decrease in average prices.

In another counterfactual, we let the supply of real estate adjust but do not allow local amenities or productivity to change. Migration of residents and jobs is more muted than in the main counterfactual where endogenous changes in amenities and productivity amplify the movement of residents and jobs to less dense places.

In yet another scenario, we allow all margins to adjust, and also let remote work contribute to productive externalities as much as on-site ($\psi = 1$). This reverses the loss in productivity from remote workers' lack of contribution to knowledge spillovers and improves welfare for non-telecommutable workers.

5.8 Covid-19: Technology or Preference Shock?

As we discussed in Section 2.2, the shift towards remote work seen since 2020 is most likely due both to improvements in remote productivity (technology) as well as shifts in norms, policies and preferences. This is the approach we take in our counterfactual where the rise in work from home occurs due to changes in both productivity and preferences. As a robustness check and also as a way to evaluate the relative importance of each explanation, we also conduct exercises in which the increase in remote work is driven purely by either technology or preferences.

In the productivity-based scenario, we calibrate the baseline as described above. Then, we keep preference parameters at their baseline levels and target the change in remote work frequency by adjusting the relative productivity parameters. This requires a 56–106% jump in remote work productivity, depending on the worker type, and yields implausibly large wage gains for remote-capable workers that range from 47% to 88%.[50] This scenario is described in greater detail in Appendix Section G.

In the preference-based scenario, we keep remote productivity at their baseline level and generate the entire increase in work from home by lowering the aversion to telecommuting. Since in our main counterfactual, productivity only grows by 8–10%, the results of this counterfactual are quite similar to our main results. An important difference is that in this scenario, average welfare gains are slightly larger and the gaps in gains between different worker types are smaller. This is because non-telecommutable workers with the same education working in the same industry are better positioned to compete with their telecommutable counterparts whose remote productivity does not change. This scenario is described in more detail in Appendix Section H.4.

6 The Great Re-Convergence

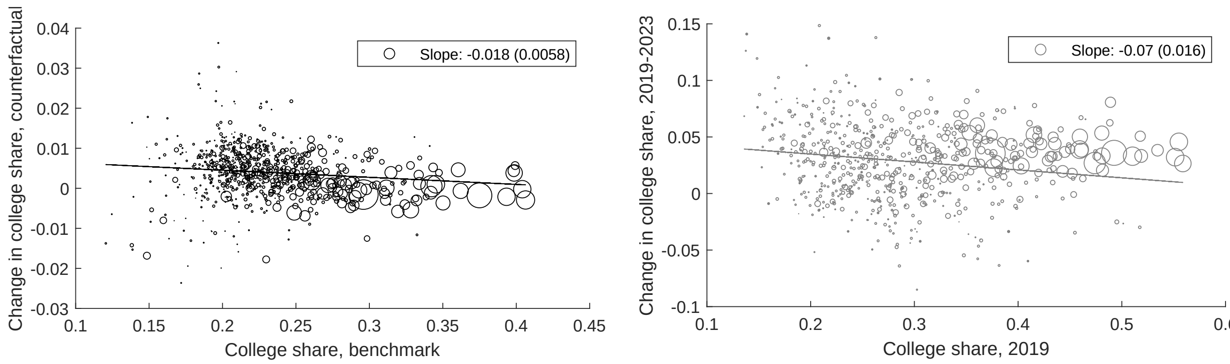
The "Great Divergence" is a much-remarked-upon trend in the decades following the 1980s.[51] It is characterized by widening gaps in economic outcomes between U.S. cities, driven in part by ever greater concentration of the highly-paid and the highly-educated in select large "superstar" cities, especially in their downtown areas. One upshot of the rise of remote work could be a "re-convergence," as newly-freed laptop workers disperse to greener pastures and increase their geographic proximity to "main street America." In this section, we will explore our model's predictions for a re-convergence within and across cities, comparing to data on changes 2019-2023.

[50] Using ACS data, Pabilonia and Vernon (2023) find that between 2019 and 2021 real wages grew by only 4.4% faster for remote workers than office-based workers.

[51] The "Great Divergence" across locations in the U.S. was first summarized in Moretti (2012). The period from 1980s follows decades of regional convergence, as documented in Blanchard and Katz (1992).

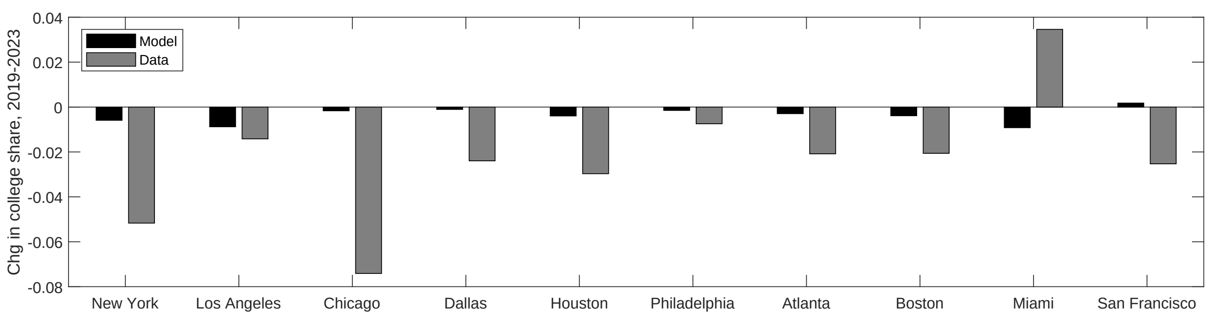
Figure 11: Reversal of the skill sorting across CZs

Panel A: Model   Panel B: Data



Note: Panel A plots the share of college graduates in a CZ in the benchmark economy and the change in the college share in the counterfactual economy. Panel B shows the same relationship for the 2019 one-year ACS sample and the change in the 2023 one-year ACS sample. Circle size is proportional to the CZ population in the benchmark economy. The legend shows slope coefficients and their standard errors.

Figure 12: Reversal of the urban revival



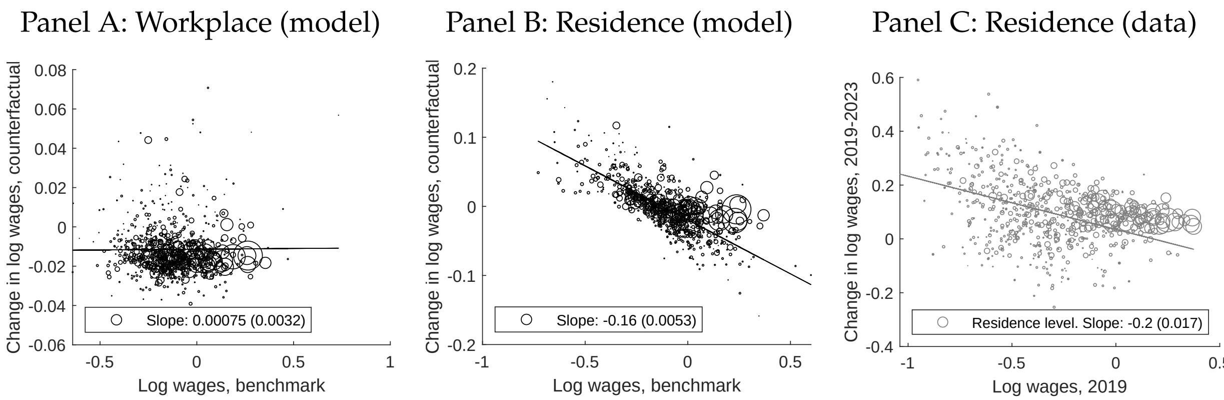
Note: The figure shows the percentage-point change in the college share in a 10 km ring around centers of ten largest CZs in the counterfactual economy (black bars) and in the data between 2019 and 2023 (gray bars). Data changes are adjusted to account for the nationwide increase in the college share. Center of a CZ is defined as the location of the city hall of the largest municipality.

6.1 Skill Sorting

Panel A of Figure 11 shows our model's predictions for the sorting of college-educated workers across CZs. Education becomes less spatially concentrated, pointing towards a partial reversal of the trends documented by Berry and Glaeser (2005), Moretti (2012), and Diamond (2016), inter alia. In panel B we provide evidence that this reversal may have already started. We estimate college shares at the commuting zone (CZ) level from one-year ACS samples in 2019 and 2023 and find that CZs with higher college shares in 2019 saw a slower growth in college shares 2019–2023.[52]

[52] The results in panel B have somewhat different magnitudes than model predictions for at least two reasons. First, it uses 1% ACS samples and our model uses a 5% sample. Second, panel B compares 2019

Figure 13: Changes in wage inequality across CZs



Note: Panel A shows the relationship between demeaned log average wages paid to workers who *work* in a given CZ in the benchmark economy and the log change in wages in the counterfactual. Panel B shows the same relationship for workers who *live* in a given CZ. Panel C shows the relationship for wages earned by residents of an CZ in the 2019 ACS sample and the change in the 2023 ACS sample. Circle size is proportional to CZ population in the benchmark. The legend shows best-fit slope coefficients and their standard errors.

Our model also predicts that skill will become less concentrated in city centers. Couture and Handbury (2020) documented growing concentration of college graduates around the centers of U.S. cities since 2000 and linked this "urban revival" to increased consumption of non-tradable services. As discussed in the previous section, our model suggests that some of these services may follow remote workers, who are predominantly college-educated, out of the urban centers. Combined with less frequent commuting, this makes city centers less attractive for college graduates and, as shown in Figure 12, our model predicts a fall in college shares in the centers of nine out of ten largest CZs.[53] According to the comparison of 2019 and 2023 ACS data at the PUMA level, college graduates already started leaving the centers of most largest cities, and the magnitudes are much larger than what our model predicts.

6.2 Income Inequality

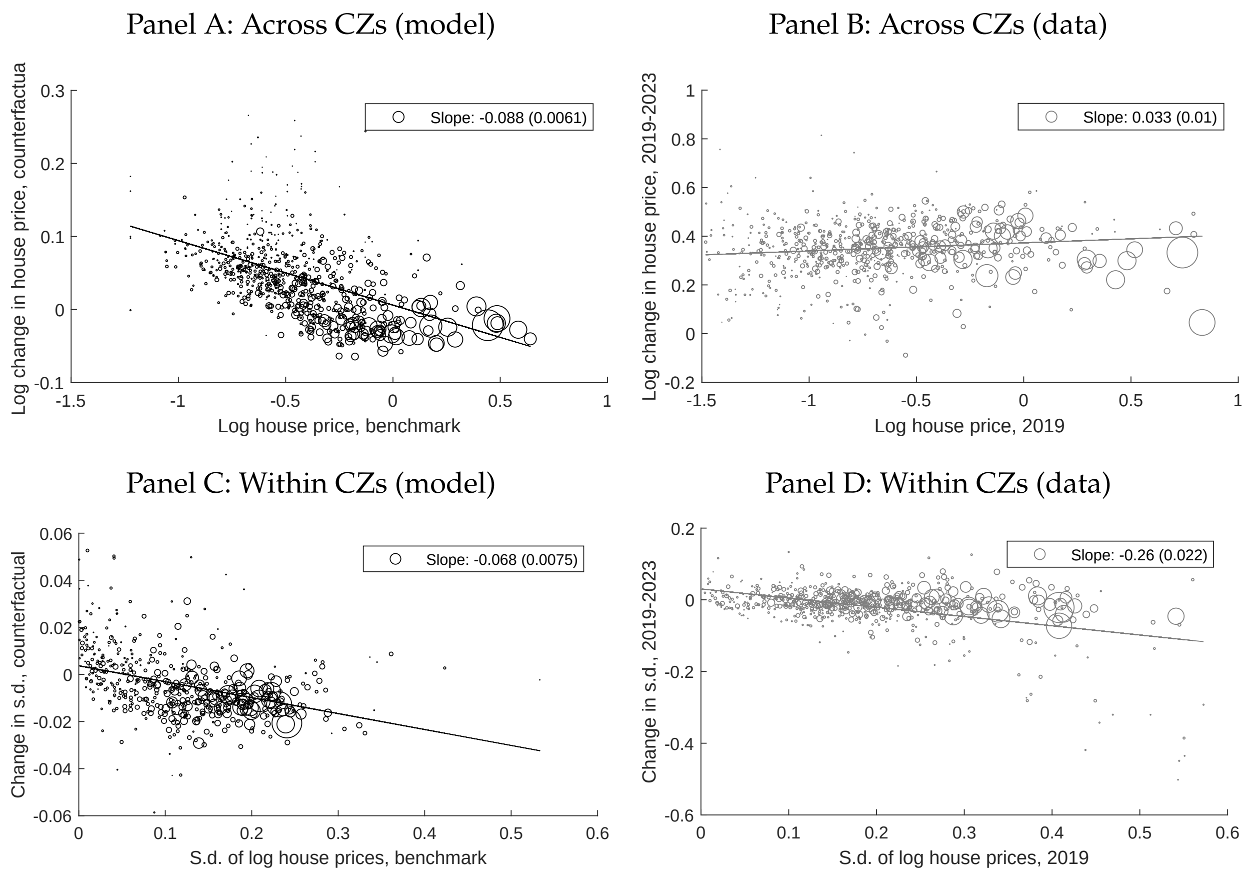
Our model predicts that differences across CZs in the average wage paid to individuals who *work* there will not change much, as shown in Panel A of Figure 13. Cities that were more productive before the pandemic will continue offering high incomes to their workers.[54] However, as telecommuting improves access to jobs in high-paying locations, the disparities across CZs in the wage of the average *resident* will fall, as shown in Panel

with 2023, while our model is calibrated to 2012–2016.

[53] City center is defined as the 10km ring around the location of the city hall of the largest municipality.

[54] Liu and Su (2023) document a reduction in the city-size wage premium during the pandemic using job-posting data, driven by occupations with high rates of work-from-home adoption.

Figure 14: Reversal of the house price divergence



Note: Panel A shows the relationship between demeaned log average house prices at the CZ level in the benchmark economy and the log change in prices in the counterfactual. Panel B shows the same relationship using prices from Zillow in December 2019 and the change between December 2019 and December 2023. Panel C shows the relationship between the population-weighted standard deviation of log house prices across model locations within an CZ in the benchmark and the change in the standard deviation in the counterfactual. Panel D shows the same relationship using prices from Zillow in December 2019 and December 2023. Circle size is proportional to CZ population in the benchmark. The legend shows best-fit slope coefficients and their standard errors.

B. This would represent a turning back of the increasing geographic income inequality documented by Moretti (2013), Giannone (2022), and Gaubert, Kline, Vergara, and Yagan (2021). Panel C shows that this reversal has already started. Using ACS data, we find a negative correlation between average wages earned by CZ residents in 2019 and wage growth 2019–2023.

6.3 House Price Dispersion

Previous research has documented increased dispersion of house prices both across cities (Van Nieuwerburgh and Weill, 2010) and within cities (Albouy and Zabek, 2016) in the decades leading up to 2020. In our model the decline in skill concentration and income inequality lead to more balanced distribution of housing demand across space, and thus presage a reduction in real estate price dispersion both across and within cities. Panel A of Figure 14 shows that CZs with high average prices in the benchmark model see a decline in prices, while more affordable CZs experience price increases. Panel C shows that the dispersion of prices across locations within CZs also falls.

In contrast to our model predictions, house price dispersion has not fallen across CZs, as shown in panel B of Figure 14. This may be due to the fact that hybrid work accounted for most of the increase in work from home and that a large part of associated migration has been within, not across, cities. Consistent with this hypothesis, we document a large reduction of within-city price variance, as shown in panel D.[55] These trends suggest that telecommuting could change the geography of housing affordability, especially so within cities. On the one hand, it may make previously expensive locations more affordable but, on the other hand, it may increase prices in places where housing is relatively cheap.

7 Conclusion

The quantitative exercises we have just reviewed indicate that the new remoteness of work does not threaten an "end to big cities" or any other kind of catastrophic upheaval. It will, however, present challenges and opportunities to certain actors in the economy. World-beating firms in places like Manhattan will have the opportunity to draw talent from a broader catchment area; at the same time, they face the challenge of maintaining their edge with fewer of the face-to-face interactions which have, in the past, facilitated innovation and excellence. Owners of commercial real estate in city centers will face the challenge of finding new uses for office space, as it seems nearly certain that demand will remain lower long-term.

The reduction in miles traveled commuting should reduce pollution and congestion, though reallocation of residents to less energy-efficient suburban homes may offset the environmental benefits. In addition, less frequent and more decentralized commuting will present a serious challenge to public transit planners who may see large drops in demand for previously popular routes.

The "re-convergence" of highly-educated workers towards the periphery may help supply the tax base and social capital to improve public services and institutions in places where these have lost their luster over the past several decades, though it may also erode

[55]These findings are consistent with the trends documented in Gupta, Mittal, Peeters, and Van Nieuwerburgh (2022) and Althoff, Eckert, Ganapati, and Walsh (2022), inter alia.

the tax base of some urban cores. It should also, in the long run, ease housing affordability concerns that have recently beset big cities. At the same time, our framework predicts that the overall welfare gains will be very unequally distributed across occupation types, and that there will be no fall in the overall income inequality which so many see as an important social and political challenge.

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Appendix

A Data

A.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.

A.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.[56]

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

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

where age_k is the average age in tract k; $sexratio_k$ is the proportion of males to females in local labor force; $race_{r,k}$ is the local share of race $r \in \{Asian, Black, Hispanic, White\}$ in the tract; $ind_{d,k}$ is the local share of jobs in industry d; and $occ_{o,k}$ is the local share of jobs in occupation o.[57] The estimated wage index is the sum of the constant and the

[56]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 $\geq \$100,000$.

[57]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

tract fixed effect: $\hat{w}_k^0 \equiv \hat{\alpha} + \hat{\epsilon}_k$. We then build wage indices for each location j, $\hat{w}_j^0$, as the employment-weighted average of $\hat{w}_k^0$ 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.[58] Let the college wage premium for model location j be designated ϕ_j^H, and for the sake of concision of presentation let us also define a non-college wage "premium" $\phi_j^L = 1$. Let the tradable industry premium for model location j be defined as ρ_j^G, while the non-tradable "premium" is $\rho_j^S = 1$.

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: $\hat{w}_{mj}^s / \hat{w}_{m'j}^{s'} = \left(\phi_j^s \rho_j^m\right) / \left(\phi_j^{s'} \rho_j^{m'}\right)$ 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: $\sum_s \sum_m \hat{w}_{mj}^s \pi_{mj}^s = \hat{w}_j^0$, where conditional choice probabilities $\pi_{mj}^s \equiv \sum_i \sum_o \pi_{mij}^{so}$, 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 $\pi_{mj} \equiv \sum_s \sum_i \sum_o \pi_{mij}^{so}$ for each location, and observe $\pi_{m0}^s \equiv \sum_i \sum_j \sum_o \pi_{mij}^{so}$ at the economy-wide level, and assume that the educational composition of industry does not vary by location: $\pi_{mj}^s = \pi_{mj} \pi_{m0}^s$.

Manipulating these two sets of conditions, we can calculate $\hat{w}_{mj}^s$ as follows. First, the average wage for college-educated workers in the tradable sector, as a function of $\hat{w}_j^0$, is $\hat{w}_{Gj}^H = \hat{w}_j^0 / \sum_s \sum_m \frac{\phi_j^s \rho_j^m}{\phi_j^H \rho_j^G} \sum_i \sum_o \pi_{mij}^{so}$. Then, wages for other workers are $\hat{w}_{mj}^s = \frac{\phi_j^s \rho_j^m}{\phi_j^H \rho_j^G} \hat{w}_{Gj}^H$. These are then translated into wages in the model w_{mj}^s, according to the following equation:

$$w_{mj}^s = \frac{\left(\hat{w}_{mj}^s\right)^\alpha}{\alpha^\alpha (1-\alpha)^{1-\alpha}} \left(\frac{\sum_i \sum_o \pi_{mij}^{so}}{\sum_i \sum_o \pi_{mij}^{so} \Omega_{mij}^{so}} \right)^\alpha. \tag{A.2}$$

A.3 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

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.

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

(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. The sample comprises 83,512 observations. 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.

A.4 Local Rent Indices

We measure local rents by constructing hedonic rent indices at the level of PUMAs. 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).[59] To construct local rent indices, we use self-reported rents and estimate the following regression,

$$\ln \mathbf{q}_{\iota,it} = \beta_0 + \boldsymbol{\beta}_1 \mathcal{X}_{\iota,it} + \varphi_i + \varphi_t + \varepsilon_{\iota,it}, \tag{A.3}$$

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 $\mathbf{Q}_i \equiv \exp\left(\beta_0 + \varphi_i\right)$.

A.5 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.[60] Travel times are reported for a little over 4 million trajectories, a small fraction of all possible bilateral

[59]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.

[60]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.

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 times.

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.

B Existence and Uniqueness of an Equilibrium

Consider a simplified version of our model with fixed floorspace supply, single industry, no heterogeneity in education, and no externalities in residential amenities. Also, let all workers have an occupation that allows telecommuting. 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

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

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

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

where $\bar{H}_{Ri}$ is the exogenous supply of residential floorspace and $\Phi^{1/\epsilon}$ is expected utility. Let

$\mathbb{Q}^1_{ij} \equiv q_j^{-(1-\alpha)(\zeta-1)}$, $\tilde{\mathbb{Q}}^1_{ij} \equiv \mathbb{Q}^1_{ij} e^{\kappa t_{ij}}$, and $\mathbb{Q}^2_{ij} = \nu^{\zeta-1} q_i^{-(1-\alpha)(\zeta-1)} e^{\kappa t_{ij}(1+\alpha(\zeta-1))}$, as well as $\mathbb{Q}_{ij} \equiv \mathbb{Q}^1_{ij} + \mathbb{Q}^2_{ij}$ and $\tilde{\mathbb{Q}}_{ij} \equiv \tilde{\mathbb{Q}}^1_{ij} + \mathbb{Q}^2_{ij}$.

Note that the system (B.1)–(B.3) has the form of system (1) in Allen, Arkolakis, and Li (2020) and can be written as $\mathcal{X}_{ih} = \sum_{j \in \mathcal{I}} \mathcal{F}_{ijh}\left(\mathcal{X}_{j1}, ..., \mathcal{X}_{jH}\right)$, 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:

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

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

That is, existence and uniqueness may depend on location-specific outcomes; however, we can check the domain of $\left\{\tilde{\mathbb{Q}}^1_{ij}/\tilde{\mathbb{Q}}_{ij}, \mathbb{Q}^1_{ij}/\mathbb{Q}_{ij}, \mathbb{Q}^2_{ji}/\tilde{\mathbb{Q}}_{ji}, \mathbb{Q}^2_{ji}/\mathbb{Q}_{ji}\right\}$ to obtain maximum absolute values of (B.4) and (B.5), given values of α, γ, ϵ, ζ, λ, κ, and ν from our calibrated model (see Tables 2 and 3).[61] 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

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

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 1.0084, marginally greater than 1. 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,

[61] Our calibrated model has multiple values of ν and ζ depending on education and industry. We use weighted-average values of each parameter.

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. This is because commuting costs and idiosyncratic location preferences jointly constitute a congestion force. 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 $\lambda < 0.084$, 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 0.82, and there exists a unique equilibrium. Since we assumed that in this version of the model all workers can telecommute, even though in the data only 34% of workers can work remotely, the latter result is highly relevant and, all else equal, makes the uniqueness of an equilibrium in our quantitative model a likely outcome.

C Model Quantification

C.1 Estimation of the Fréchet elasticity

To obtain the value of the Fréchet elasticity of location preference shocks ϵ, we construct a log-likelihood function that combines the number of commuters on each (i, j) link and the probability of commuting along this link:

$$\ln \mathcal{L} \equiv \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{I}} N_{ij} \ln \left[\frac{\bar{X}_i \bar{E}_j e^{-(\kappa+\tau)\epsilon t_{ij}}}{\sum\limits_{i' \in \mathcal{I}} \sum\limits_{j' \in \mathcal{I}} \bar{X}_{i'} \bar{E}_{j'} e^{-(\kappa+\tau)\epsilon t_{i'j'}}} \right]. \tag{C.1}$$

In this expression, 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.[62] We estimate the value of $(\kappa + \tau)\epsilon$ using Poisson pseudo maximum likelihood

[62]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.

Table C.1: Estimation of the Fréchet Elasticity of Location Choice

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

Note: This table reports estimated coefficients for equation (C.1). Standard errors are in parentheses. Estimation includes residence and workplace fixed effects.

(PPML).[63] Prior to estimation, we set $N_{ij} = 0$ for all pairs with commuting times of more than 3 hours one way.[64] As reported in Table C.1, our estimate of $(\kappa + \tau)\epsilon$ is 0.0443. To recover ϵ, we use the value $\kappa + \tau = 0.011$ and obtain $\epsilon = 0.0443/0.011 = 4.026$.

C.2 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, ς^s_m, ζ^s_m, 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, ζ^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 (3.12) 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 variance of commuting frequencies for each (m, s) for the interval $\theta \in [0.2, 0.8]$: $\text{Var}(\theta^m_s | \theta \in [0.2, 0.8])$.
   (d) 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.

[63]We use PPML rather than OLS because 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.

[64]Out of 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, 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.

(e) 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.

(f) 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 (A.2); (ii) find disposable income using equation (3.10).[65]

(g) Combine equations (3.15) and (3.18) to find ω_{mj}:

$$\omega_{mj} = \left[1 + \left(\frac{w^H_{mj}}{w^L_{mj}} \right)^{\frac{1+\alpha(\xi-1)}{\alpha\xi}} \left(\frac{\sum_o \sum_i \pi^{Lo}_{mij} \Omega^{Lo}_{mij}}{\sum_o \sum_i \pi^{Ho}_{mij} \Omega^{Ho}_{mij}} \right)^{\frac{1}{\xi}} \right]^{-1} \tag{C.2}$$

(h) Solve for labor productivity in the non-tradable sector using the data on prices of non-tradables and equation (3.21).

(i) Compute the ratio between mean wages in tradable/non-tradable sectors.

(j) Compute for each industry/education pair the ratio between mean wages for telecommutable workers with $\theta > 0.8$, and those with $\theta < 0.2$.

(k) 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.

(l) Update the work-from-home 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.

(m) Update the work-from-home 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.

(n) 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.

(o) 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.

[65] As discussed in Section C.3, 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.

(p) Return to step (2a) and repeat the sequence, unless moments computed in steps (2a), (2b), (2c), (2d), (2i), and (2j) 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 (3.26) 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 (3.25) 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).
6. Compute floorspace demand H_i and then compute construction sector productivities, $\tilde{\phi}_i \equiv \phi_i\Lambda_i$, using equations (3.23) and (3.24) as follows: $\tilde{\phi}_i = H_i q_i^{-\frac{1}{\eta_i}}(1-\eta_i)^{-\frac{1-\eta_i}{\eta_i}}$.

C.3 Proof of Proposition 1: Existence and Uniqueness of Inversion

In what follows we prove that there exists a unique set of parameters consistent with the data being an equilibrium of the model.[66] 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:

$$\hat{E}_{mj}\hat{E}^s_j = E_{mj}E^s_j w^s_{mj}. \tag{C.3}$$

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

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

[66]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.

$$D^H_{Wj}\left(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right) \equiv N^H_{Wj} - \sum_i N^H_{Ri} \sum_o \left[\frac{\left(\hat{E}_{Sj}\hat{E}^H_j \Phi^{Ho}_{Sij}\right)^\epsilon}{\sum_{j'}\left(\hat{E}_{Sj'}\hat{E}^H_{j'}\Phi^{Ho}_{Sij'}\right)^\epsilon} n^{Ho}_{RSi} + \frac{\left(\hat{E}^H_j \Phi^{Ho}_{Gij}\right)^\epsilon}{\sum_{j'}\left(\hat{E}^H_{j'}\Phi^{Ho}_{Gij'}\right)^\epsilon} n^{Ho}_{RGi} \right] = 0, \tag{C.5}$$

$$D_{WSj}\left(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right) \equiv N_{WSj} - \sum_i N_{RSi} \sum_o \left[\frac{\left(\hat{E}_{Sj}\hat{E}^L_j \Phi^{Lo}_{Sij}\right)^\epsilon}{\sum_{j'}\left(\hat{E}_{Sj'}\hat{E}^L_{j'}\Phi^{Lo}_{Sij'}\right)^\epsilon} n^{Lo}_{RSi} + \frac{\left(\hat{E}_{Sj}\hat{E}^H_j \Phi^{Ho}_{Sij}\right)^\epsilon}{\sum_{j'}\left(\hat{E}_{Sj'}\hat{E}^H_{j'}\Phi^{Ho}_{Sij'}\right)^\epsilon} n^{Ho}_{RSi} \right] = 0, \tag{C.6}$$

where $\Phi^{so}_{mij} \equiv \frac{1}{g_{ij}d^{so}_{mij}} \frac{\Omega^{so}_{mij}}{p_i^\beta q_i^\gamma}$ and $n^{so}_{Rmi} \equiv N^{so}_{Rmi}/N_{Rmi}$.[67] 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 $D^s_{Wj}\left(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right)$ 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 $\{\epsilon, \kappa, \tau, \alpha, \zeta^s_m, \nu^s_m\}$ 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 (C.4) for all j; (2) conditional on $\hat{\mathbf{E}}_S$, there exists a unique vector $\hat{\mathbf{E}}^H$ that solves (C.5) 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 (C.6) 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 C.1. Given the parameters $\{\epsilon, \kappa, \tau, \alpha, \zeta^s_m, \nu^s_m, \varsigma^s_m\}$ 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 (C.4), (C.5), and (C.6) 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 (C.4), (C.5), and (C.6), 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 $\left\{\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right\}$

[67] 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.

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:

$$D^L_{Rj}\left(\mathbf{X}^L, \mathbf{X}^H, \mathbf{X}_S\right) \equiv N^L_{Rj} - \sum_j N^L_{Wj} \sum_o \left[\frac{\left(X_{Si} X^L_i \Phi^{Lo}_{Sij}\right)^\epsilon}{\sum_{i'} \left(X_{Si'} X^L_{i'} \Phi^{Lo}_{Si'j}\right)^\epsilon} n^{Lo}_{WSj} + \frac{\left(X^L_i \Phi^{Lo}_{Gij}\right)^\epsilon}{\sum_{i'} \left(X^L_{i'} \Phi^{Lo}_{Gi'j}\right)^\epsilon} n^{Lo}_{WGj} \right] = 0, \tag{C.7}$$

$$D^H_{Rj}\left(\mathbf{X}^L, \mathbf{X}^H, \mathbf{X}_S\right) \equiv N^H_{Rj} - \sum_j N^H_{Wj} \sum_o \left[\frac{\left(X_{Si} X^H_i \Phi^{Ho}_{Sij}\right)^\epsilon}{\sum_{i'} \left(X_{Si'} X^H_{i'} \Phi^{Ho}_{Si'j}\right)^\epsilon} n^{Ho}_{WSj} + \frac{\left(X^H_i \Phi^{Ho}_{Gij}\right)^\epsilon}{\sum_{i'} \left(X^H_{i'} \Phi^{Ho}_{Gi'j}\right)^\epsilon} n^{Ho}_{WGj} \right] = 0, \tag{C.8}$$

$$D_{RSj}\left(\mathbf{X}^L, \mathbf{X}^H, \mathbf{X}_S\right) \equiv N_{RSj} - \sum_j N_{WSj} \sum_o \left[\frac{\left(X_{Si} X^L_i \Phi^{Lo}_{Sij}\right)^\epsilon}{\sum_{i'} \left(X_{Si'} X^L_{i'} \Phi^{Lo}_{Si'j}\right)^\epsilon} n^{Lo}_{WSj} + \frac{\left(X_{Sj} X^H_i \Phi^{Ho}_{Sij}\right)^\epsilon}{\sum_{i'} \left(X_{Si'} X^H_{i'} \Phi^{Ho}_{Si'j}\right)^\epsilon} n^{Ho}_{WSj} \right] = 0. \tag{C.9}$$

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 C.2. Given the parameters $\{\epsilon, \kappa, \tau, \alpha, \zeta^s_m, \nu^s_m, \varsigma^s_m\}$ 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 (C.7), (C.8), and (C.9) hold for all j.

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

Decomposition of wages and employment amenities. We have shown the uniqueness of composite employment amenities that incorporate wages (equation C.3). Given that we observe wages by education and industry for each model location, we can now decompose the amenities in the tradable sector $\hat{\mathbf{E}}^s_G$ into a non-wage component $\mathbf{E}^s_G$ and wages. We can also determine the college premium, w^H_{Sj}/w^L_{Sj}, but not wage levels, in the non-tradable sector.

Lemma C.3. Given the parameters $\{\epsilon, \kappa, \tau, \alpha, \zeta^s_m, \nu^s_m, \varsigma^s_m\}$ observables $\left\{\mathbf{N}_{Wm}, \mathbf{N}_{Rm}, \mathbf{q}, \mathbf{p}, \mathbf{t}, \hat{\mathbf{w}}^s_G\right\}$, there exists a unique vector $\mathbf{E}^s_G$ 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 $\mathbf{X}^s_m$ implies that choice probabilities are also unique, conditional on observables. Here each element of $\mathbf{X}^s_m$ is $X^s_{mi} = X^s_i X_{mi}$ This means that there is a unique mapping between education-industry-specific wages in the tradable sector observed in the data, $\hat{w}^s_{Gj}$, and their model counterpart, w^s_{Gj}, as given by equation (A.2). Once wages are known, we can solve for $E^s_j = \hat{E}^s_j / w^s_{Gj}$, 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

$$\frac{w^H_{Sj}}{w^L_{Sj}} = \frac{\hat{E}^H_j \hat{E}_{Sj}}{\hat{E}^L_j \hat{E}_{Sj}} \frac{\hat{E}^L_j}{\hat{E}^H_j}, \tag{C.10}$$

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 C.4. Given the parameters $\{\epsilon, \kappa, \tau, \alpha, \zeta^s_m, \nu^s_m, \varsigma^s_m\}$, 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 (C.2), the zero-profit condition (3.20), and the land and floorspace market clearing conditions, (3.23) and (3.24). □

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 (C.10), 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 (3.14).

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

Lemma C.5. Given the parameters $\{\epsilon, \kappa, \tau, \alpha, \zeta_m^s, \nu_m^s, \varsigma_m^s\}$, observables $\left\{\mathbf{N}_{Wm}, \mathbf{N}_{Rm}, \mathbf{q}, \mathbf{p}, \mathbf{t}, \hat{\mathbf{w}}_G^s\right\}$, employment amenities in the tradable sector $\mathbf{E}_G^s$, college wage premium in the non-tradable sector w_{Sj}^H/w_{Sj}^L, residential amenities $\mathbf{X}_m^s$, and productivities $\mathbf{A}_m$ there exist unique vectors a_m and x_m^s.

Proof. The results follow immediately from equations that determine local productivity and amenities, (3.25) and (3.26). □

D In focus: New York Metropolitan Area

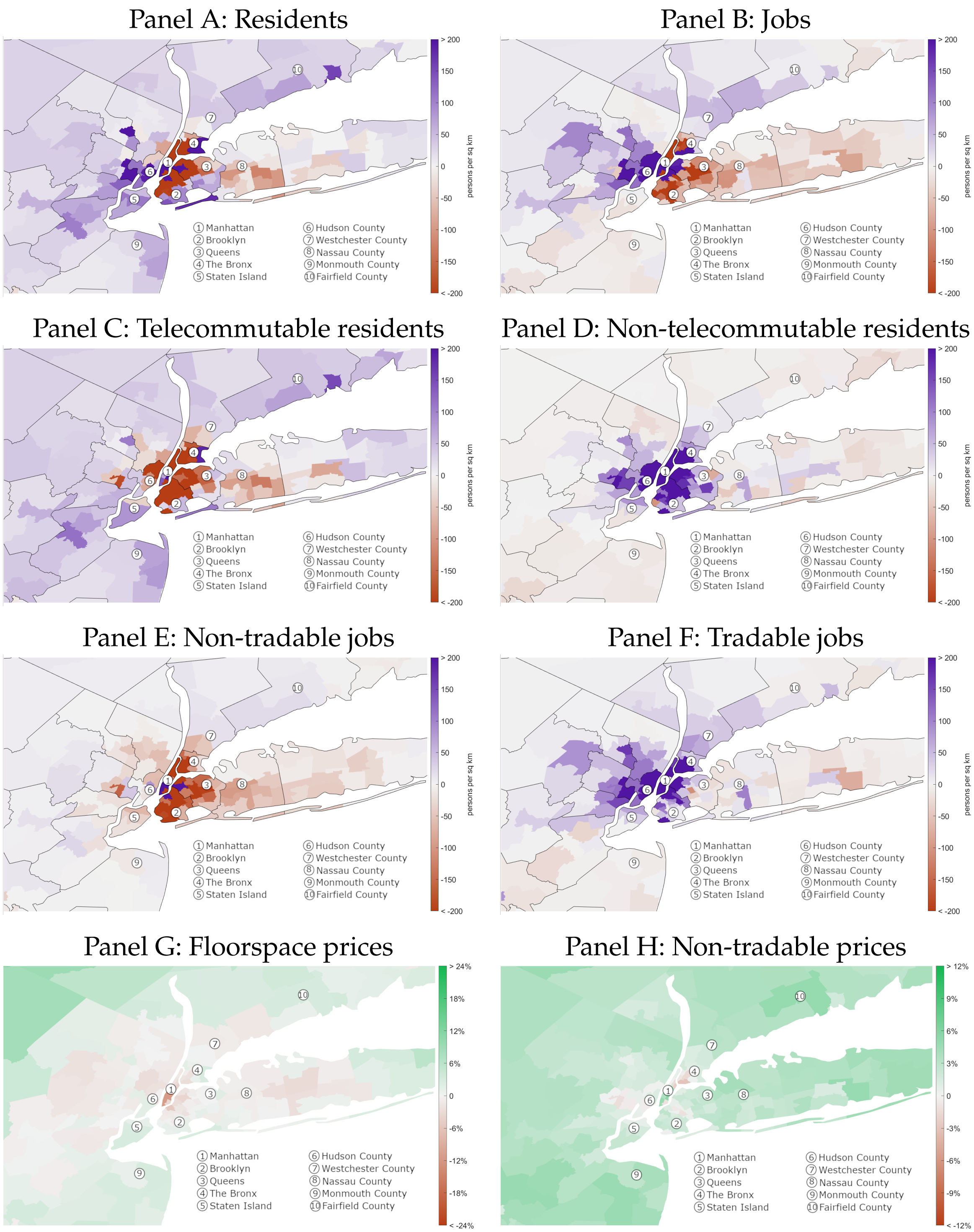
A closer look at the New York metro area gives us a more concrete idea of how predicted changes in jobs and residents play out at the intra-city level. In panel A of Figure D.1 we see that there is a large predicted movement of residents out of most of Manhattan, Brooklyn, and Queens. The Bronx, Staten 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 nationwide patterns we reviewed earlier as well as with migration evidence during the Covid-19 pandemic (Ramani and Bloom, 2021).

Panel B shows changes in jobs. Downtown and midtown Manhattan, 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 see job losses.

On the aggregate, the residential population of the New York CZ does not change but employment goes up by 2.6%. Job gains exceed population gains because, with more common remote work, more workers can access the attractive New York's labor market without having to live there. These workers tend to live in nearby metro areas where housing is more affordable. For example, Philadelphia's residential population grows slightly, by 0.3%, even though the number of jobs there falls by 0.5%.

As panel C makes clear, workers with telecommutable occupations overwhelmingly leave central areas and move to peripheral areas–the same pattern we see countrywide. In panel D, we see workers with non-telecommutable occupations move downtown in significant numbers, off-setting some of the telecommutable exodus.

Figure D.1: New York metro area, predicted changes in residents, jobs, and prices



Note: The maps show absolute changes in residents and jobs betweeen the benchmark and the counterfactual economies in panels A to F, and percentage changes in prices in panels G and H.

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

Panel G maps changes in floorspace prices, which are most strongly negative in downtown Manhattan, and positive in many outlying areas. Panel H 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.

E Measuring Welfare Changes

Overall welfare. Our measure of worker's welfare is V^{so}, given by (3.8). Since indirect utility 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 compute the percentage change in the weighted-average of V^{so}, i.e., $V \equiv \sum_s \sum_o \mathrm{l}^{so} V^{so}$. In our calculations, we adjust the counterfactual disutility of commuting, d^{so}_{mij}, to reflect changes in commuting frequencies. But because we do not take a position on whether the calibrated work-from-home aversion reflects genuine worker preferences or other kinds of non-pecuniary barriers to remote work, we do not adjust the changes in ς^s_m when computing welfare gains.

Sources of welfare gains. We are interested in the relative roles of changes in consumption, commuting costs, and amenities. To measure the part from *consumption only*, we compute

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

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

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

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

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

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

$$\sum_i \eta_i q_i H_i. \tag{E.4}$$

F Further Discussion of Alternative Counterfactuals

In this section, we study alternative counterfactuals in order to understand which channels are important in driving resident and job reallocations, as well as aggregate changes. We start with a world in which the aversion to telecommuting decreases but workers are unable to move and floorspace supply does not change (counterfactual 1). Then we switch on the reallocation of workers to new residences and jobs (counterfactual 2). After that, floorspace supply adjusts (counterfactual 3). Next, residential amenities adjust (counterfactual 4), and then local productivity adjusts (counterfactual 5). This last stage brings us all the way up to our original focus point–the long run with full adjustment. 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 by setting $\psi = 1$ (counterfactual 6).

Table F.1 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.

In counterfactual (2), when workers are allowed to choose new jobs and residences but residential and commercial floorspace supply in each location remain the same, non-telecommutable workers are able to increase their income substantially 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 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

Table F.1: 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	4.5	5.8	3.8	3.8	-0.4	3.8
non-college, non-telecommutable	1.3	4.0	0.4	0.5	-6.3	0.5
non-college, telecommutable	8.9	8.4	8.1	8.1	6.9	8.2
college, non-telecommutable	1.7	4.1	0.2	0.1	-7.7	0.0
college, telecommutable	5.4	6.1	5.2	5.1	2.8	5.1
Floorspace prices, % chg						
residential	11.0	16.1	1.3	0.8	-1.8	0.4
commercial	-8.8	-15.1	–	–	–	–
Non-tradable goods prices, % chg	-0.6	1.2	1.9	1.7	2.3	1.6
Average time to work, % chg	0.0	30.5	37.0	37.9	46.8	38.6
Time spent commuting, all workers, % chg	-17.0	-18.6	-21.4	-21.2	-25.4	-21.1
Time spent commuting, commuters ($\theta = 1$), % chg	0.0	-0.4	-0.5	-0.2	-0.5	0.2
Distance traveled, all workers, % chg	-17.3	-19.0	-21.9	-21.4	-25.9	-21.1
Average WFH days/week, chg	0.6	0.8	0.9	0.9	1.1	0.9
Welfare, % chg						
all workers	8.8	10.8	14.1	14.2	12.7	14.4
non-college, non-telecommutable	-0.6	-0.3	-0.6	-0.6	-6.9	-0.5
non-college, telecommutable	23.4	28.6	36.8	37.2	41.5	37.6
college, non-telecommutable	-0.4	0.0	-0.7	-0.8	-8.0	-0.8
college, telecommutable	12.2	14.1	19.9	20.0	22.5	20.1
Landlord income, % chg	18.2	29.7	3.6	3.4	-0.8	3.3
due to change in demand	18.5	31.4	4.0	4.1	-0.1	4.0
due to reallocation to low η_i	-0.3	-1.7	-0.5	-0.7	-0.7	-0.8

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 3.8). Since in the first counterfactual workers cannot move, welfare changes in column (1) are measured as changes in the utility from consumption and commuting.

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.[68]

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

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 3.6% 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 that we discuss in Section 5, we see the impact of reduced agglomeration externalities from having workers out of the office. Income gains are cut across the board, in each category of worker. Among the six counterfactuals, this one is the only one where non-telecommutable workers experience income losses as a result of negative productivity externalities from less work done in person.

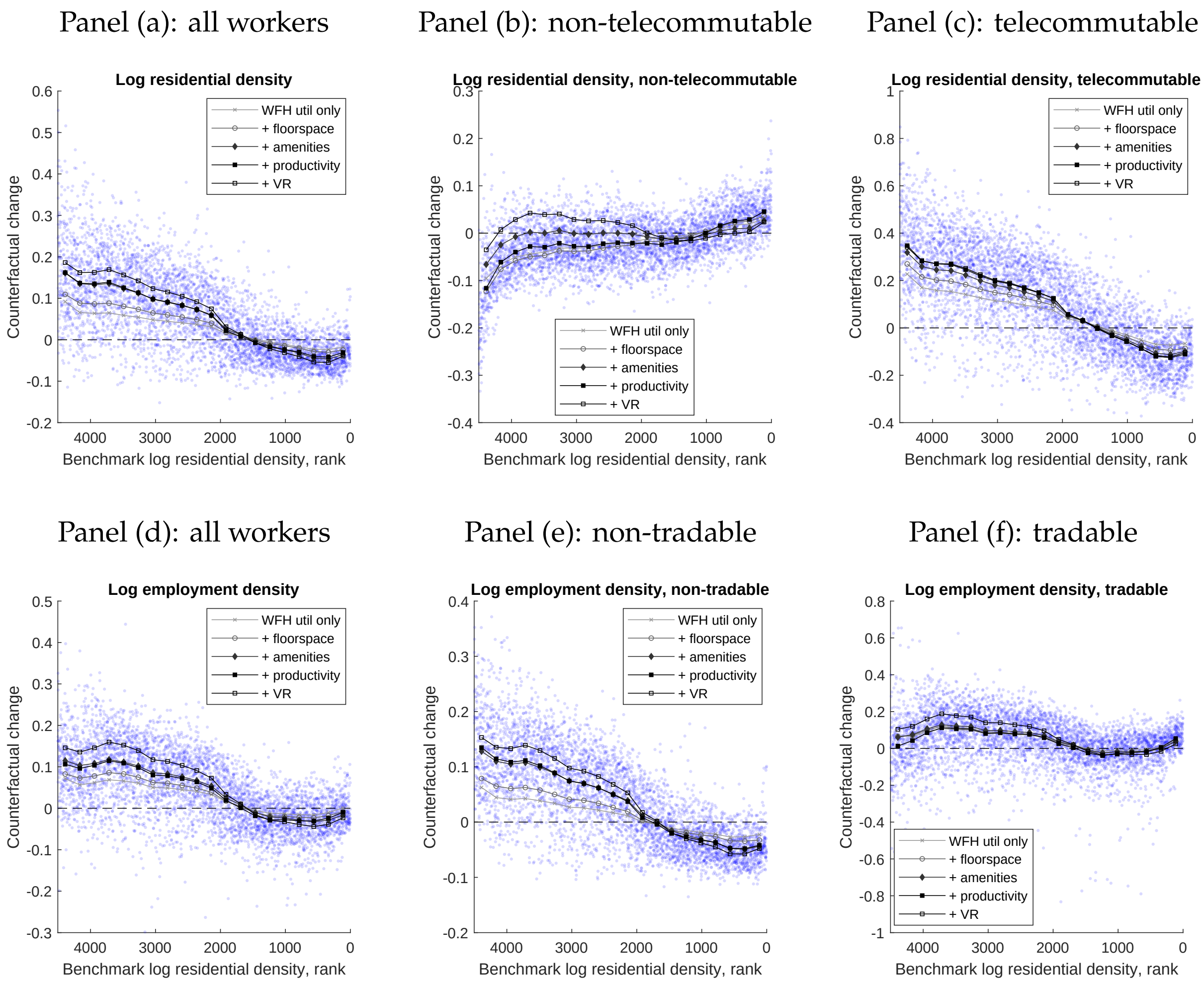
In counterfactual (6) working at home contributes to productive externalities in the main job site as much as working on site ($\psi = 1$). This could happen if remote interaction technology advances to the point that it can fully simulate the experience of being co-located with one's collaborators thus eliminating any disadvantage remote work has in sparking spontaneous spillovers.[69] Comparing columns (6) and (4) of Table F.1, we can see that income losses from reduced productivity are neatly reversed under this alternative assumption.

The top three panels in Figure F.1 plot 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.

The bottom three panels in Figure F.1 show reallocations of jobs across the second through sixth counterfactuals. As with residents, each successive step accentuates the

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

Figure F.1: Changes in residents and jobs, counterfactuals (2)–(6)



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

main pattern of reallocation towards less dense locations. Glancing at panel (e), it is clear this is mostly driven by non-tradable sector jobs following the movement of residents. Looking at panel (f), 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.

Table G.1: Work from home productivity parameters

Parameter	Description	Benchmark	Counterfactual	% change
	Productivity of remote work:			
ν_S^L	non-college, non-tradable	0.9929	2.0416	105.62%
ν_G^L	non-college, tradable	0.9961	1.9828	99.06%
ν_S^H	college, non-tradable	0.9896	1.5402	55.63%
ν_G^H	college, tradable	0.9990	1.7845	78.63%

Note: The table shows calibrated values of the work from home productivity parameters in the benchmark and the counterfactual economy where the entire increase in work from home is driven by an increase in remote work productivity.

G Counterfactual: Increased Productivity of Remote Work

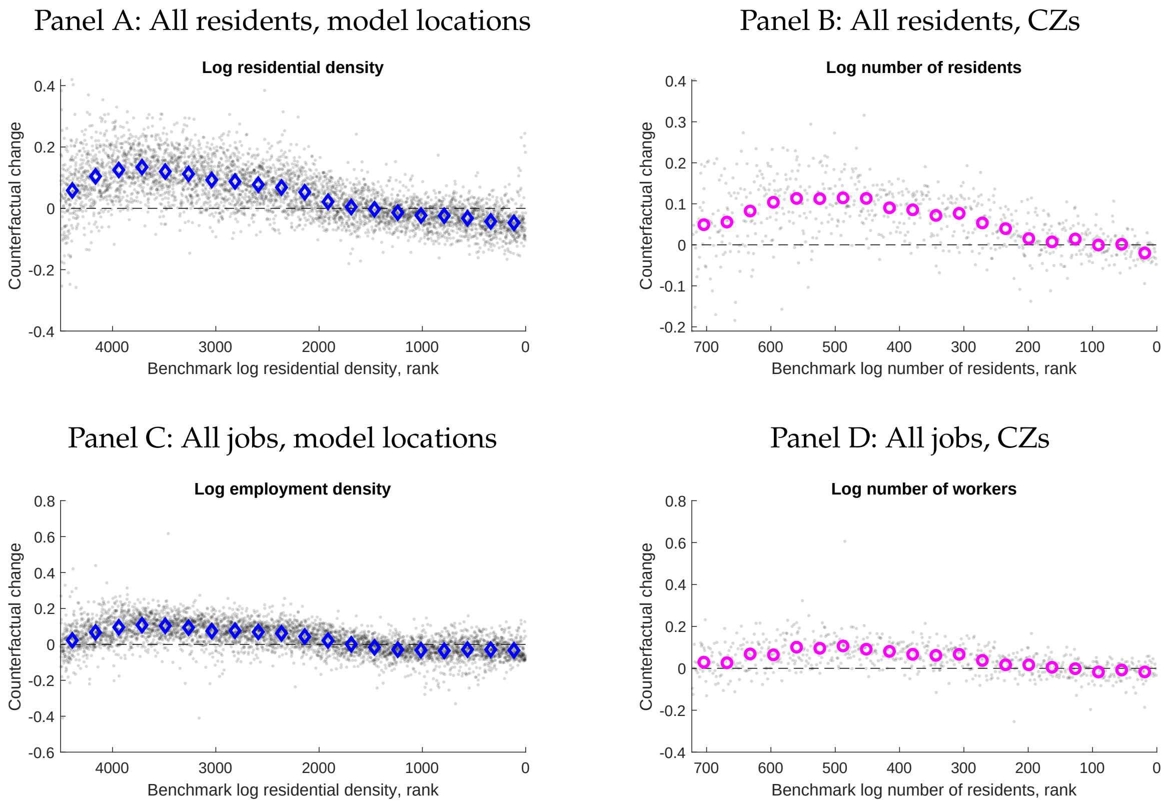
In this section we consider a counterfactual in which increased working from home is due solely to increased productivity, rather than due to a combination of an increased productivity and changes in preferences as in the baseline counterfactual.[70] While many of the patterns are similar to those seen in the baseline, it produces unrealistic increases in the wages of telecommuters and gigantic welfare gains. Table G.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 56–106% depending on the type of worker.

Distributions of residents and jobs. Figure G.1 shows changes in residents and jobs. Comparing it with Figures 6 and 7, we can see that the overall patterns are similar. 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. The only notable difference is that in this counterfactual relocations to the least dense locations are much smaller. This is because incomes of those who can telecommute skyrocket, as we will see in Table G.2 and a small number of high-income remote workers bid out others as they move to the most remote locations.

Aggregate results and welfare effects. Table G.2 reports aggregate results from this counterfactual. Comparing with Table 8, 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 36% more, with the increase driven entirely by telecommutable workers. Among these, college workers earn 47% more, while non-

[70]In Appendix Section H.4, we also discuss a counterfactual where work from home increases due to a change in preferences only and productivity of remote work does not change.

Figure G.1: Changes in Residents and Employmnet



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 CZs and the counterfactual change in log total residents. Panels C and D repeat the analysis for changes in jobs. 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.

college workers earn 88% 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 2019–2023. Finally, we compare this counterfactual's predictions about reallocations of residents and changes in rents with observed migration and changes in housing rents and prices between 2019 and 2023, as we did in Section 5.5. Comparing Table G.3 with Table 7, we see that the predictions of both models are quite comparable.

Table G.2: Aggregate results

		non-college			college		
	all workers	all	non-tel.	tel.	all	non-tel.	tel.
Average time to work, % chg	54.5	55.6	-1.3	119.2	52.0	-1.3	66.2
Time spent commuting, % chg	-24.3	-22.7	-1.3	-56.6	-28.8	-1.3	-40.8
Average WFH days/week, chg	1.1	1.1	–	2.6	1.3	–	2.6
Income, % chg	35.5	35.9	-2.3	87.5	34.8	-1.4	46.6
Floorspace prices, % chg	17.6	18.0	19.2	16.2	16.8	17.9	16.4
Non-tradables prices, % chg	7.4	7.4	7.5	7.4	7.3	7.4	7.3
Welfare, % chg							
consumption only	24.2	24.5	-11.1	72.1	23.7	-9.9	34.5
+ commuting	21.5	21.0	-10.6	65.0	22.3	-9.4	32.9
+ amenities	21.4	21.1	-8.0	61.5	21.8	-4.7	30.8
total welfare	45.8	41.9	-10.0	134.5	57.3	-8.8	64.5

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.

H Robustness

H.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 H.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.

Table G.3: Changes from 2019 to 2023, model vs. data

Panel A: Residents

	(1)	(2)	(3)	(4)	(5)	(6)
Log chg residents, model	0.147	0.139	0.0644	-0.0399	0.230	0.238
	(0.0292)	(0.0370)	(0.0395)	(0.0498)	(0.0709)	(0.0761)
Level of obs.	ML	ML	ML	ML	CZ	CZ
Density control	no	yes	no	yes	no	yes
CZ fixed effects	no	no	yes	yes	–	–
Observations	4502	4502	4453	4453	723	723
R-squared	0.00557	0.00560	0.383	0.385	0.0144	0.0145

Panel B: House rents

	(1)	(2)	(3)	(4)	(5)	(6)
Log chg prices, model	0.486	0.226	0.568	0.497	-2.044	-1.998
	(0.0831)	(0.0926)	(0.0821)	(0.0979)	(1.005)	(1.245)
Level of obs.	ML	ML	ML	ML	CZ	CZ
Density control	no	yes	no	yes	no	yes
CZ fixed effects	no	no	yes	yes	–	–
Observations	1334	1334	1293	1293	172	172
R-squared	0.0250	0.0510	0.492	0.493	0.0238	0.0238

Note: In panel A, the dependent variable is the log change in residents between December 2019 and December 2023 constructed from the ACS. In panel B, the dependent variable is the log change in house rents between December 2019 and December 2023 constructed from Zillow. Standard errors are in parentheses. The regressions are estimated at the level of model locations ("ML"), with or without CZ fixed effects, or at the level of CZs ("CZ"). Regressions at the model location level with CZ fixed effects have fewer observations because some CZs correspond to model locations. *, **, and *** indicate 10%, 5%, and 1% significance levels.

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

In our main counterfactual, we calibrated somewhat larger reductions in work-from-home aversion for non-college workers. This gives this group of workers a boost to counterfactual welfare gains. 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 work from home aversion parameter, ς_m^s, is 46% for all types of workers. Column 3 of Table H.1 compares the results of this counterfactual to the main counterfactual (column 1). Overall, the results are quite similar. The welfare gains of telecommutable college graduates become larger and the losses of non-telecommutable college graduates become smaller. At the same time, for non-college graduates the gains turn smaller. This implies that the

Table H.1: Aggregate results, robustness counterfactuals

	(1) Main CF	(2) $\tau = 0$	(3) Same chg ς_m^s	(4) Same η_i	(5) Fixed ν_m^s
Income, % chg					
all workers	-0.4	-2.4	1.0	-1.0	1.3
non-college, non-telecommutable	-6.3	-4.8	-2.0	-6.1	-1.7
non-college, telecommutable	6.9	1.2	5.2	5.6	5.2
college, non-telecommutable	-7.7	-6.2	-2.7	-8.2	-2.4
college, telecommutable	2.8	-1.2	2.0	1.6	2.7
Floorspace prices, % chg					
residential	-1.8	-3.9	-1.4	1.5	-1.0
commercial	-1.8	-3.9	-1.4	1.5	-1.0
Non-tradable goods prices, % chg	2.3	3.1	1.7	2.0	2.1
Average time to work, % chg	46.8	240.5	44.7	50.7	45.3
Time spent commuting, all workers, % chg	-25.4	-24.3	-25.2	-25.2	-25.4
Time spent commuting, commuters ($\theta = 1$), % chg	-0.5	-0.3	-0.2	0.0	-0.3
Distance traveled, all workers, % chg	-25.9	-25.8	-25.3	-24.8	-25.7
Average WFH days/week, chg	1.1	1.1	1.1	1.1	1.1
Welfare, % chg					
all workers	12.7	61.5	14.0	14.1	13.9
non-college, non-telecommutable	-6.9	-6.1	-2.6	-5.5	-2.6
non-college, telecommutable	41.5	130.0	33.3	43.8	38.3
college, non-telecommutable	-8.0	-7.1	-2.7	-8.2	-2.9
college, telecommutable	22.5	69.3	28.2	22.9	21.7
Landlord income, % chg	-0.8	-3.3	0.5	-48.1	0.9
due to change in demand	-0.1	-2.2	1.2	-48.1	1.6
due to reallocation to low η_i	-0.7	-1.2	-0.7	0.0	-0.7

Note: The table reports results of several alternative counterfactuals, as described in the text.

gap in welfare gains between college and non-college workers would be even greater if we assumed the same reduction in work from home aversion for all worker types.

H.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. At the same time, these elasticities are significantly lower than those estimated in prior literature (see the discussion in Section 4.2.3).

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 estimated in Saiz (2010), to all model locations. Column 4 of Table H.1 compares the results of this counterfactual to the main counterfactual (column 1). Most results are quite close to the main counterfactual, which suggests that our predictions are robust to our choice of housing supply elasticities.

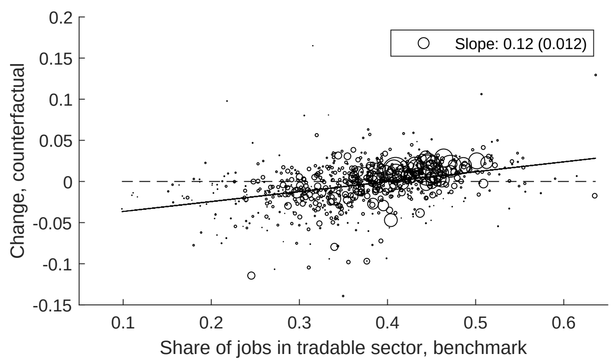
H.4 No Increase in Productivity of Remote Work

Our counterfactual results depend, to some extent, on the calibrated increase of the relative productivity of remote work. While in the benchmark economy, on-site and remote work are nearly equally productive, in the counterfactual remote work is 7–10% more productive (see Table 4). This means that telecommutable workers can increase their income simply by working from home more often. To understand the role of the increase in work from home productivity, we fix ν_m^s at its benchmark level for all types, and rerun the main counterfactual. The results in column 5 of Table H.1 show that, if remote work productivity does not improve, then the income of those who can work from home does not go up as much, but also the income of those who cannot falls by much less. This is because non-telecommutable workers with the same education working in the same industry are better positioned to compete with their telecommutable counterparts. In this scenario, average welfare gains are slightly larger and the gaps in gains between different worker types are smaller.

I Sectoral Specialization of Cities

One dimension in which cities may diverge is their sectoral specialization. As we saw in Figure 1, work from home is more common in tradable industries. Thus, cities that specialize in tradable output can increase their degree of specialization by being able to hire workers from a broader radius. Indeed, Figure I.1 shows that CZs that have a larger employment share in the tradable sector add more tradable jobs in the counterfactual economy.

Figure I.1: Divergence in sectoral specialization

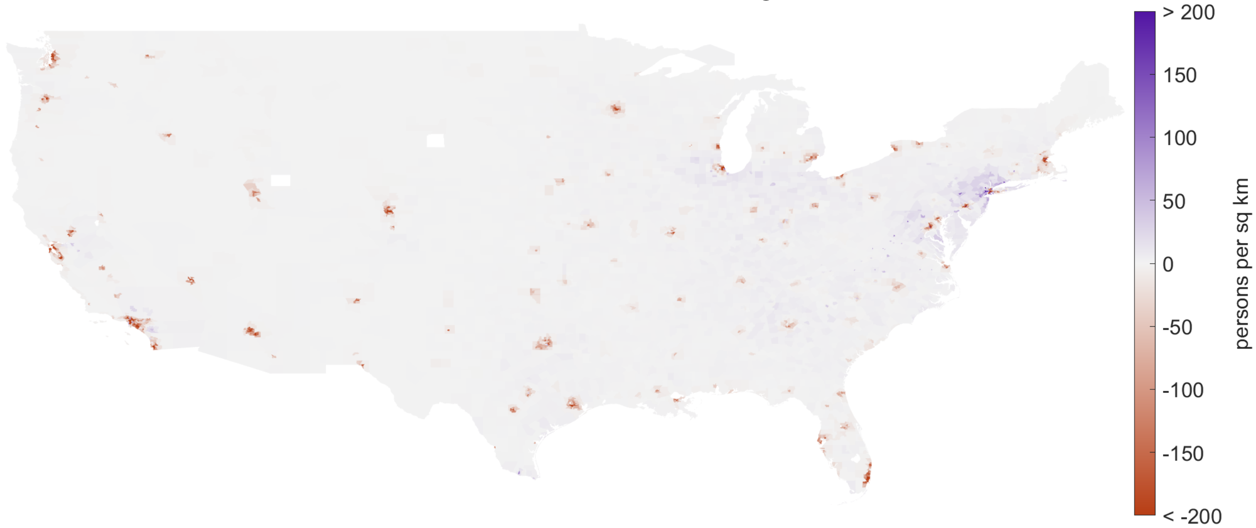


Note: The figure shows the relationship between shares of jobs at the CZ level in the benchmark economy and change in the shares in the counterfactual. Circle size is proportional to CZ population in the benchmark. The legend shows best-fit slope coefficients and their standard errors.

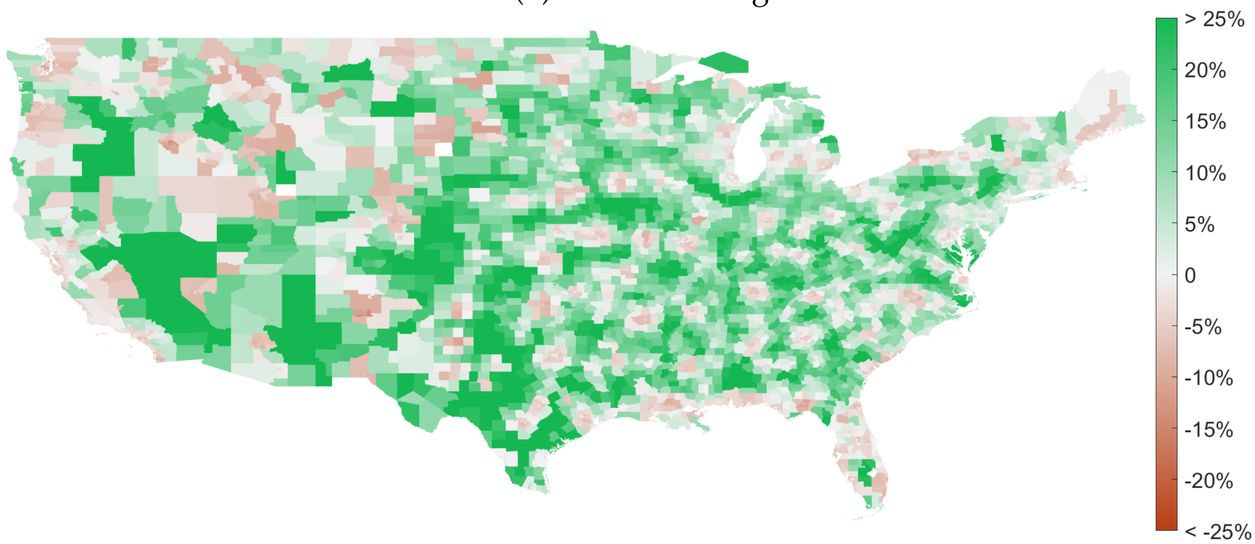
J Additional Figures, Tables, and Maps

Figure J.1: Density of residents

Panel (a): absolute changes



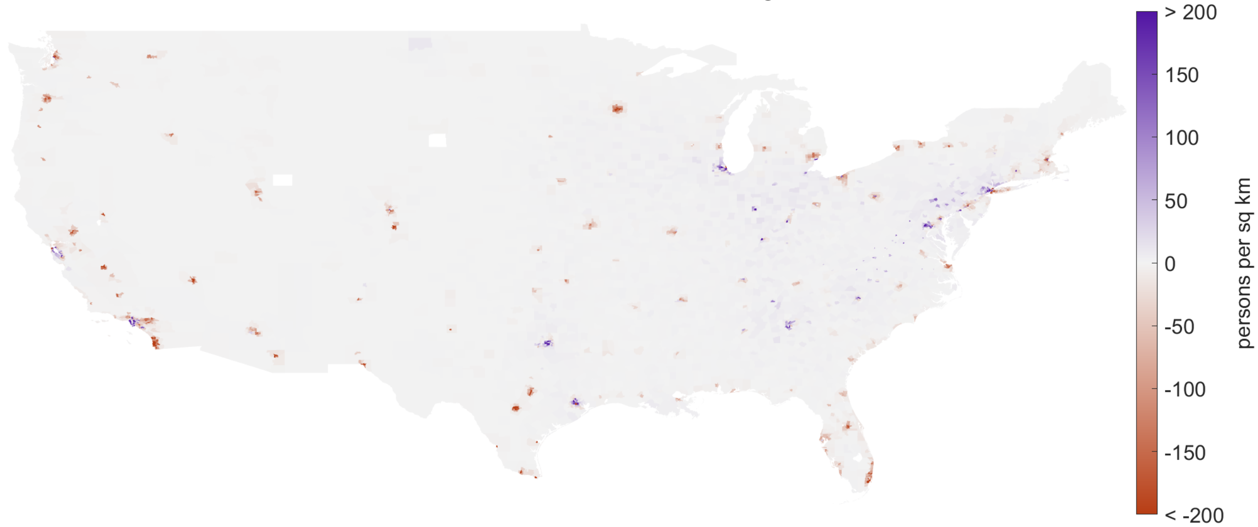
Panel (b): relative changes



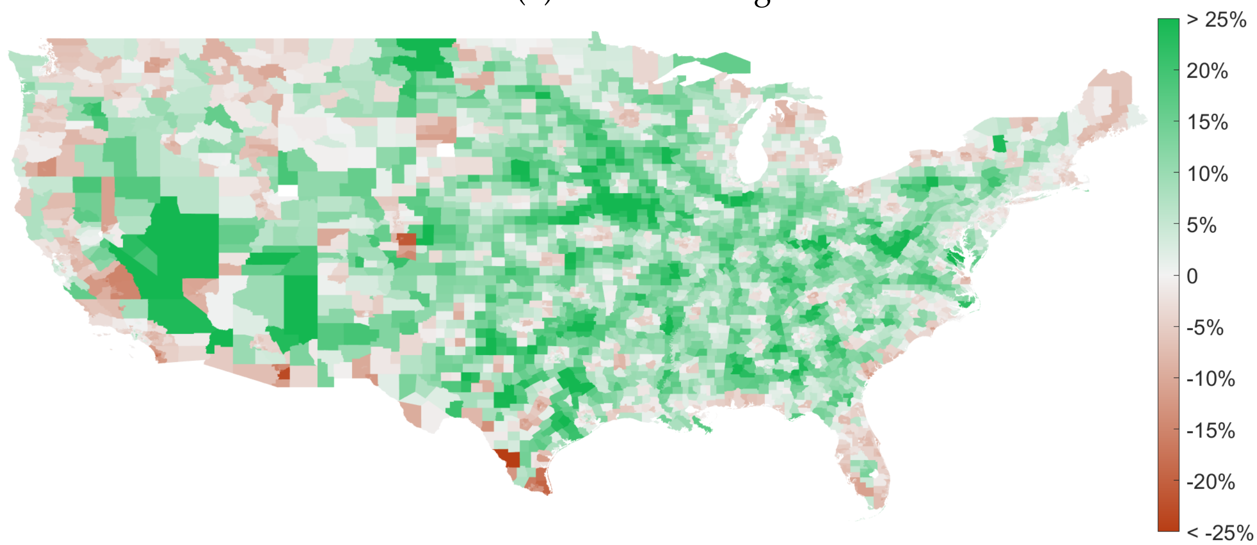
Note: Panel (a) shows absolute changes in the number of residents per square kilometer in each model location in the main counterfactual where the aversion for work from home falls and all endogenous variables adjust. Panel (b) shows percentage changes.

Figure J.2: Density of jobs

Panel (a): absolute changes

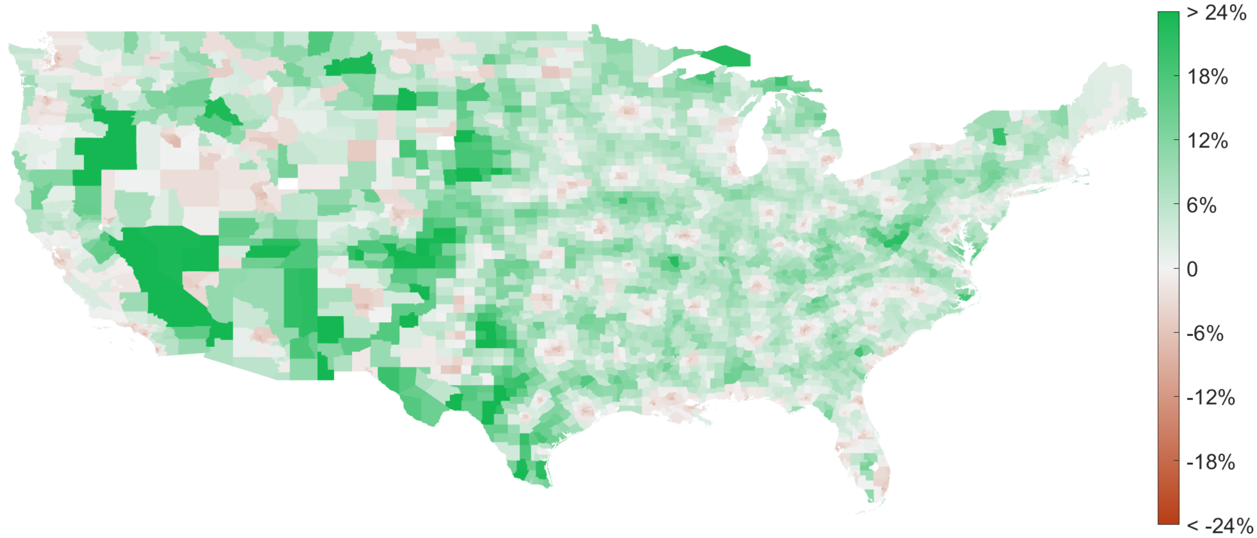


Panel (b): relative changes



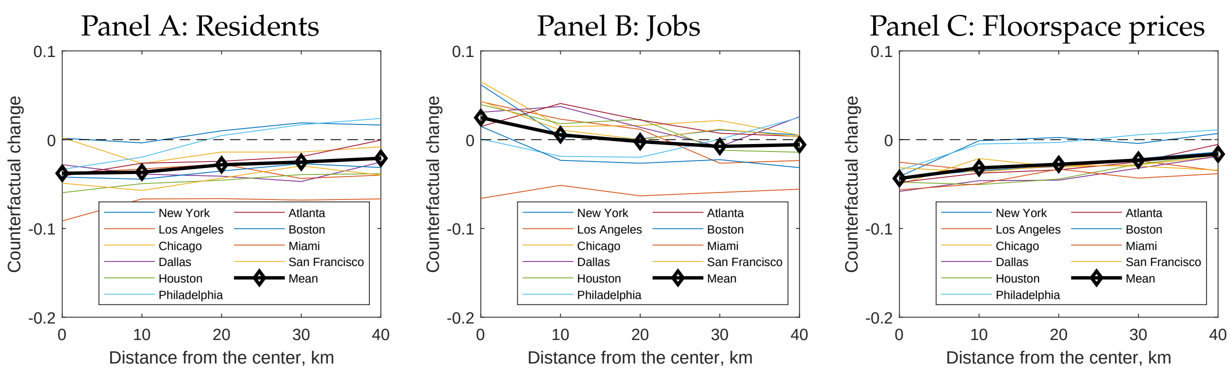
Note: Panel (a) shows absolute changes in the number of jobs per square kilometer in each model location in the main counterfactual where the aversion for work from home falls and all endogenous variables adjust. Panel (b) shows percentage changes.

Figure J.3: 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 J.4: Change in residents, jobs, and floorspace prices in top-10 largest CZs



Note: Panel A shows the relationship between the change in the log number of residents of a model location in the main counterfactual and the location's distance to the center for top-10 largest CZs. Panels B and C repeat the analysis for jobs and floorspace prices. Center of a CZ is defined as the location of the city hall of the largest municipality in the CZ.