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, jobs, and housing costs since 2019. 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 *work-from-home 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 nearly 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.

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

In aggregate, the average worker lives 45% 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 24% to 33%, which may have major impacts on travel patterns and call into question the current administrative definitions of CZs.

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 the supply of housing and 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), Rappaport (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* 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 Online Appendix Figure J.1, 74.3% of college workers in tradable industries have jobs that can be done mostly or completely from home, compared to just 17.8% 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 Online Appendix Section A.1 for more details. Focusing on full-time workers who are not self-employed, we find that 35% 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 22%.[3] We dub these gaps by education and industry *Stylized Fact #2*.

[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), Mongey, Pilossoph, and Weinberg (2021), and Adams-Prassl, Boneva, Golin, and Rauh (2022).

[3]We calculate 26.3/(26.3 + 48) = 0.35 and 3.9/(3.9 + 13.9) = 0.22, from Online Appendix Figure J.1.

How frequent is telecommuting? Using the data from SIPP, we investigate how often remote workers dial it in from home. As Online Appendix Table J.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 Online Appendix Figure J.2; see Online Appendix Section A.3 for more details on the data.[5] We shall refer to this relationship as *Stylized Fact #4*. It is consistent 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 1.

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

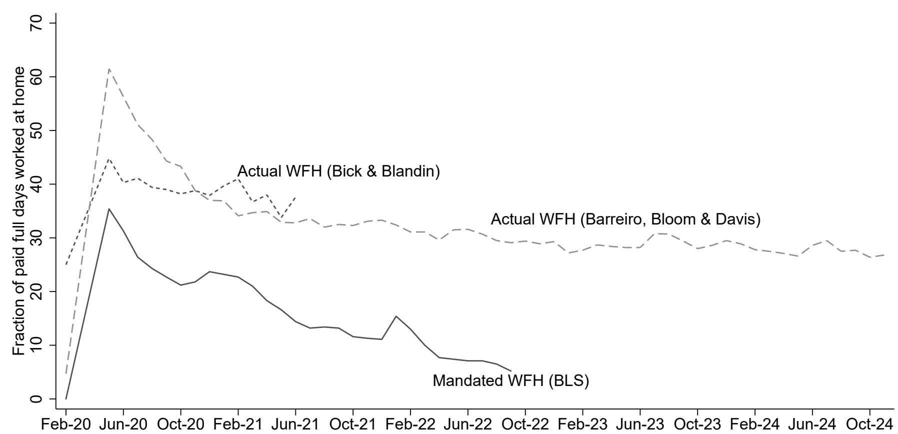
[4]An advantage of the SIPP data is that it allows us to calculate numbers for each frequency from a single data source applying a consistent methodology. Mas and Pallais (2020) also report some numbers related to work from home frequency, but the variance in definitions across the patchwork of data 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.

[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 1: 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 telework 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).

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 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 1. 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 counterfactual 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 $\mathrm{l}^{HN} + \mathrm{l}^{LN} + \mathrm{l}^{HT} + \mathrm{l}^{LT} = 1$.

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

[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.

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]

In what follows, we will refer to ς^s_m as the "aversion to telecommuting." Assuming that ς^s_m takes a value greater than 1 (as it does for all worker categories in our calibration), it lends itself to a range of interpretations, 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

[10] A related study by Lennox (2020) builds a quantitative spatial model of Australia and studies a fall in transport costs as a proxy for an increase in remote work.

[11] To put it another way: Does $\varsigma^s_m > 1$ 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 $\varsigma^s_m > 1$ imply that these other impediments turn out to be large enough to dominate workers' positive taste for remote work.

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

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

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

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

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

$$N^{so}_{Ri} = \sum_{m}\sum_{j}\pi^{so}_{mij}. \tag{3.5}$$

Summing $\pi^{so}_{ij|m}$ over j, we obtain the probability that a worker chooses to live in location i: $\pi^{so}_{i|m} = (\sum_{i'}\sum_{j'}(v^{so}_{mi'j'})^{\epsilon})^{-1}X^{s}_{mi}p_i^{-\beta}q_i^{-\gamma}CMA^{so}_{i|m}$. Summing $\pi^{so}_{ij|m}$ over i, we obtain the probability that a worker in chooses to work in location j: $\pi^{so}_{j|m} = (\sum_{i'}\sum_{j'}(v^{so}_{mi'j'})^{\epsilon})^{-1}E^{s}_{mj}FMA^{so}_{j|m}$. In these two expressions, $CMA^{so}_{i|m}$ and $FMA^{so}_{j|m}$ 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

[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.

the access to workers from workplace location j, and are defined as:

$$CMA^{so}_{i|m} \equiv \sum_j \frac{E^s_{mj}\tilde{w}^{so}_{mij}}{d^{so}_{mij} g_{ij}} \qquad \text{and} \qquad FMA^{so}_{j|m} \equiv \sum_i \frac{X^s_{mi}\tilde{w}^{so}_{mij}}{p^{\beta}_i q^{\gamma}_i d^{so}_{mij} g_{ij}}. \tag{3.6}$$

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

$$N^s_{WCj} = \sum_m \sum_i \left[\theta^{sT}_{mij}\pi^{sT}_{mij} + \pi^{sN}_{mij}\right] \qquad \text{and} \qquad N^s_{WTj} = \sum_m \sum_i (1-\theta^{sT}_{mij})\pi^{sT}_{mij}. \tag{3.7}$$

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

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

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

[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.

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 to θ, we obtain

$$\theta^{sT}_{mij} = \left[1 + \left(\nu^s_m \left(\frac{q_j}{q_i} \right)^{1-\alpha} \right)^{\zeta^s_m - 1} \left(\frac{e^{\kappa t_{ij}}}{\varsigma^s_m} \right)^{1+\alpha\left(\zeta^s_m - 1\right)} \right]^{-1}. \tag{3.12}$$

Thus, a worker chooses to work remotely more often, i.e., chooses lower θ, when telework is relatively productive (large ν^s_m), floorspace at home is relatively cheap (large q_j/q_i), the aversion to work from home is low (small ς^s_m), 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 Online Appendix Table J.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_{mj}^{s} so as to maximize profit: $p_{mj}Y_{mj} - w_{mj}^{L}y_{mj}^{L} - w_{mj}^{H}y_{mj}^{H}$. Profit maximization implies the following equilibrium relationship between non-college wages and output prices in each industry,

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

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:

$$\frac{w_{mj}^{H}}{w_{mj}^{L}} = \frac{1-\omega_{mj}}{\omega_{mj}}\left(\frac{y_{mj}^{L}}{y_{mj}^{H}}\right)^{\frac{1}{\xi}}. \tag{3.15}$$

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

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

[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.

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 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

[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

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 Online 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 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

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.

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 Online 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 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 prices of floorspace we use the Zillow Home Value Indices aggregated from the zip code level to the level of model locations, supplemented with hedonic rent indices for each PUMA using self-reported housing rents from the ACS for the period from 2012 to 2016. Online 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 Online 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. We use the data up to September 2024. The survey is representative of the U.S. labor force.

[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.

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 1 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 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 1. We find that remote work is nearly as productive as on-site work with relative productivity ranging from 0.99 to 0.999.[23] These values are consistent with existing empirical evidence.[24]

[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 Online Appendix Figure J.1.

[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

The calibrated values of aversion to remote work ς^s_m and the elasticity of substitution between on-site and remote work ζ^s_m are shown in Table 1. 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 $\bar{\theta}^s_m \equiv \sum_o \sum_i \sum_j \pi^{so}_{mij}\theta^{so}_{mij} / \sum_o \sum_i \sum_j \pi^{so}_{mij}$. 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 in the non-tradable than in the tradable industry, with values ranging from 3.78 to 6.27. The calibrated aversion parameters range from 2.35 to 3.08, 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

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 1: Work from home parameters

Parameter	Description	Value	Source or Target
	Distribution of worker types:		
$\mathfrak{l}^{LN}$	non-college, non-telecom.	0.422	ACS and Barrero, Bloom, and Davis (2021)
$\mathfrak{l}^{LT}$	non-college, telecommutable	0.288	—
$\mathfrak{l}^{HN}$	college, non-telecommutable	0.079	—
$\mathfrak{l}^{HT}$	college, telecommutable	0.211	—
	Productivity of remote work:		
ν_S^L	non-college, non-tradable	0.993	Barrero, Bloom, and Davis (2021)
ν_G^L	non-college, tradable	0.996	—
ν_S^H	college, non-tradable	0.990	—
ν_G^H	college, tradable	0.999	—
	Aversion to work from home:		Average commuting frequency:
ς_S^L	non-college, non-tradable	3.080	$\bar{\theta}_S^L = 0.969$
ς_G^L	non-college, tradable	2.526	$\bar{\theta}_G^L = 0.939$
ς_S^H	college, non-tradable	2.715	$\bar{\theta}_S^H = 0.913$
ς_G^H	college, tradable	2.348	$\bar{\theta}_G^H = 0.815$
	Elasticity of substitution between on-site and remote work:		Variance of WFH frequency:
ζ_S^L	non-college, non-tradable	5.540	$\text{Var}(\theta_S^L \mid \theta \in [0.2, 0.8]) = 0.036$
ζ_G^L	non-college, tradable	6.267	$\text{Var}(\theta_G^L \mid \theta \in [0.2, 0.8]) = 0.041$
ζ_S^H	college, non-tradable	5.179	$\text{Var}(\theta_S^H \mid \theta \in [0.2, 0.8]) = 0.035$
ζ_G^H	college, tradable	3.777	$\text{Var}(\theta_G^H \mid \theta \in [0.2, 0.8]) = 0.028$
κ	Elasticity of commuting cost to commuting time	0.008	Ahlfeldt, Redding, Sturm, and Wolf (2015) and Tsivanidis (2019)
τ	Elasticity of distance penalty g_{ij} to commuting time	0.003	Ratio between non-telecommuters' and telecommuters' distance to work = 0.334
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.

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 $\tau = 0.003$. Finally, we recover $\kappa = 0.011 - \tau = 0.008$.

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., $\psi = 1$.

Table 2: 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	0.6997	Ratio between average wages in the tradable and non-tradable sectors = 1.06
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	4.1294	Estimated

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

4.2.2 Other Parameters

Parameters not directly related to work from home are reported in Table 2. 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 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 Online 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 0.045424. Then, to recover ϵ, we use the value $\kappa + \tau = 0.011$, as discussed in Section 4.2.1, and obtain $\epsilon = 0.045424/0.011 = 4.1294$. Estimation details are provided in Online Appendix Section C.

[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).

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, $(1-\eta_i)/\eta_i$, 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 Online Appendix Section H.3, we show that most results change little if we use the nationwide average elasticity from Saiz (2010) for all locations.

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 equilibrium of the model.*

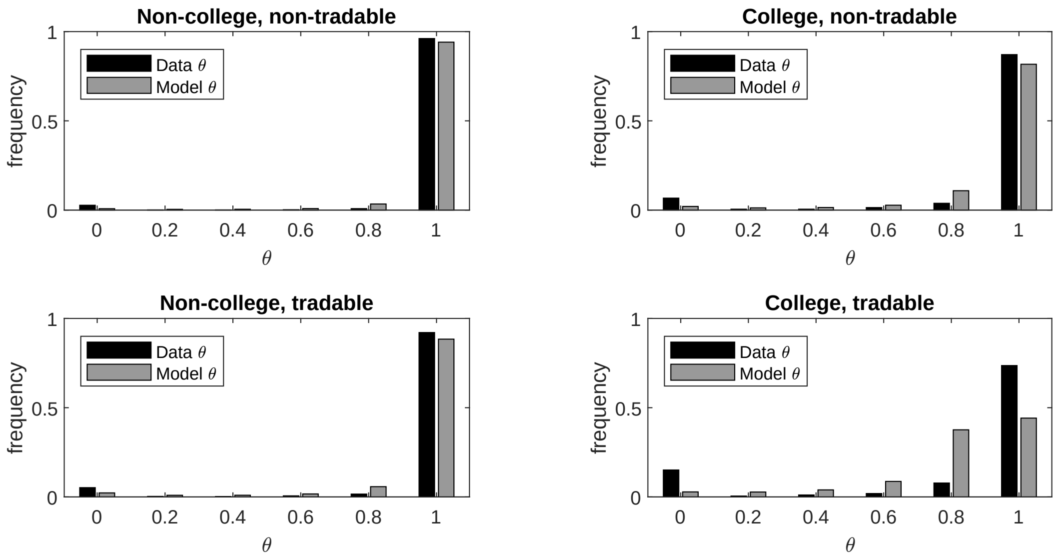
[27] We take the 2011 total floorspace elasticities estimated with the FMM-IV model (variable *gamma11b_space_FMM*). For locations with missing elasticity data, we impute the elasticities by first regressing available elasticities on a cubic polynomial of population density (the R^2 of this regression 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.

Figure 2: Commuting frequency, benchmark model vs. data



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 $\theta = 0$.

Proof. The proof follows closely the proof of a similar result in Ahlfeldt, Redding, Sturm, and Wolf (2015). See Online 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. Online Appendix Figure J.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 59.6%, 59.1%, 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. Online Appendix Figure J.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: 3.4%, 7.5%, 10.5%, and 28.3%.

[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.

The model ably reproduces *stylized fact #3*, as demonstrated in Figure 2. 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 $\pi_{ij} \equiv \sum_s \sum_o \sum_m \pi^{so}_{mij}$ is an untargeted moment that we can use to evaluate our model.[32] We find that the correlation between model and data flows is 0.92.

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. These two changes can be interpreted as a positive demand shock for remote work and a positive supply shock of remote labor. 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]

Table 3 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 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 Online

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

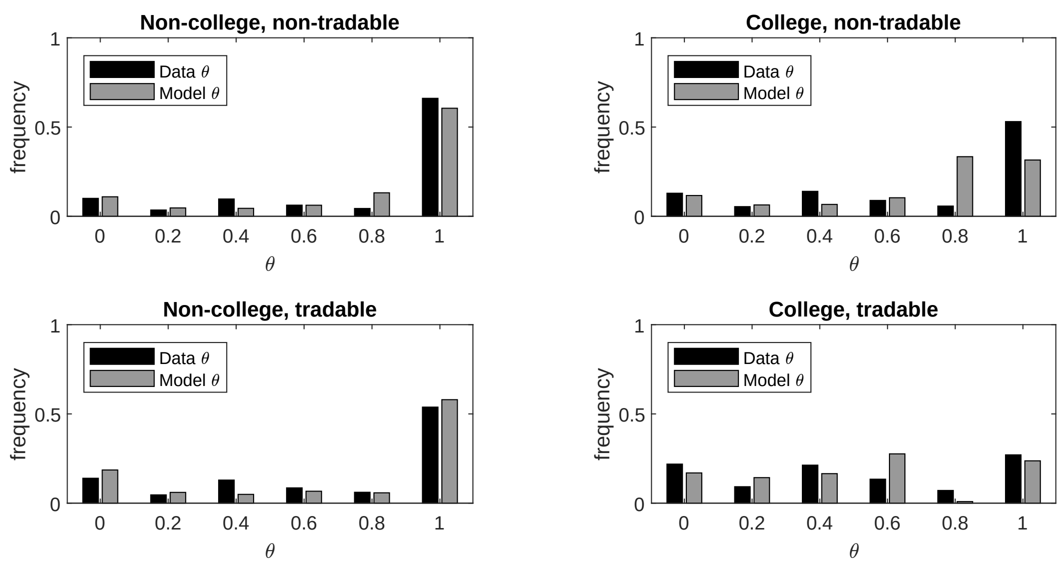
[33]As discussed in Section 3.6, the equilibrium of the model need not be unique. We follow Tsivanidis (2019) in focusing on the counterfactual equilibrium that is computed using the benchmark equilibrium as the starting point and turns out to be unique. Such counterfactual equilibria may be more likely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

Table 3: Work from home productivity and aversion parameters

Parameter	Description	Benchmark	Counterfactual	% change	Target
	Productivity of remote work:				
ν_S^L	non-college, non-tradable	0.993	1.072	8.0%	
ν_G^L	non-college, tradable	0.996	1.095	9.9%	
ν_S^H	college, non-tradable	0.990	1.081	9.2%	
ν_G^H	college, tradable	0.999	1.098	9.9%	
	Aversion to work from home:				
ς_S^L	non-college, non-tradable	3.080	1.745	-64.2%	$\bar{\theta}_S^L = 0.779$
ς_G^L	non-college, tradable	2.526	1.538	-64.8%	$\bar{\theta}_G^L = 0.699$
ς_S^H	college, non-tradable	2.715	1.946	-44.9%	$\bar{\theta}_S^H = 0.697$
ς_G^H	college, tradable	2.348	1.513	-62.0%	$\bar{\theta}_G^H = 0.512$

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 3: Commuting frequency, counterfactual model vs. survey prediction

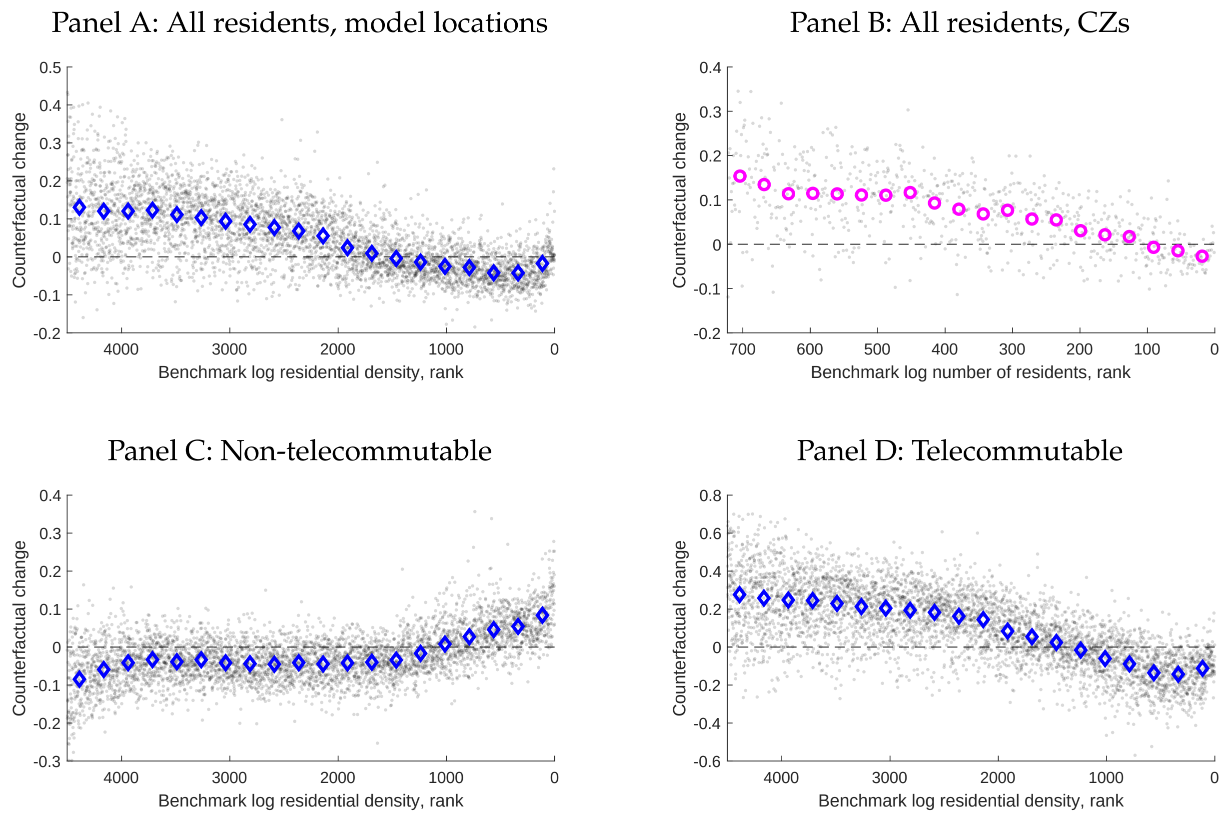


Note: "Data" reflects predicted post-pandemic distribution of days per week worked on site from the survey by Barrero, Bloom, and Davis (2021). A bar at a given θ includes values $\theta \pm 0.1$. Values of $\theta > 0.9$ are included with $\theta = 1$, and values of $\theta < 0.1$ with $\theta = 0$.

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 3 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 2, we see a sizable increase in hybrid and full-time remote work even though most workers still commute to the office every day.

Figure 4: 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^{th} percentile, from the 5^{th} to the 10^{th}, etc.

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.

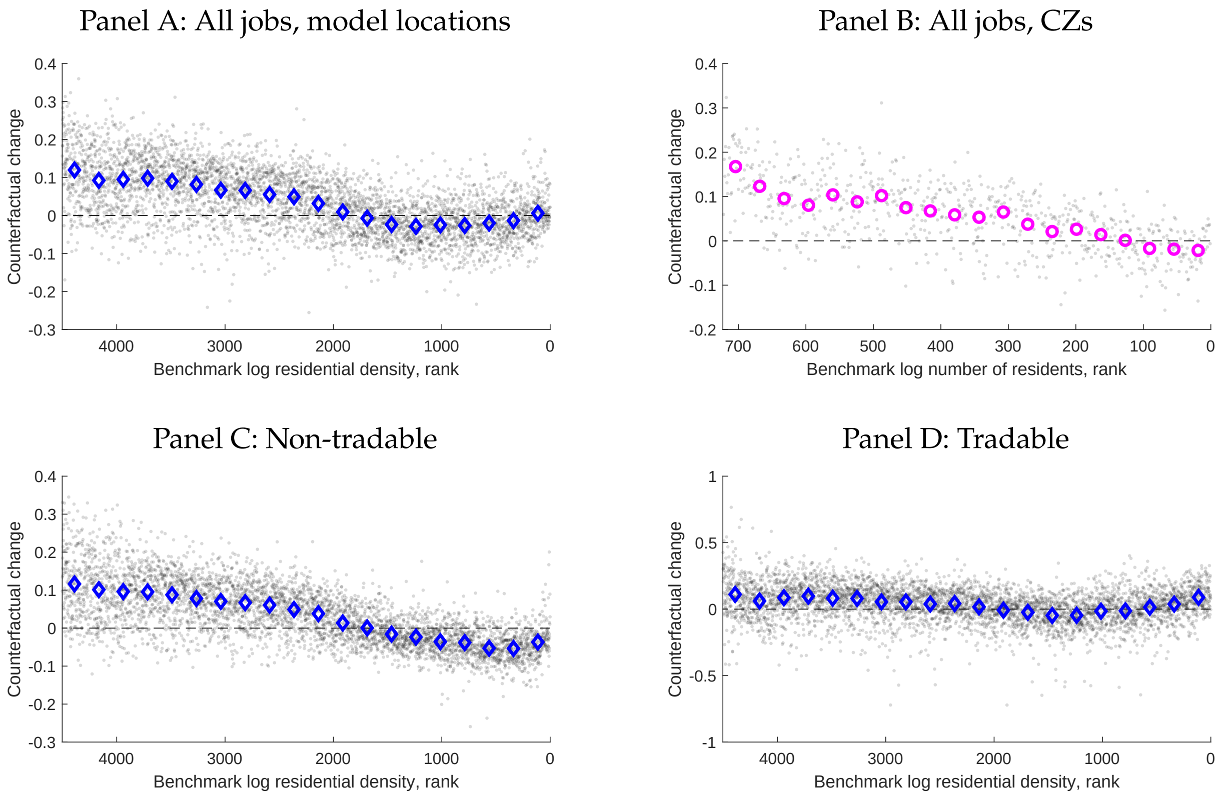
5.2 Residents, Jobs and Real Estate Prices

Distribution of residents. As panels A and B in Figure 4 show, residents move away from the densest locations and biggest cities, towards sparser locations and smaller cities. While there is much heterogeneity in the changes not explained by the crude ranking of locations and cities, the *average* trend is monotonic.[34]

While panel D of Figure 4 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.

[34]Online Appendix Figure J.3 displays predicted changes on a map.

Figure 5: 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 5th percentile, from the 5th to the 10th, etc.

Distribution of jobs. In contrast to the reallocation of residents, job movements are not entirely monotonic in residential density. As panel A in Figure 5 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.[35]

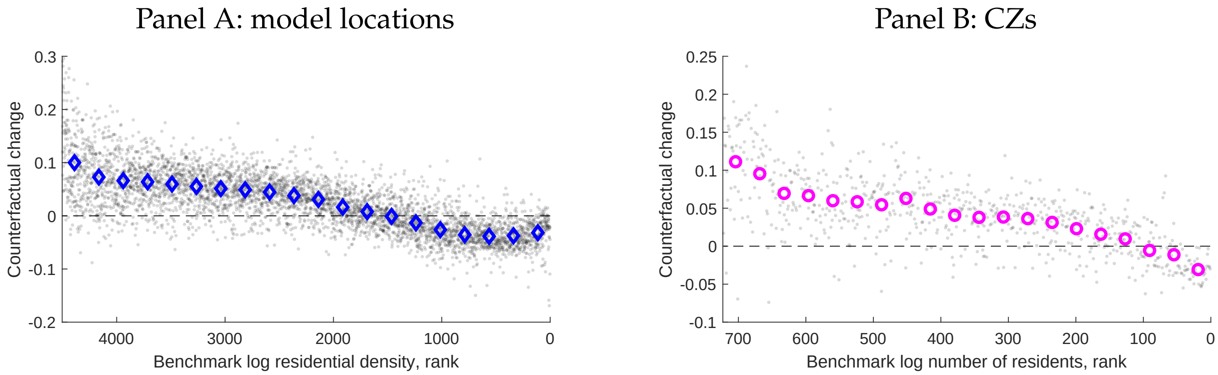
Panel C shows that non-tradable jobs monotonically follow the source of their demand, residents, to less dense locations. This means that the mixed pattern shown in panel A must be due to shifts in tradable sector jobs, shown in panel D. Thanks to the weakening of spatial frictions in the labor market, 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.[36] 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

[35]Online Appendix Figure J.4 maps predicted changes.

[36]The correlation between log productivity in the tradable sector and log residents per square km is 0.68.

Figure 6: 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^{th} percentile, from the 5^{th} to the 10^{th}, etc.

locations, changes in floorspace prices show a clear negative slope in initial density, as can be seen in Figure 6. Prices decrease in most top-quartile locations and increase in 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. Online Appendix Figure J.5 displays predicted price changes on a map.

Changes within cities. In Online Appendix Figure J.6, 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 Online 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.

5.3 Model Validation

Since 2020 there have been 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 use aggregated LODES data at the model location level to measure changes in worker counts by residence between 2019 and 2022. We then regress observed changes on model-predicted changes, and report the results in Table 4, panel A.

Column (1) corresponds to a specification with no controls, and shows a positive, statistically significant relationship between model predictions and observed changes.[37] Moreover, this

[37] Haslag and Weagley (2024) study interstate migration since 2020 and find that 12% of moves were influenced

Table 4: Changes since 2019, model vs. data

Panel A: Residents, 2019–2022

	(1)	(2)	(3)	(4)	(5)	(6)
Log chg residents, model	1.613***	0.698***	1.229***	0.0263	1.123**	0.756
	(0.132)	(0.169)	(0.0860)	(0.103)	(0.354)	(0.413)
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	0.0322	0.0478	0.902	0.910	0.0138	0.0178

Panel B: Jobs, 2019–2022

	(1)	(2)	(3)	(4)	(5)	(6)
Log chg jobs, model	0.236**	-0.421***	0.124	-0.646***	0.0633	-0.195
	(0.0782)	(0.0920)	(0.130)	(0.138)	(0.155)	(0.188)
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	4221	4221	4169	4169	678	678
R-squared	0.00216	0.0405	0.378	0.410	0.000245	0.00888

Panel C: House rents, 2019–2023

	(1)	(2)	(3)	(4)	(5)	(6)
Log chg rents, model	0.541***	0.0921	0.709***	0.597***	-2.474	-3.043
	(0.106)	(0.122)	(0.106)	(0.132)	(1.329)	(1.687)
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	1324	1324	1285	1285	171	171
R-squared	0.0193	0.0556	0.502	0.503	0.0201	0.0218

Note: In panels A and B, the dependent variables are the log changes in residents and jobs, respectively, from 2019 to 2022 from the LODES. In panel C, the dependent variable is the log change in house rents from December 2019 to December 2023 from Zillow. 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 in columns (3) and (4) have fewer observations because some CZs correspond to model locations. Regressions in panel B have fewer observations because LODES workplace data is not available for Arkansas, Michigan, and Mississippi for 2019 or 2022. Regressions in panel C have fewer observations because Zillow rent data is not available for most model locations. Standard errors are in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels.

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

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.

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 our model predictions are strongly correlated with observed changes. 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's predictions are positively correlated with observed shifts *across* CZs, although its predictive power vanishes when we control for density.

Jobs. As for residents, we use the LODES data to measure changes in worker counts by workplace between 2019 and 2022. We then regress observed changes in jobs on the model-predicted changes, and report the results in Table 4, panel B.

Column (1) shows that our model's predictions and changes in the data are positively correlated. However, in column (2) the relationship disappears once we take into account density. Columns (3) to (6) in which we either control for CZ fixed effects or run regressions at the CZ level show that our model does not predict the observed changes in jobs across locations. One possible reason could be that many firms saw post-pandemic changes as transitory and did not relocate in response, while our model's predictions are long-run and assume permanent changes in work-from-home aversion and productivity.

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.[38] We use the same sequence of specifications as we did for migration, and report the results in Table 4, panel C.

Column (1) shows a positive, significant relationship between model predictions and 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. 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 12 below confirms that, 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.

Role of density. In Figures 4, 5, and 6, we demonstrated the role that population density plays in the movement of residents and jobs, and changes in floorspace prices in our model. Do

[38]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.

these relationships also hold in the data? While numerous studies mentioned earlier showed that since 2020 residents moved toward less dense areas, and rents and prices increased more in less dense locations, it would be useful to revisit those findings and check if they hold at the level of our model locations.[39]

In Online Appendix Table J.2, we show that changes in residential population are indeed negatively correlated with initial density. In addition, we find that the relationship is stronger for college graduates than for workers without a college degree. This resonates with Figure 4 that shows that the movement of telecommutable workers (who are likely to be college graduates) away from density is very strong, while the relationship between density and relocation for non-telecommutable workers is weak. Jobs too move away from density but the slope of the relationship is smaller than for residents. However, while the model predicts a much stronger movement towards less dense locations of non-tradable firms than their tradable counterparts, we did not find the same difference in Figure 5. Finally, we find a negative relationship between density and rent growth in the data, just as Figure 6 predicts.

5.4 Why do workers move?

In Figure 4 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). We run a regression of log changes in residents between the benchmark and the counterfactual on logs of these four variables in the benchmark economy, separately for telecommutable and non-telecommutable workers, and thus obtain the elasticity of residential moves with respect to each of the four variables. Table 5 reports the coefficients for each variable and its contribution to the R^2 from the Shapley decomposition. 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 coefficients in Figure 7.

Non-telecommutable workers move to places with lower house prices and higher non-tradable prices, although, as we can see from Panel A of Figure 7, these two factors matter primarily for relocations into low-density areas. However, as we saw in Figure 4, non-telecommutable workers tend to move towards denser locations, and thus, towards higher CMA. As can be seen from Table 5, most of the variation in the R^2 comes from the CMA. 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 commute times and higher wages.

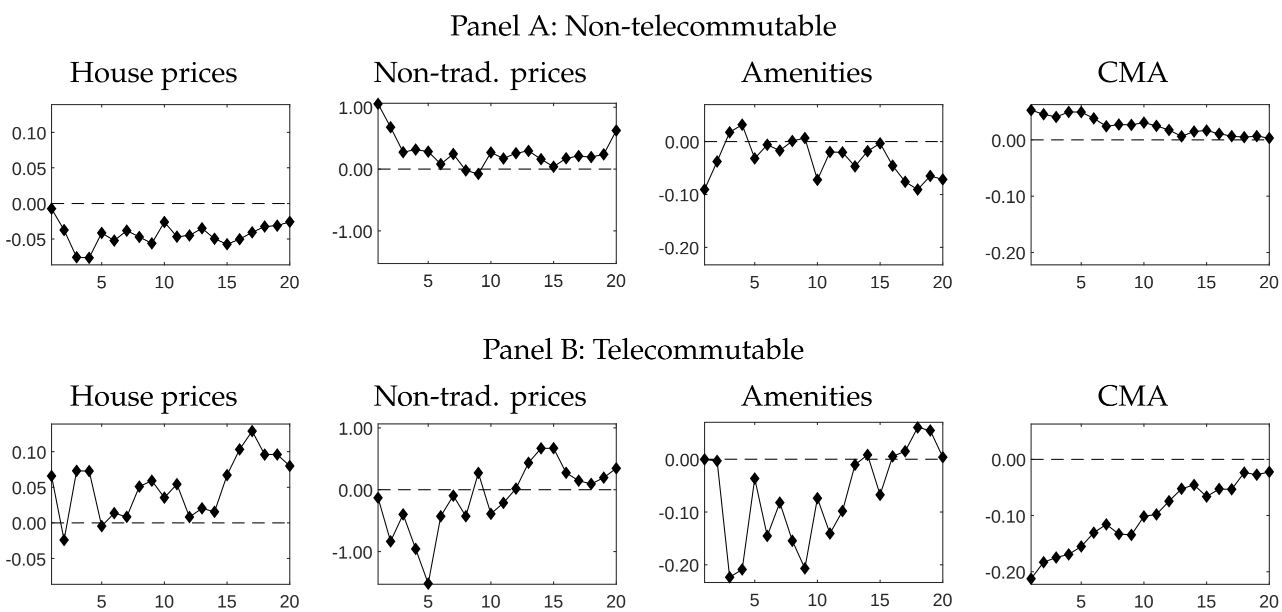
[39] Althoff, Eckert, Ganapati, and Walsh (2022) and Haslag and Weagley (2024) documented a reallocation of residents from the densest to the least dense CZs and counties during the pandemic. The relationship between density and price or rent growth during the pandemic has also been documented. Gupta, 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.

Table 5: Importance of location characteristics for reallocation of workers

	Non-telecommutable		Telecommutable	
	Coeff.	R^2 share	Coeff.	R^2 share
House prices	-0.06***	0.05	0.11***	0.05
Non-trad. prices	0.35***	0.11	0.09*	0.07
Amenities	0.00	0.01	-0.22***	0.10
CMA	0.04***	0.21	-0.13***	0.29
R^2		0.38		0.50

Note: This table shows the values of coefficients and contributions to the R^2 from regressions of log resident changes on log house prices, non-tradable prices, amenities, and CMA in the benchmark economy, separately for non-telecommutable and telecommutable workers. Amenities and CMA are weighted-averages of skill-specific values in each location. Contributions to the R^2 are obtained from the Shapley R^2 decomposition. Due to rounding, the contributions may not sum exactly ot the value of the regression R^2 in the last row. *, **, and *** indicate 10%, 5%, and 1% significance levels.

Figure 7: Importance of location characteristics for reallocation of workers, by density



Note: This figure shows the values of coefficients (on y-axis) of log house prices, non-tradable prices, amenities, and CMA in the benchmark economy from a regression of log resident changes on these variables. Each regression is run separately for each ventile of population density (on x-axis) in the benchmark economy.

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. As a result, prices and amenities explain a significantly greater portion of relocation patterns for telecommutable workers relative to their non-telecommutable counterparts. Figure 4, shows them moving to less dense locations, producing the expected negative correlations for amenities and CMA in Table 5. In panel B of Figure 7, 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. 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.

5.5 Why do jobs move?

We now conduct an exercise similar to the one in Section 5.4, but for jobs. We particularly hope to shine light on the motives of tradable firms, who in Figure 5 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 8.

Non-tradable jobs' 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 non-tradable firms' location choices are of necessity driven much more by shifting demand rather than costs.

Tradable jobs also generally move towards lower rents, regardless of density. Firms who relocate to the most dense locations are also able to benefit from the high productivity of those places. Both of these motives lead them to places that have somewhat higher wages, though the coefficient values suggest that the higher labor cost is more than offset by lower floorspace cost or higher productivity. FMA appears to have little explanatory power.

5.6 Commuting and Welfare

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

Commuting. The average worker lives 45% farther in commuting time from their workplace.[41] Yet they still spend 25% less time commuting, because the average frequency of remote work 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, 24% of workers live and work in different

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

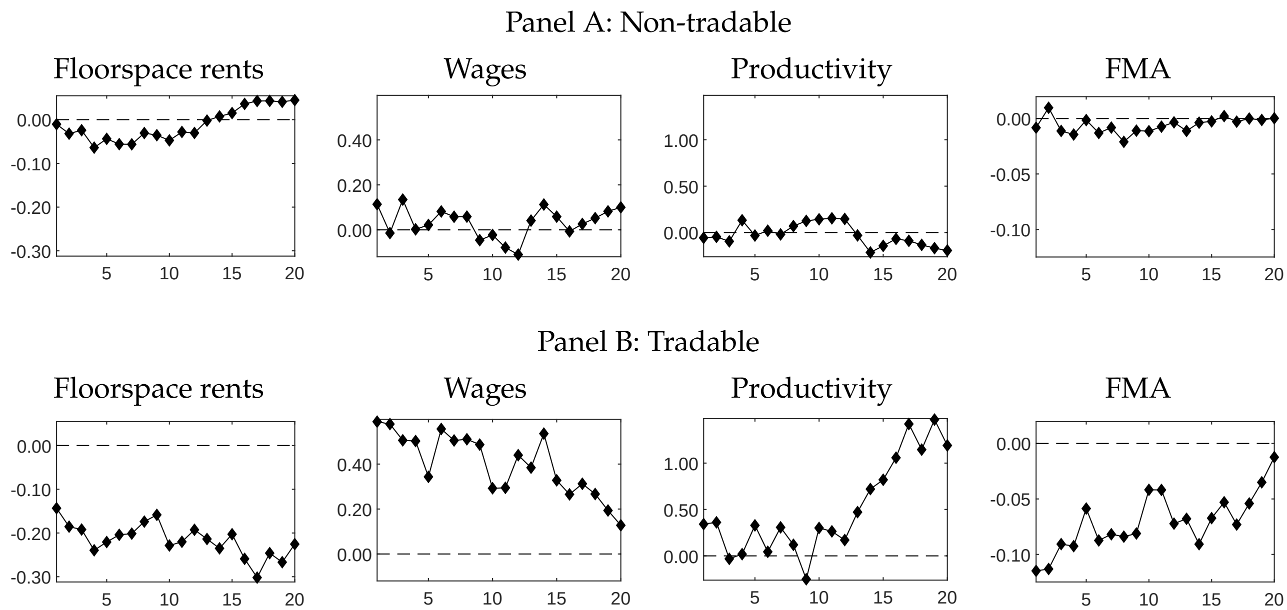
[41] Using matched employer-employee data for the U.S., Akan, Barrero, Bloom, Bowen, Buckman, Davis, Pardue, and Wilke (2024) show that the average distance between employers and employees rose from 10 miles in 2019 to 27 miles in 2023.

Table 6: Importance of location characteristics for reallocation of jobs

	Non-tradable		Tradable	
	Coeff.	R^2 share	Coeff.	R^2 share
Floorspace rents	-0.04***	0.09	-0.20***	0.18
Wages	0.14***	0.03	0.32***	0.10
Productivity	0.03**	0.02	0.69***	0.06
FMA	-0.04***	0.15	-0.05***	0.06
R^2		0.30		0.39

Note: This table shows the values of coefficients and contributions to the R^2 from regressions of log job changes on log floorspace rents, wages, productivity, and FMA in the benchmark economy, separately for non-tradable and tradable jobs. Wages and FMA are weighted-averages of skill-specific values in each location. Contributions to the R^2 are obtained from the Shapley R^2 decomposition. Due to rounding, the contributions may not sum exactly ot the value of the regression R^2 in the last row. *, **, and *** indicate 10%, 5%, and 1% significance levels.

Figure 8: Importance of location characteristics for reallocation of jobs, by density



Note: This figure shows the values of coefficients (on y-axis) of log floorspace rents, wages, productivity, and FMA in the benchmark economy from a regression of log job changes on these variables. Each regression is run separately for each ventile of population density (on x-axis) in the benchmark economy.

CZs. In the counterfactual economy, this number goes up to 33% as remote work increases the average distance between residence and workplace.

Income and inequality. Workers' income falls marginally, by 1.5%, 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.[42]

Among non-telecommutable workers, those without a college degree experience a 6.3% fall

[42] 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 7: 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	45.2	46.8	-0.3	99.6	41.9	-0.4	53.4
Time spent commuting, % chg	-25.1	-23.2	-0.3	-60.7	-30.3	-0.4	-43.4
Average WFH days/week, chg	1.1	1.1	–	2.6	1.3	–	1.7
Income, % chg	-1.5	-1.9	-6.3	4.1	-0.9	-8.2	1.5
Floorspace prices, % chg	-2.0	-1.9	-1.2	-2.9	-2.4	-1.5	-2.8
Non-tradables prices, % chg	2.2	2.2	2.4	1.9	2.4	2.7	2.2
Welfare, % chg							
consumption only	-2.7	-3.0	-7.5	3.0	-2.1	-9.5	0.3
+ commuting	-1.4	-2.2	-7.4	4.9	0.2	-9.2	3.4
+ amenities	-0.9	-1.9	-6.0	3.8	0.6	-6.5	3.1
total welfare	11.3	9.1	-6.6	37.6	18.2	-8.1	21.1

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.

in income, while college graduates see an 8.2% 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 2%, due to the net movement of residents and jobs to peripheral locations with lower building costs and higher housing supply elasticities. Telecommutable workers pay nearly 3% 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.

Prices of non-tradables increase by 2.2%. This can be attributed to a combination of the increase in income, and a movement of demand to less-dense places which tend to also have lower workplace amenities for the non-tradable sector.[43]

Workers' welfare and landowners' income. In Table 7, we break down welfare gains by incrementally considering the effects of consumption, commuting, and amenities.[44] Combined consumption of housing, tradable, and non-tradables goods goes up for telecommuters and down for non-telecommuters, declining by 2.7% on average. This is the net result of a 1.5% decrease in income and a 2.2% increase in the price of non-tradables, partly offset by the 2% fall in floorspace prices. The reduction in time commuting yields small gains for non-

[43]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.

[44]Welfare decomposition is described in Online Appendix Section E.

telecommutable workers and large gains for the remote-capable.[45] 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 11.3%. This is the net result of large gains for telecommutable workers and smaller losses for the rest.[46] An important contributor to telecommuters' gains is that less 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. It explains the large difference between the last and the second to last rows in the welfare decomposition. 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 1%. This demand is allocated to places with higher supply elasticity (and, therefore, lower land share), and thus floorspace prices decline by 2%. 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 1.7%.

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. Online 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 15% jump in residential prices and a 16% 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.

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

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

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 51–86% jump in remote work productivity, depending on the worker type. The increase in productivity acts as a remote labor demand shock and yields implausibly large wage gains for remote-capable workers that range from 41% to 68%.[47] This scenario is described in greater detail in Online 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 Online Appendix Section H.4.

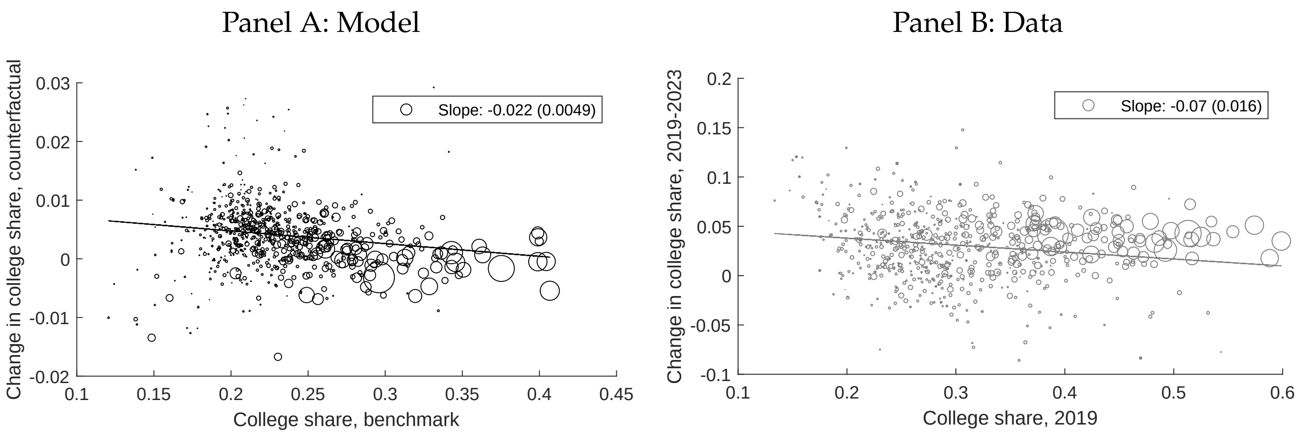
6 The Great Re-Convergence

The "Great Divergence" is a much-remarked-upon trend in the decades following the 1980s.[48] 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.

[47] 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.

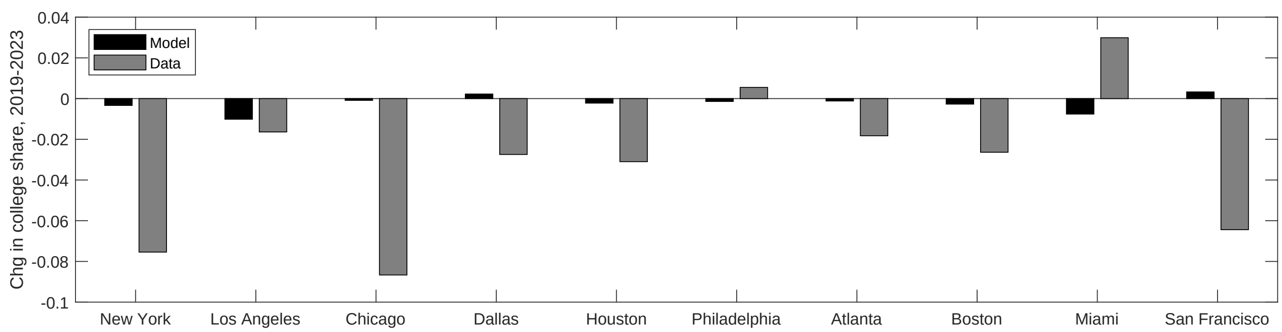
[48] The "Great Divergence" across locations in the U.S. was first summarized in Moretti (2012). The period from 1980s follows decades of regional convergence, as documented in Blanchard and Katz (1992).

Figure 9: Reversal of the skill sorting across CZs



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 10: 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.

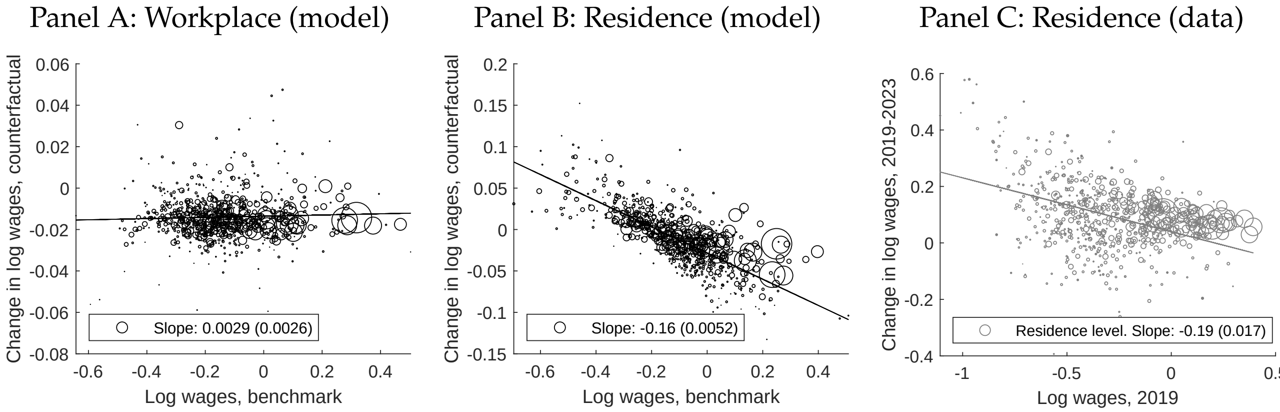
6.1 Skill Sorting

Panel A of Figure 9 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.[49]

Our model also predicts that skill will become less concentrated in city centers. Couture

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

Figure 11: 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.

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 10, our model predicts a fall in college shares in the centers of nine out of ten largest CZs.[50] 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.

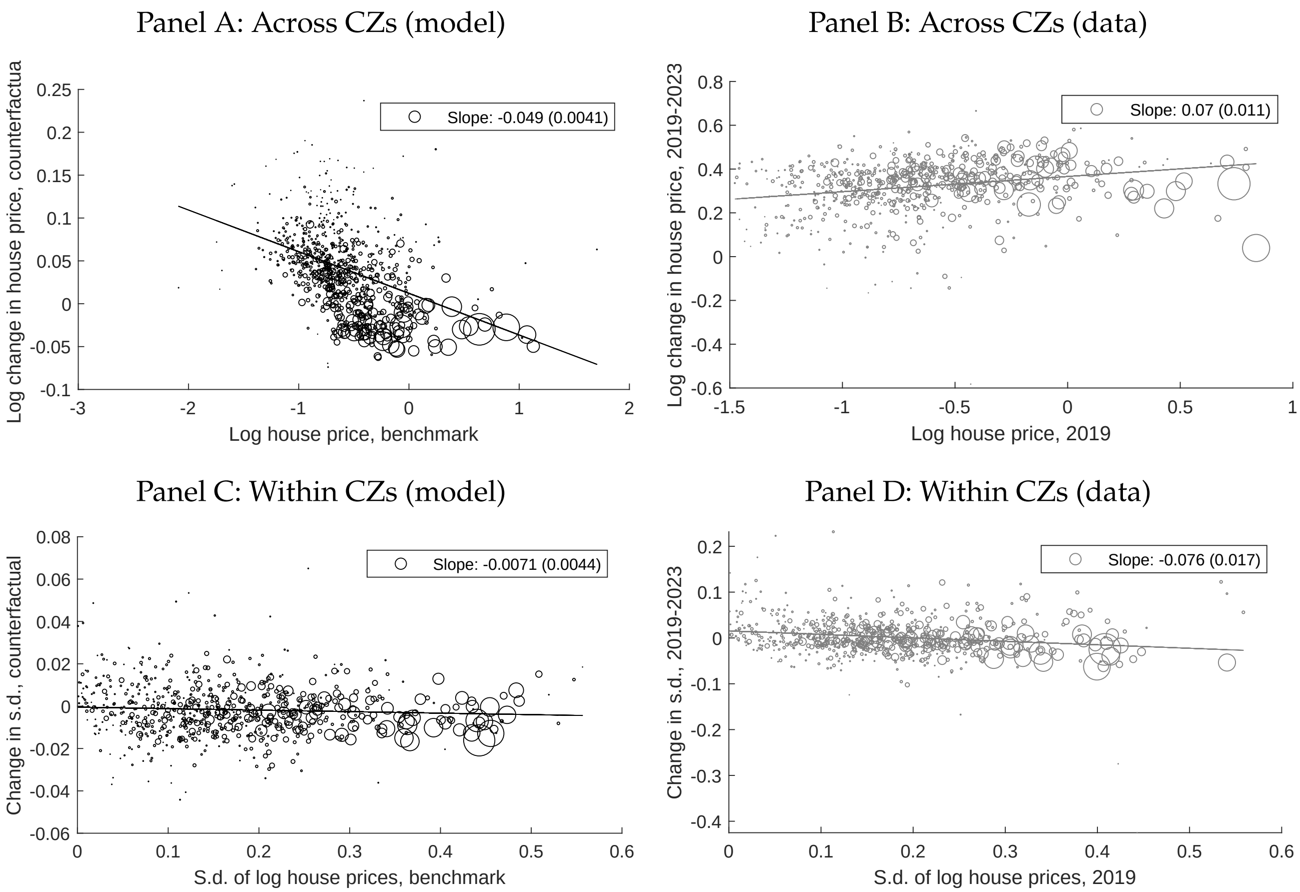
6.2 Income Inequality

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 11. Cities that were more productive before the pandemic will continue offering high incomes to their workers.[51] 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 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.

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

[51] 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 12: 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.

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 12 shows that CZs with high average prices in the benchmark model see a decline in prices, while more affordable CZs experience price increases. In contrast to our model predictions, house price dispersion has not fallen across CZs, as shown in panel B. 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 convergence of within-city price variance, as shown in panel D.[52] While in our model the convergence is weaker (panel C), many large CZs experience a reduction in the within-city price variance.

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 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.

Data Availability. The data and code underlying this research are available on Zenodo at https://doi.org/10.5281/zenodo.19445011.

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