

# 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 a permanent increase in the attractiveness of telework that leads to greater adoption of hybrid and fully remote work. To validate our model, we show that our simulation robustly predicts local changes in residents and housing prices observed 2019–2022. 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

*JEL Codes:* E24, J81, R23, R41

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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 nearly one-half of American workers to telecommute. What started as an emergency response has for many become a new norm: in early 2023, three years after the initial shock, work from home still accounted for nearly one third of all full paid days of work. Surveys show the average employer planning for at least 20% of paid work days to be remote over the long term.

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, it seems possible that workers with remote or “hybrid” jobs nominally located in one 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 land use between neighborhoods, 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 employment, and develop a quantitative framework capable of analyzing the full range of likely reallocations, both within and across cities. We divide the continental United States into 4,502 locations, and allow each worker to choose any pair of residence and job sites. Some workers are able to substitute on-site effort with work done from home. Being able to produce output at home saves them from costly commuting, and may induce them to choose a more distant residence location. On the other hand, when working remotely, they have a different level of productivity and have to procure floorspace for a home office. Their choice of how often to work on site versus at home also depends on a preference shifter we label *work-from-home aversion*, representing tastes, norms, and institutional policies regarding remote work. We show that, because telework allows firms to hire workers from a broader “catchment area,” the range of parameter values for which a unique equilibrium is guaranteed is narrower than in a conventional 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 observed wage differences between remote and on-site workers, 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. While the values of work from home aversion are similar for all types, the productivity of remote work is higher for the college-educated and for workers in tradable industries, and the elasticity of substitution is lower in the tradable sector.

We simulate a permanent increase in remote work by lowering work from home aversion to the level that rationalizes the share of work done from home predicted in the surveys of long-run expectations about remote work by [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 5% of the population. Workers who can work from home decentralize, ending up much farther from their jobs. Those who cannot work remotely move closer to their workplaces. Around two-thirds of these relocations occur *across* metro areas, and the remaining one-third *within* metro areas, underlining the importance of allowing for both types of moves.

The average worker lives 50% further from their place of work, but spends 20% less time commuting, pointing to potential reductions in traffic congestion and vehicle use. The share of workers living in one metro area and working in another increases by a third from 18% to nearly 24%, which may have major impacts on travel patterns and call into question the current administrative definitions of commuting zones.

As model validation, we show that our counterfactual results are a robust predictor of changes in population seen year-over-year between December 2019 and December 2022, both within and across metro areas, as well as of house price changes within metro areas.

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 metro areas, a fall in residential income inequality, and a fall in spatial house price inequality both within and across metro areas. We review available data for 2019–22, and find trends broadly consistent with our model predictions.

Our framework builds on quantitative spatial models of joint job and residence choice at the city level, 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 (2021), Davis, Ghent, and Gregory (2022), Kyriakopoulou and Picard (2021), and Monte, Porcher, and Rossi-Hansberg (2023) 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 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 (2022) and Monte, Porcher, and Rossi-Hansberg (2023) 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 and changes in real estate prices during the pandemic, e.g., Althoff, Eckert, Ganapati, and Walsh (2022), Brueckner, Kahn, and Lin (2021), Haslag and Weagley (2022), 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), and Veuger, Hoxie, and Brooks (2023), 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 the counterfactual experiments and tests the predictions of our model against local changes in residents and real estate prices 2019–22. 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

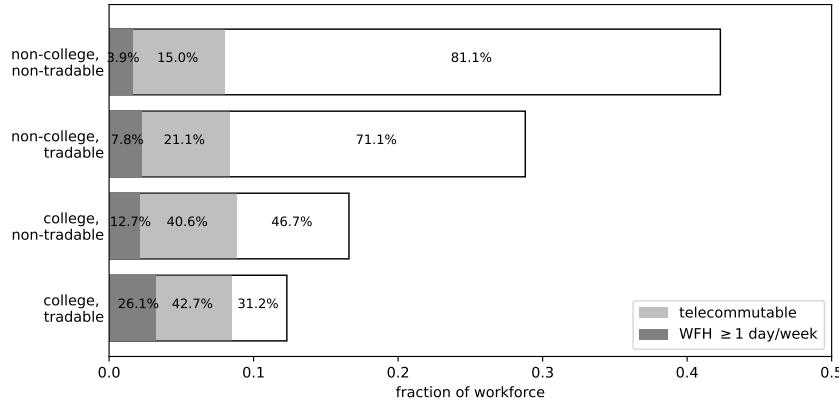
In order to construct a sensible model of remote work in the U.S. context, we should first make ourselves familiar with some basic facts. First of all, *who* can telecommute, and of those, who actually does? Second, *what* does this telecommuting entail? In particular, how frequently do remote workers work from home, and what are their average wages relative to non-remote workers? Third, *where* do telecommuters tend to 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.<sup>1</sup> Using data on full-time workers in the 48 contiguous states and Washington,

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<sup>1</sup>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.

Figure 1: Telecommutability and uptake



*Note:* Bar length corresponds to the share of each worker type in the labor force. Dark-gray areas represent workers who report at least one paid full day/week worked from home from SIPP. Light-gray represents those with telecommutable professions who do not work remotely. White areas represent those in non-telecommutable occupations. Numbers in each color area report the fraction with each commuting status.

D.C. from the American Community Survey ([ACS](#)), we calculate that the U.S. workforce between 2012–2016 was composed of 28.9% college workers, 12.3% in tradable and 16.6% in non-tradable industries; and 71.1% non-college workers, 28.8% in tradable and 42.3% in non-tradable industries.

**Who can telecommute?** To measure *telecommutability*, i.e., the ability to telecommute, we combine occupational classifications from [Dingel and Neiman \(2020\)](#) with our data. We find that 33.6% of workers in our sample have jobs that can be done from home. We also find that college workers and those in tradable industries are more likely to have such a job—an observation we label *Stylized Fact #1*. As shown in Figure 1, 68.8% of college workers in tradable industries have jobs that can be done mostly or completely from home, compared to just 18.9% of non-college workers in non-tradable industries.<sup>2</sup>

**Who does telecommute?** These differences are compounded by further gaps in telecommuting *uptake*. To measure uptake, we use data from the 2018 Survey of Income and Program Participation ([SIPP](#)); see Appendix Section A.1 for more details. Focusing on full-time workers who are not self-employed, we find that 38% of college workers in tradable industry with telecommutable occupations actually do work from home at least one full paid day a week; while uptake for non-college, non-tradable workers is only 21%.<sup>3</sup> We dub these gaps by education and industry *Stylized Fact #2*.

**How frequent is telecommuting?** Using the data from SIPP, we investigate how often remote workers dial it in from home. As Table 1 shows, a notable feature of the distribution

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

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

Table 1: Frequencies of working from home, 2018

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

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

Table 2: Relative earnings of telecommuters

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

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

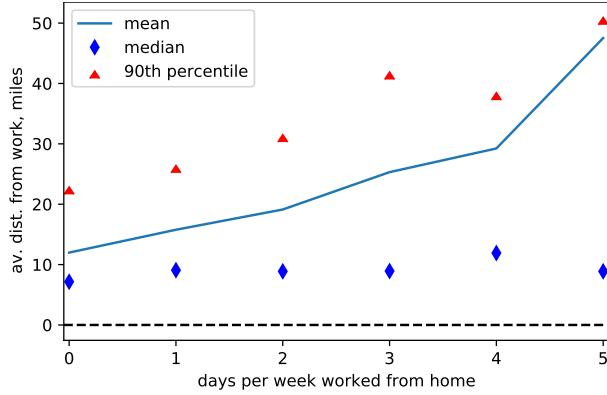
for each worker category is *bi-modality*: most are full-time on-site or full-time at home.<sup>4</sup> We call this *Stylized Fact #3*. The bimodality is less pronounced for college-educated workers in tradable industries. For them, hybrid work (i.e., one to four days per week) accounts for over 11% of paid workdays.

**How much do telecommuters earn?** In Table 2 we report that at least from 2012–2016, telecommuters did not appear to earn any less on average than their counterparts who belonged to a telecommutable occupation but worked on-site full time, even after controlling for a wide array of observable characteristics including age, occupation, industry, and geographic location; see Appendix Section A.2 for more details on the data. On the

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<sup>4</sup>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 reports 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 underestimate the amount of hybrid work in the data. ATUS and GSS appear to report more common hybrid work than SIPP ([Davis, Ghent, and Gregory, 2022](#)), 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.f1](https://www.bls.gov/news.release/flex2.t03.htm#cps_jf_table3.f1).

Figure 2: Telecommute frequency versus distance to workplace



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

contrary, for every category except for non-college workers in non-tradable industries, we observe a modest work from home wage premium. We call this *Stylized Fact #4*. This does not necessarily mean that working from home is more productive and the premium could be a result of unobserved differences between remote and non-remote workers. In Section 4.4, we discuss the evidence on work-from-home productivity in detail.

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

## 2.2 Covid-19: A Telework Shock

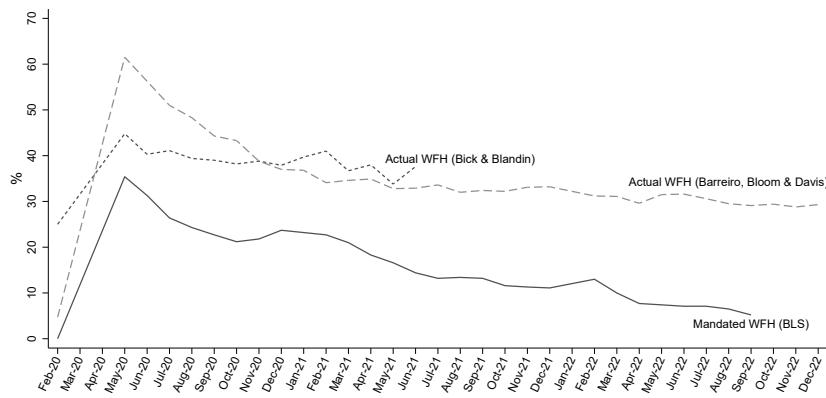
In 2018, no more than 8% of paid full workdays were remote, based on data from SIPP. When the Covid-19 pandemic began in early 2020, lockdowns and distancing moved over one third of the workforce from offices to their homes, as shown in Figure 3.

This sudden upheaval sparked consternation in many but, in survey after survey of workers and managers, an interesting pattern emerged. It was all going rather better than almost anyone had expected. Companies and workers had found ways to adjust without losing too much productivity, and many found a lot to like about remote work. So much so, that surveys by [Barrero, Bloom, and Davis \(2021\)](#) suggest a full 22% of paid workdays will be remote even after the pandemic.<sup>6</sup>

<sup>5</sup>[Zhu \(2012\)](#) also found that telecommuters live at a farther distance from work than commuters.

<sup>6</sup>Other surveys indicated that remote work will be more common post-pandemic: [Bartik, Cullen, Glaeser,](#)

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



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

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

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

The first hypothesis does not seem to be supported by the trends shown in Figure 3. The share of *mandated* remote work has fallen from 35% in May 2020 to 5% in mid-2022.

Luca, and Stanton (2020), Ozimek (2020), Bick, Blandin, and Mertens (2021), inter alia.

<sup>7</sup>[Van Nieuwerburgh \(2023\)](#) describes the debate between different explanations for the rise in work from home.

At the same time, *actual* working from home, as measured in a survey by Barrero, Bloom, and Davis (2021), has stabilized at around 30%. We therefore believe it is highly likely that some combination of the latter three hypotheses are playing a role. Our theoretical model described in Section 3 incorporates both preference and technology shocks. Nonetheless, in Section 5 we will present evidence that a *preference shock* is more plausible as a primary explanation for changes in work-from-home behavior than a *technology shock*. We leave the possible role of workplace coordination as a potential topic of future research.

### 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.<sup>8</sup> 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  $l^{HN} + l^{LN} + l^{HT} + l^{LT} = 1$ .

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.<sup>9</sup> 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

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<sup>8</sup>Examples of telecommutable occupations are architects and call center representatives. Examples of non-telecommutable occupations include dentists and plumbers.

<sup>9</sup>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.

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  $\iota$  of education level  $s$  and occupation  $o$ , conditional on a choice of location  $i$  as a residence,  $j$  as a worksite, and a choice of  $m$  as an industry, imply the indirect utility of

$$\mu_{m,\iota} \xi_{ij,\iota} v_{mij}^{so}(\theta).$$

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  $\Phi_{\text{loc}}(\xi) = \exp(-\xi^{-\epsilon})$ . The common component of indirect utility is

$$v_{mij}^{so}(\theta) \equiv \frac{X_{mi}^s E_{mj}^s}{p_i^\beta q_i^\gamma} \frac{\tilde{w}_{mij}^{so}(\theta)}{d_{ij}(\theta) g_{ij}}. \quad (3.1)$$

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.  $X_{mi}^s$  is a residential amenity and  $E_{mj}^s$  is an employment amenity. Disposable income  $\tilde{w}_{mij}^{so}$  depends on  $\theta$  in a way which we will discuss later in this section.

The disutility of commuting  $d_{mij}^{so}(\theta)$  also depends on  $\theta$  and is given by

$$d_{mij}^{so}(\theta) \equiv \theta e^{\kappa t_{ij}} + (1 - \theta) \varsigma_m^s, \quad (3.2)$$

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  $\varsigma_m^s > 0$  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  $e^{kt_{ij}}$  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  $\theta$ , ranging from 0 when  $\theta = 1$  to  $\zeta_m^s$  when  $\theta = 0$ . This functional form of the disutility of commuting highlights the role of telecommuting in reducing the importance of distance to work.<sup>10</sup>

In what follows, we will refer to  $\zeta_m^s$  as the “aversion to telecommuting.” Assuming that  $\zeta_m^s$  takes a value greater than 1 (as it does for all worker categories in our calibration), it lends itself to a range of interpretations, not all of which fall within the realm of worker “preferences” or average tastes per se. For example, they could also reflect worker concerns about career advancement, which may be easier to achieve in the office; or restrictions against work-from-home imposed by convention, or bias, or employer regulations.

We also allow for reasons not directly related to commuting to cause workers to prefer shorter commutes between work and home.<sup>11</sup> We represent these with the distance penalty  $g_{ij} \equiv e^{\tau t_{ij}}$ , with  $\tau > 0$  determining the strength of distance dependence.<sup>12</sup> This dependence is necessary for model predictions to conform with the distance-commute frequency relationship reported in Section 2: even workers who rarely come to the office tend to live at commutable distances from their job site. In Appendix Section I.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  $\theta$ , discussed later, as  $\theta_{mij}^{so}$ ; and the associated indirect utility, disposable income, and disutility of commuting as  $v_{mij}^{so}$ ,  $\tilde{w}_{mij}^{so}$ , and  $d_{mij}^{so}$ . Given indirect utilities characterized by equation (3.1), and the Fréchet distribution of shocks, it is straightforward to show that the measure of workers of education level  $s$  and occupation  $o$  who choose industry  $m$ , residence  $i$  and job site  $j$  is given by

$$\pi_{mij}^{so} = l^{so} \pi_m^{so} \pi_{ij|m}^{so}, \quad (3.3)$$

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<sup>10</sup>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.

<sup>11</sup>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.

<sup>12</sup>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.

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

$$\pi_m^{so} = \frac{\left[ \sum_i \sum_j (v_{mij}^{so})^{\epsilon} \right]^{\frac{1}{\epsilon}}}{\sum_{m'} \left[ \sum_i \sum_j (v_{m'i}^{so})^{\epsilon} \right]^{\frac{1}{\epsilon}}} \quad \text{and} \quad \pi_{ij|m}^{so} = \frac{(v_{mij}^{so})^{\epsilon}}{\sum_{i'} \sum_{j'} (v_{mi'j'}^{so})^{\epsilon}}. \quad (3.4)$$

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

$$N_{Ri}^{so} = \sum_m \sum_j \pi_{mij}^{so}. \quad (3.5)$$

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

$$N_{WCj}^s = \sum_m \sum_i [\theta_{mij}^{sT} \pi_{mij}^{sT} + \pi_{mij}^{sN}] \quad \text{and} \quad N_{WTj}^s = \sum_m \sum_i (1 - \theta_{mij}^{sT}) \pi_{mij}^{sT}. \quad (3.6)$$

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

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

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

### 3.1.1 Allocation of Time Between On-Site and Remote Work

Workers supply one unit of work time inelastically. This is a common assumption. What is different in our model is that some workers—those in telecommutable occupations—choose how to divide their work time between the job site and home. 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:  $n^\alpha h^{1-\alpha}$ .<sup>13</sup>

Tasks done at home may be different from those done at the job site. Reflecting this, overall effective labor supply of a worker is a constant elasticity of substitution combination of labor on-site and at home, with the elasticity of substitution for each education level

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<sup>13</sup>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.

and industry  $\zeta_m^s > 1$ :

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

Parameter  $\nu_m^s > 0$  is the relative productivity of working from home. It represents all possible reasons why a given worker may produce a different quantity of output while working at home, such as a different work environment, lack of supervision, or the difficulty of coordinating with co-workers. Variables  $h_{WC}$  and  $h_{WT}$  are the amounts of on-site and home floorspace, respectively, rented by the worker.<sup>14</sup> A worker of education level  $s$  in industry  $m$  takes as given that they will be paid a wage  $w_{mj}^s$  for each unit of effective labor they supply to their employer. Thus, the worker's disposable income is the compensation paid by the firm less floorspace expenses,

$$\tilde{w}_{mij}^{so}(\theta) \equiv w_{mj}^s z_m^s(\theta, h_{WC}, h_{WT}) - q_j h_{WC} - q_i h_{WT}.$$

Income-maximizing choices of floorspace of a worker who commutes to the job site a fraction  $\theta$  of time yield optimal effective labor supply

$$z_{mij}^{so}(\theta) = \left( (1-\alpha) w_{mj}^s \right)^{\frac{1-\alpha}{\alpha}} \Omega_{mij}^{so}(\theta),$$

and disposable income

$$\tilde{w}_{mij}^{so}(\theta) = \alpha (1-\alpha)^{\frac{1-\alpha}{\alpha}} (w_{mj}^s)^{\frac{1}{\alpha}} \Omega_{mij}^{so}(\theta), \quad (3.9)$$

where

$$\Omega_{mij}^{so}(\theta) \equiv \left[ \left( \theta^\alpha q_j^{-(1-\alpha)} \right)^{\frac{\zeta_m^s - 1}{1+\alpha(\zeta_m^s - 1)}} + \left( \nu_m^s (1-\theta)^\alpha q_i^{-(1-\alpha)} \right)^{\frac{\zeta_m^s - 1}{1+\alpha(\zeta_m^s - 1)}} \right]^{\frac{1}{\alpha} \frac{1+\alpha(\zeta_m^s - 1)}{\zeta_m^s - 1}}. \quad (3.10)$$

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,  $\tilde{w}_{mij}^{so}(\theta)/d_{ij}(\theta)$ , with respect to  $\theta$ , we obtain

$$\theta_{mij}^{sT} = \left[ 1 + \left( \nu_m^s \left( \frac{q_j}{q_i} \right)^{1-\alpha} \right)^{\zeta_m^s - 1} \left( \frac{e^{kt_{ij}}}{\zeta_m^o} \right)^{1+\alpha(\zeta_m^s - 1)} \right]^{-1}. \quad (3.11)$$

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<sup>14</sup>For simplicity of exposition, we specify floorspace rent as a choice by the worker; firms' payments to workers compensate both labor and floorspace. There exists an isomorphic specification in which firms rent floorspace directly.

Thus, a worker chooses to work from home more often, i.e., chooses lower  $\theta$ , when telework is relatively productive (large  $v_m^s$ ), floorspace at home is relatively cheap (large  $q_j/q_i$ ), the aversion to work from home is low (small  $c_m^o$ ), 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  $\theta$ , and a superficial interpretation of the production function given by (3.8) might lead us to believe that an allocation in which large numbers of workers make “corner” choices of nearly full-time in the office or full-time at home would be impossible. This would be inconsistent with Table 1 that shows that such choices are common in the data (*stylized fact #3*).

We need not worry, however. Large number of residence-workplace pairs ensures that there is a rich distribution of commuting times. Optimal in-office time, given by equation (3.11), is clearly able to be close to zero when commuting time  $t_{ij}$  is high and close to one when it is low. As is shown in Figure 4, the model has little difficulty replicating the empirical distributions of remote work frequency.

## 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

$$Y_{mj} = A_{mj} \left[ \omega_{mj} \left( y_{mj}^L \right)^{\frac{\xi-1}{\xi}} + (1 - \omega_{mj}) \left( y_{mj}^H \right)^{\frac{\xi-1}{\xi}} \right]^{\frac{\xi}{\xi-1}}, \quad (3.12)$$

where  $y_{mj}^s$  represents the total effective labor rented from workers with education  $s$ ,  $\omega_{mj}$  determines the weight of non-college labor in the production function,  $A_{mj}$  is the productivity of industry  $m$  in location  $j$ , and  $\xi$  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.<sup>15</sup>

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<sup>15</sup>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.

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,

$$\frac{w_{mj}^L}{p_{mj}} = A_{mj} \omega_{mj}^{\frac{\xi}{\xi-1}} \left[ 1 + \left( \frac{1 - \omega_{mj}}{\omega_{mj}} \right)^\xi \left( \frac{w_{mj}^L}{w_{mj}^H} \right)^{\xi-1} \right]^{\frac{1}{\xi-1}}. \quad (3.13)$$

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 relative input level of each skill type:

$$\frac{w_{mj}^H}{w_{mj}^L} = \frac{1 - \omega_{mj}}{\omega_{mj}} \left( \frac{y_{mj}^L}{y_{mj}^H} \right)^{\frac{1}{\xi}}. \quad (3.14)$$

### 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

$$H_i = K_i^{1-\eta_i} (\phi_i L_i)^{\eta_i}, \quad (3.15)$$

where  $K_i$  and  $L_i$  are the inputs of the tradable good and land, and  $\eta_i$  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  $\Lambda_i$  units of buildable land which serves as the upper bound on the developers' choice of land:  $L_i \leq \Lambda_i$ . Parameter  $\phi_i$  stands for the local land-augmenting productivity of floorspace developers.<sup>16</sup> Let  $q_i$  be the equilibrium price of floorspace. Then the equilibrium supply of floorspace in location  $i$  is

$$H_i = \phi_i (1 - \eta_i)^{\frac{1-\eta_i}{\eta_i}} q_i^{\frac{1-\eta_i}{\eta_i}} L_i. \quad (3.16)$$

### 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

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<sup>16</sup>The productivity may depend on terrain, climate, land use regulations, etc.

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,  $y_{mj}^s = \sum_o \sum_i \pi_{mij}^{so} z_{mij}^{so}$ , which implies that equilibrium effective labor supply is

$$y_{mj}^s = \left( (1 - \alpha) w_{mj}^s \right)^{\frac{1-\alpha}{\alpha}} \sum_o \sum_i \pi_{mij}^{so} \Omega_{mij}^{so}. \quad (3.17)$$

Applying equation (3.17) to equation (3.14), we obtain the equilibrium college wage premium,

$$\frac{w_{mj}^H}{w_{mj}^L} = \left( \frac{1 - \omega_{mj}}{\omega_{mj}} \right)^{\frac{\alpha\xi}{1+\alpha(\xi-1)}} \left( \frac{\sum_o \sum_i \pi_{mij}^{Lo} \Omega_{mij}^{Lo}}{\sum_o \sum_i \pi_{mij}^{Ho} \Omega_{mij}^{Ho}} \right)^{\frac{\alpha}{1+\alpha(\xi-1)}}. \quad (3.18)$$

Wage levels can then be found by plugging in this expression in equation (3.13).

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

$$p_{Sj} Y_{Sj} = \left( p_{Sj} A_{Sj} \right)^{\frac{1}{\alpha}} (1 - \alpha)^{\frac{1-\alpha}{\alpha}} \omega_{Sj}^{\frac{\xi}{\alpha(\xi-1)}} \left( \sum_o \sum_i \pi_{Sij}^{Lo} \Omega_{Sij}^{Lo} \right) \left[ 1 + \left( \frac{1 - \omega_{Sj}}{\omega_{Sj}} \right)^\xi \left( \frac{w_{Sj}^L}{w_{Sj}^H} \right)^{\xi-1} \right]^{\frac{1+\alpha(\xi-1)}{\alpha(\xi-1)}}. \quad (3.19)$$

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

$$p_{Sj} A_{Sj} = \frac{(\beta W_i)^\alpha}{(1 - \alpha)^{1-\alpha} \omega_{Sj}^{\frac{\xi}{\alpha-1}} \left( \sum_o \sum_i \pi_{Sij}^{Lo} \Omega_{Sij}^{Lo} \right)^\alpha} \left[ 1 + \left( \frac{1 - \omega_{Sj}}{\omega_{Sj}} \right)^\xi \left( \frac{w_{Sj}^L}{w_{Sj}^H} \right)^{\xi-1} \right]^{-\frac{1+\alpha(\xi-1)}{\alpha(\xi-1)}}. \quad (3.20)$$

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

$$H_i = H_{Ri} + H_{WCi} + H_{WTi}. \quad (3.21)$$

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  $\eta_i$  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:

$$l_i = \frac{\eta_i q_i H_i}{\Lambda_i}. \quad (3.22)$$

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:

$$q_i = \frac{1}{\eta_i^{\eta_i} (1 - \eta_i)^{1-\eta_i}} \left( \frac{l_i}{\phi_i} \right)^{\eta_i}. \quad (3.23)$$

### 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:

$$A_{mj} = a_{mj} \left( \frac{N_{WCj} + \psi N_{WTj}}{\Lambda_j} \right)^\lambda. \quad (3.24)$$

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  $\psi$  has important consequences for welfare effects of telecommuting.

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

$$X_{mi}^s = x_{mi}^s \left( \frac{N_{Ri}}{\Lambda_i} \right)^\chi, \quad (3.25)$$

where  $\chi > 0$  is the elasticity of amenities with respect to the local density of residents.<sup>17</sup> The positive relationship between residential density and amenities represents in reduced form the greater propensity for amenities, such as parks or schools, to locate in proximity

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<sup>17</sup>We abstract from spatial spillovers of productivity or amenities across locations. They are highly localized, as found in [Ahlfeldt, Redding, Sturm, and Wolf \(2015\)](#) and other studies. Given that locations in our quantitative model are relatively large, the effect of these spillovers may not be first-order.

to greater concentrations of potential users.<sup>18</sup>

## 3.6 Equilibrium

**Definition 3.1.** Given local fundamentals,  $a_{mj}$ ,  $x_{mi}^s$ ,  $E_{mj}^s$ ,  $\phi_i$ ,  $\eta_i$ , and  $\Lambda_i$ ; bilateral commute times,  $t_{ij}$ ; population shares,  $l^{so}$ ; and economy-wide parameters,  $v_m^s$ ,  $\zeta_m^s$ ,  $l^{so}$ ,  $\psi$ ,  $\alpha$ ,  $\beta$ ,  $\gamma$ ,  $\epsilon$ ,  $\sigma$ ,  $\zeta_m^s$ ,  $\xi$ ,  $\kappa$ ,  $\tau$ ,  $\lambda$ , and  $\chi$ ; a *spatial equilibrium* consists of allocations of workers to industries, residences, and job-sites,  $\pi_{mij}^{so}$ ; allocations of work time between on-site and remote,  $\theta_{mij}^{so}$ ; productivities,  $A_{mj}$ ; residential amenities,  $X_{mj}^s$ ; college and non-college wages,  $w_{mj}^H$  and  $w_{mj}^L$ ; effective labor supplies,  $y_{mj}^s$ ; 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), (3.11), (3.24), (3.25), (3.13), (3.18), (3.17), (3.23), (3.16), (3.20), (3.19), and (3.22) are satisfied.

### 3.6.1 Existence and Uniqueness

While our model has a number of extensions compared to a “standard” quantitative spatial equilibrium model with commuting such as [Ahlfeldt, Redding, Sturm, and Wolf \(2015\)](#), our main innovation is the introduction of work from home. In Appendix Section B, we evaluate equilibrium properties of a simplified model with exogenous floorspace supply, single industry, and no heterogeneity in education or occupation, but with remote work.

We show that, in general, 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 firm market access to potential workers (or “catchment area”) because they do not have to commute daily. As a result, even modest values of the productive externality parameter  $\lambda$  can lead to multiple equilibria.

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<sup>18</sup>We assume that all residents contribute equally to amenity externalities, although it is also possible that telecommuters contribute more to local amenities by spending more time in the area of their residence. Another important channel of amenity adjustments in response to work from home are local services financed by state or municipal taxes. [Agrawal and Brueckner \(2022\)](#) use a spatial equilibrium model with remote work to study how relocations of residents and jobs may affect local tax revenues.

## 4 Quantification

In this section we describe how we build our model into a quantitative description of industry, residence, workplace, and telecommuting decisions made by U.S. workers in the years leading up to 2020. We focus our analysis on the 48 contiguous United States and the District of Columbia from 2012–2016.<sup>19</sup>

We define a model location as the intersection of a Census Public Use Microdata Area (PUMA) and a county.<sup>20</sup> 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 location is a county. 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 and occupation type,  $I^{so}$ , is calculated from 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  $j$ :  $\hat{w}_{mj}^s$ . In our model, firms pay workers for their labor as well as for floorspace expenses. We convert observed wages  $\hat{w}_{mj}^s$  into their model counterpart  $w_{mj}^s$  by applying commuting flows and effort predicted by the model. To estimate wage differences between on-site workers and telecommuters, we also use ACS data. More details can be found in Appendix Sections A.2 and A.3.

**Non-tradable goods prices.** We use the Bureau of Economic Analysis Regional Price Parities for the “Services other than real estate” category as a proxy for non-tradable output prices. We use data at the metropolitan statistical area (MSA) level, if available,

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<sup>19</sup>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.

<sup>20</sup>The Census Bureau designs PUMAs to have between 100,000 and 200,000 residents. Thus, large metropolitan areas have many model locations: the New York metro area has 147 distinct model locations.

and apply the same price level to all locations within a single MSA. For the remaining locations, we apply the state non-metropolitan price level from the database.

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

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

## 4.2 Parameterization

Model parameters can be divided into three sets: those we set externally, those we estimate (both listed in Table 3), and those we calibrate internally (summarized in Table 5).

### 4.2.1 Externally Set Parameters

We set the consumption share of housing,  $\gamma = 0.24$ , following Davis and Ortalo-Magné (2011). Valentinyi and Herrendorf (2008) estimate that the combined share of land and structures in the U.S. is equal to 0.18. Thus, we set the labor share in the production of tradable and non-tradable goods,  $\alpha$ , equal to 0.82. The elasticity of substitution between college and non-college labor,  $\xi$ , is set to 2, in the middle of the range between 1.5 and 2.5 reported by Card (2009). We set the Fréchet elasticity of the distribution of industry choice shocks,  $\sigma$ , equal to 1.4, following Lee (2020).

We borrow the values of the elasticities of local productivity and amenities with respect to density from Hebligh, Redding, and Sturm (2020), and set  $\lambda = 0.086$  and  $\chi = 0.172$ .<sup>21</sup> To evaluate the sensitivity of our results to these two values, we run counterfactual experiments where each of these values is set to zero. Naturally, reallocations of residents and jobs are less pronounced but the results do not change in any major way; see Appendix G for details.

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,  $\psi$ . 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 5.5 we will present results for the scenario in which remote work does not inhibit productive externalities, i.e.,  $\psi = 1$ .

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<sup>21</sup>Meta-analysis of estimated density elasticities in Ahlfeldt and Pietrostefani (2019) finds that 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).

Table 3: Externally determined and estimated parameters

Parameter	Description	Value	Comments
$\gamma$	consumption share of housing	0.24	<a href="#">Davis and Ortalo-Magné (2011)</a> .
$\alpha$	labor share in production	0.82	<a href="#">Valentinyi and Herendorf (2008)</a>
$\xi$	elasticity of substitution between college and non-college labor	2	middle of the 1.5–2.5 range in <a href="#">Card (2009)</a>
$\sigma$	Fréchet elasticity of industry shock	1.4	<a href="#">Lee (2020)</a>
$\epsilon$	Fréchet elasticity of location shock	4.026	estimated—see Section 4.2.2
$\lambda$	elasticity of local productivity to employment density	0.086	<a href="#">Heblich, Redding, and Sturm (2020)</a>
$\chi$	elasticity of local amenity to population density	0.172	<a href="#">Heblich, Redding, and Sturm (2020)</a>
$\psi$	contribution of telecommuters to productivity externalities	{0,1}	we run separate counterfactuals with $\psi = 0$ and $\psi = 1$
$\kappa + \tau$	elasticity of commuting cost to commuting time	0.011	average of estimates from <a href="#">Ahlfeldt, Redding, Sturm, and Wolf (2015)</a> and <a href="#">Tsivanidis (2019)</a>
$\eta_i$	price elasticity of floorspace supply	various	<a href="#">Baum-Snow and Han (2021)</a>

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

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  $\kappa$ ). Second, it increases the distance penalty (with elasticity  $\tau$ ). 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  $g_{ij}d_{mij}^{so} = e^{(\kappa+\tau)t_{ij}}$ , 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. Below we calibrate  $\tau$  and thus identify  $\kappa$ .

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.<sup>22</sup> 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

<sup>22</sup>The model locations for which no estimates exist are mostly rural. Since, according to [Baum-Snow and Han \(2021\)](#), there is a strong negative relationship between elasticity and population density, we assume that the elasticity in these places takes the maximum observed value.

Table 4: Estimation of the Fréchet Elasticity of Location Choice

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

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

than previous studies have found.<sup>23</sup> In Appendix Section I.3 we show that the results of our counterfactuals change little if we use higher values of the elasticity.

#### 4.2.2 Estimation of the Fréchet Elasticity of Location Choice

To obtain the value of the Fréchet elasticity  $\epsilon$ , we construct the log-likelihood function that combines the number of commuters on each  $(i, j)$  link and the probability of commuting along this link:

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

In this expression,  $N_{ij}$  is the number of commuters from  $i$  to  $j$  in the LODES data,  $\bar{X}_i$  and  $\bar{E}_j$  are origin and destination fixed effects that subsume all relevant local variables that appear in the conditional location choice probability (equation 3.4), and  $t_{ij}$  is the commuting time from  $i$  to  $j$ .<sup>24</sup> At this stage, we cannot separately identify  $\kappa + \tau$  and  $\epsilon$ , and we estimate the value of  $(\kappa + \tau)\epsilon$  using Poisson pseudo maximum likelihood (PPML).<sup>25</sup> Prior to estimation, we set  $N_{ij} = 0$  for all pairs with commuting times of more than 3 hours one way.<sup>26</sup> As

<sup>23</sup>At the level of our model locations, elasticities vary from 0 to 0.95, and the population-weighted mean is 0.45. Thus,  $\eta_i$  ranges from 0.51 to 1 and the mean is 0.72. For comparison, [Saiz \(2010\)](#) estimates the elasticities to be on average 1.75 at the metro area level. [Baum-Snow and Han \(2021\)](#) discuss the reasons for this discrepancy. Moreover, in our model the parameter  $\eta_i$  corresponds to the land share in the production. Thus, the mean land share in our model is higher than most existing estimates: e.g., [Albouy and Ehrlich \(2018\)](#) find that the land share is about 1/3 for the U.S.

<sup>24</sup>Because LODES and CTPP do not distinguish commuters and telecommuters, we estimate this relationship assuming that all observations commute to the job site all the time, i.e., are workers with  $\theta = 1$ . Moreover, because we only observe employment levels but not flows by either industry or education, we cannot estimate the Fréchet elasticity separately for different worker types.

<sup>25</sup>We use PPML rather than OLS because 98.4% of location pairs in our data have zero flows. As [Dingel and Tintelnot \(2020\)](#) show, the sparse nature of commuting matrices may result in biased OLS estimates of the Fréchet elasticity and poor model fit.

<sup>26</sup>Out of 139 mln commuters we observe in LODES, 9.8 mln travel between locations that are over 3 hours apart. While some of these observations could be full-time telecommuters, due to reasons outlined in [Graham, Kutzbach, and McKenzie \(2014\)](#), many of these long commutes arise due to errors in assigning work or residence locations. In addition, the evidence in Figure 2 shows that most telecommuters do not

reported in Table 4, our estimate of  $(\kappa + \tau)\epsilon$  is 0.0443. To recover  $\epsilon$ , we use the chosen value  $\kappa + \tau = 0.011$ , as discussed in Section 4.2.1, and obtain  $\epsilon = 0.0443/0.011 = 4.026$ .

### 4.2.3 Model Calibration and Inversion

**Work-from-home parameters.** The calibrated values of relative productivity  $v_m^s$ , the elasticity of substitution between on-site and remote work  $\zeta_m^s$ , and aversion to remote work  $\varsigma_m^s$ , are shown in Table 5. While we jointly calibrate these and several other parameters, these three sets of parameters are primarily determined by three sets of targets.

The first set is comprised of the relative wages of remote workers. In our model, we calculate, for workers in each industry and education group, the average wage of telecommutable workers who work on-site less than 20% of the time,  $\bar{w}_m^{sT}(\theta < 0.2)$ ; and more than 80% of the time,  $\bar{w}_m^{sT}(\theta > 0.8)$ . We target each ratio  $\bar{w}_m^{sT}(\theta < 0.8)/\bar{w}_m^{sT}(\theta > 0.8)$  to the type-specific work-from-home wage premium from Table 2.

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.  $0.2 \leq \theta \leq 0.8$ . We target this middle range so that the moment is more distinct from the average frequency, which is heavily influenced by the masses of workers with  $\theta < 0.2$  and  $\theta > 0.8$ . 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  $\theta$  close to 0 or 1, and the larger will be the variance of  $\theta$ 's in the quantitative model.

The third set of targets is comprised of mean fractions of time worked on-site for workers in each industry and education group  $\bar{\theta}_m^s \equiv \sum_o \sum_i \sum_j \pi_{mij}^{so} \theta_{mij}^{so} / \sum_o \sum_i \sum_j \pi_{mij}^{so}$ . We target each ratio to match the type-specific averages calculated from SIPP data.

The calibrated relative productivity of remote work reported in Table 5 is (a) higher in the tradable than in the non-tradable industry, and (b) higher for college than for non-college workers. This establishes a clear hierarchy, with non-college workers in the non-tradable sector being about 2% less productive working remotely, and college workers in the tradable sector being about 20% more productive. 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 to 4.4. The calibrated aversion parameters are around 3 for each category, indicating large non-pecuniary barriers to remote work for all types of workers.<sup>27</sup>

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live extremely far from their employers and therefore are unlikely to be dropped from our analysis.

<sup>27</sup>One paper which takes a related approach, [Davis, Ghent, and Gregory \(2022\)](#), calibrates pre-pandemic relative productivities of approximately 0.35 for both high and low-skilled workers. Combined with worker-

Table 5: Internally calibrated parameters

Parameter	Description	Value	Target
$\nu_S^L$	Productivity of remote work: non-college, non-tradable	0.9734	WFH mean wage differentials: $\bar{w}_S^{LT}(\theta < 0.1)/\bar{w}_S^{LT}(\theta > 0.9) = 0.985$
$\nu_G^L$	non-college, tradable	1.1351	$\bar{w}_G^{LT}(\theta < 0.1)/\bar{w}_G^{LT}(\theta > 0.9) = 1.026$
$\nu_S^H$	college, non-tradable	1.0114	$\bar{w}_S^{HT}(\theta < 0.1)/\bar{w}_S^{HT}(\theta > 0.9) = 1.024$
$\nu_G^H$	college, tradable	1.2054	$\bar{w}_G^{HT}(\theta < 0.1)/\bar{w}_G^{HT}(\theta > 0.9) = 1.052$
$\zeta_S^L$	Elasticity of substitution between on-site and remote work: non-college, non-tradable	4.1884	Variance of WFH frequency: $\text{Var}(\theta_S^L \theta \in [0.2, 0.8]) = 0.0356$
$\zeta_G^L$	non-college, tradable	3.8924	$\text{Var}(\theta_G^L \theta \in [0.2, 0.8]) = 0.0367$
$\zeta_S^H$	college, non-tradable	4.3548	$\text{Var}(\theta_S^H \theta \in [0.2, 0.8]) = 0.0351$
$\zeta_G^H$	college, tradable	3.0330	$\text{Var}(\theta_G^H \theta \in [0.2, 0.8]) = 0.0273$
$\zeta_S^L$	Aversion to work from home: non-college, non-tradable	3.0565	Average commuting frequency: $\bar{\theta}_S^L = 0.97$
$\zeta_G^L$	non-college, tradable	2.9367	$\bar{\theta}_G^L = 0.94$
$\zeta_S^H$	college, non-tradable	3.1087	$\bar{\theta}_S^H = 0.91$
$\zeta_G^H$	college, tradable	2.9130	$\bar{\theta}_G^H = 0.82$
$\beta$	Consumption share of non-tradables	0.6895	Ratio between average wages in the tradable and non-tradable sectors = 1.23
$\tau$	Elasticity of distance penalty $g_{ij}$ to commuting time	0.0024	Ratio between telecommuters' and non-telecommuters' distance to work = 0.338

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

This implies that compared to workers in the non-tradable industry, workers in the tradable industry are more productive at home but their at-home and on-site effort is less substitutable. One interpretation of this is that in the knowledge-intensive industries (finance, IT) which make up much of the tradable sector, there is 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. We further discuss productivity parameters and evidence on work-from-home productivity in Section 4.4.

**Distance penalty.** We calibrate the elasticity of the distance penalty to the commuting time,  $\tau$ , 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

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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.

distance penalty  $g_{ij}$ . Once workers can telecommute, the distinction becomes important. If commuting cost is all that matters, our model predicts that the average telecommuter will live very far from their workplace. If, on the other hand, distance penalty is all that matters, there is no substantive difference between commuters and telecommuters in terms of residential location choices. Either of these extremes would be inconsistent with the *stylized fact #4* presented in Section 2. Thus, we first calculate the average distance in kilometers between residence  $i$  and job site  $j$ ,  $\text{dist}_{ij}$ , separately for “full-time commuters” (defined as those with  $\theta > 0.9$ ) and telecommuters ( $\theta \leq 0.9$ ). Then, we calibrate  $\tau$  so that the ratio of average distances, is the same in the model and in the data.

**Expenditure share of non-tradables.** Spending on non-tradable goods is an important determinant of wages in the non-tradable sector. Therefore, we calibrate  $\beta$ , 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.

**Model inversion.** 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  $\tilde{x}_{mi}^s \equiv x_{mi}^s\Lambda_i^{-\chi}$ , land-adjusted productivity of floorspace developers  $\tilde{\phi}_i \equiv \phi_i\Lambda_i$ , workplace amenities  $E_{mj}^s$ , and education-specific productivity shifters  $\omega_{mj}$ .<sup>28</sup>

These parameters are pinned down by using the following local data. Labor productivity parameters  $\tilde{a}_{mi}$  and  $\omega_{mj}$  are determined from observed wages by industry and skill. Floorspace productivity parameter  $\tilde{\phi}_i$  is determined from observed housing prices. Residential amenities  $\tilde{x}_{mi}^s$  are determined from 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  $x_{mi}^s = x_{mi}x_i^s$  and  $E_{mj}^s = E_{mj}E_j^s$ . 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.

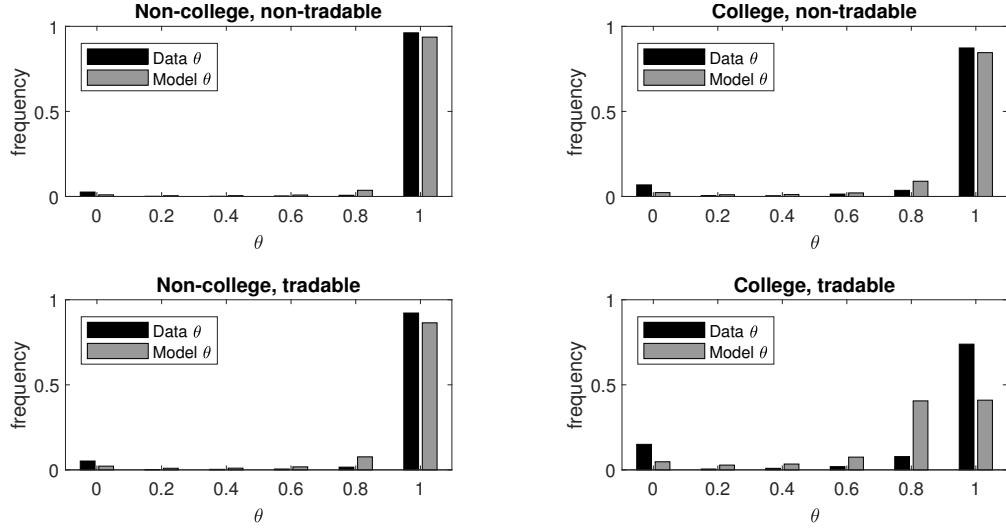
The following result states that, given observed data and economy-wide parameters, there are unique vectors of location-specific fundamentals, consistent with the equilibrium of the model.

**Proposition 1.** *Given the data,  $N_{R,mi}$ ,  $N_{W,mj}$ ,  $N_{R,i}^s$ ,  $N_{W,j}^s$ ,  $I^{so}$ ,  $\hat{w}_{mj}^s$ ,  $q_i$ ,  $p_i$ ,  $t_{ij}$ , estimated local land shares  $\eta_i$ , and economy-wide parameters,  $\alpha$ ,  $\beta$ ,  $\gamma$ ,  $\epsilon$ ,  $\zeta$ ,  $\kappa$ ,  $\lambda$ ,  $v_m^s$ ,  $\zeta_m^s$ ,  $\xi$ ,  $\sigma$ ,  $\tau$ ,  $\chi$ , and  $\psi$ , there exists a unique set of vectors,  $\tilde{a}_{mi}$ ,  $x_{mi}$ ,  $x_i^s$ ,  $\tilde{\phi}_i$ ,  $E_{mj}$ ,  $E_j^s$ , and  $\omega_{mj}$ , that is consistent with the data being an equilibrium of the model.*

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<sup>28</sup>Separate identification of land area  $\Lambda_i$  is not required for the model.

Figure 4: Telecommute frequency, data vs. benchmark model



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

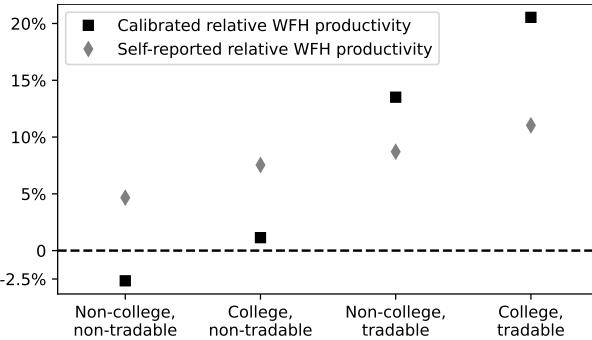
*Proof.* The proof follows closely the proof of a similar result in Ahlfeldt, Redding, Sturm, and Wolf (2015). See Appendix Section C.2  $\square$

### 4.3 Model Fit

**Stylized facts about telecommuting.** How does our model do in matching the four stylized facts laid out in Section 2.2? For *stylized fact #1*, while we match the fraction of telecommutable workers by education and the total number of workers in each industry during our calibration, the model endogenously produces the fraction of telecommutable workers by industry. Figure 1 reported that the share of those who cannot work remotely is 81.1% for non-college workers in the non-tradable sector, 71.1% for non-college workers in the tradable sector, 46.7% for college workers in the non-tradable sector, and 31.2% for college workers in the tradable sector. The corresponding numbers in our model are 77%, 75.9%, 40.4%, and 38.8%. Though the ranking is preserved, the industry telecommutability 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* across both education levels and industries. Figure 1 showed that the fraction of those who work from home at least one paid full day per week is 3.9% among non-college workers in the non-tradable sector, 7.8% for non-college workers in the tradable sector, 12.7% for college workers in the non-tradable sector, and 26.1% for college workers in the tradable

Figure 5: Work from home productivity



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

sector. The corresponding numbers in our model are 3.6%, 8%, 8.8%, and 28.2%.

The model ably reproduces *stylized fact #3*, as demonstrated in Figure 4. By targeting the mean frequency for each education-industry pair and the variance for the interior of the distribution,  $\theta \in [0.2, 0.8]$ , we can reproduce the heavy right tail and, to some extent, the bimodality of the distribution. One exception is the distribution for college graduates in tradable industries. Due to the relatively low calibrated elasticity of substitution between on-site and remote work, our model generates a lower number of full-time commuters compared to the data. *Stylized facts #4 and #5* we match by construction, as the relative wages and relative distance to the job site of telecommuters are calibration targets.

**Commuting flows.** We match residents and jobs by education and industry in each location, but leave the model free to predict commuting flows between locations. Thus  $\pi_{ij} \equiv \sum_s \sum_o \sum_m \pi_{mij}^{so}$  is an untargeted moment that we can use to evaluate our model.<sup>29</sup> We find that the correlation between model and data flows is 0.93.

#### 4.4 Work-from-Home Productivity

The finding of modestly higher productivity of remote work for most types of workers, as shown in Table 5, is consistent with empirical evidence. A study conducted during the pandemic by [Bloom, Han, and Liang \(2022\)](#) randomizes work from home on 1600 knowledge workers (engineers) in a large multinational company. It 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.<sup>30</sup> Further-

<sup>29</sup>Flows by industry, occupation, education are unobserved and cannot be compared to model flows.

<sup>30</sup>Work-from-home productivity is subject to active research. Other studies that find that remote and/or hybrid work are at least as productive as in-person work include [Bloom, Liang, Roberts, and Ying \(2015\)](#) and [Choudhury, Khanna, Makridis, and Schirrmann \(2022\)](#), among others. Studies that find productivity losses from remote work include [Emanuel, Harrington, and Pallais \(2022\)](#) and [Gibbs, Mengel, and Siemroth \(2022\)](#).

more, surveys conducted by [Barrero, Bloom, and Davis \(2021\)](#) since March 2020 indicate that workers of all types self-evaluate that they are, on average, more productive working from home. Figure 5 compares these self-reported differences in productivity with our calibrated relative productivity of remote work. It shows that, despite differences in levels, the ranking of values across categories for both our calibration and the survey is identical.

## 5 Implications of an Increase in Telecommuting

In this section, we study the long-run impact of the rise in work from home as a result of a permanent preference shock which reduces worker distaste for working from home. We explore the shifts in residence, jobs, prices, and commuting patterns predicted by our model, as well as welfare implications of these changes. To validate our approach, we show that our model's predictions align well with data on migration and house price changes 2019–22. Finally, we provide some evidence that the preference component of the Covid-19 telework shock is likely more significant than the technology shock component.

### 5.1 Counterfactual Setup

Our baseline assumption is that the increase in remote work is driven by falls in the aversion to telecommuting experienced by workers of each skill  $s$  and industry  $m$ ,  $\varsigma_m^s$ . How do we determine the size of the changes in these four parameters? [Barrero, Bloom, and Davis \(2021\)](#) conducted repeated surveys of workers where they self-report their employers' plans for the number of days per week a worker is expected to work remotely post-Covid. The survey is representative of the U.S. labor force. From these data we calculate a post-pandemic mean on-site working frequency for each worker type, and lower the aversion to remote work to match it.<sup>31</sup> 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 5.5.

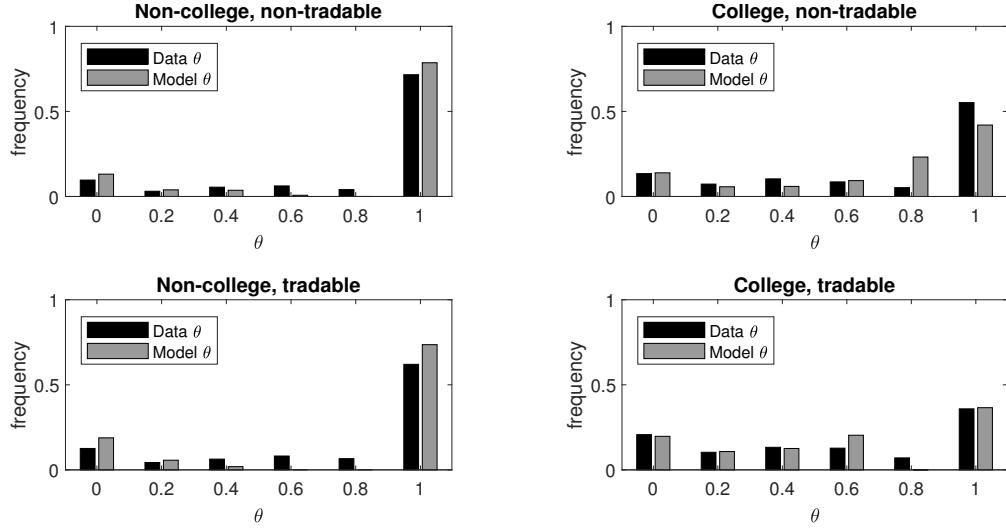
Figure 6 compares the distributions of commuting frequency indicated by the [Barrero, Bloom, and Davis \(2021\)](#) survey with those predicted in the counterfactual. In spite of the fact that only one moment—the mean—from each distribution is targeted, the two sets of distributions line up very well. Compared to the pre-pandemic distribution shown in

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(2022).

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

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



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

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

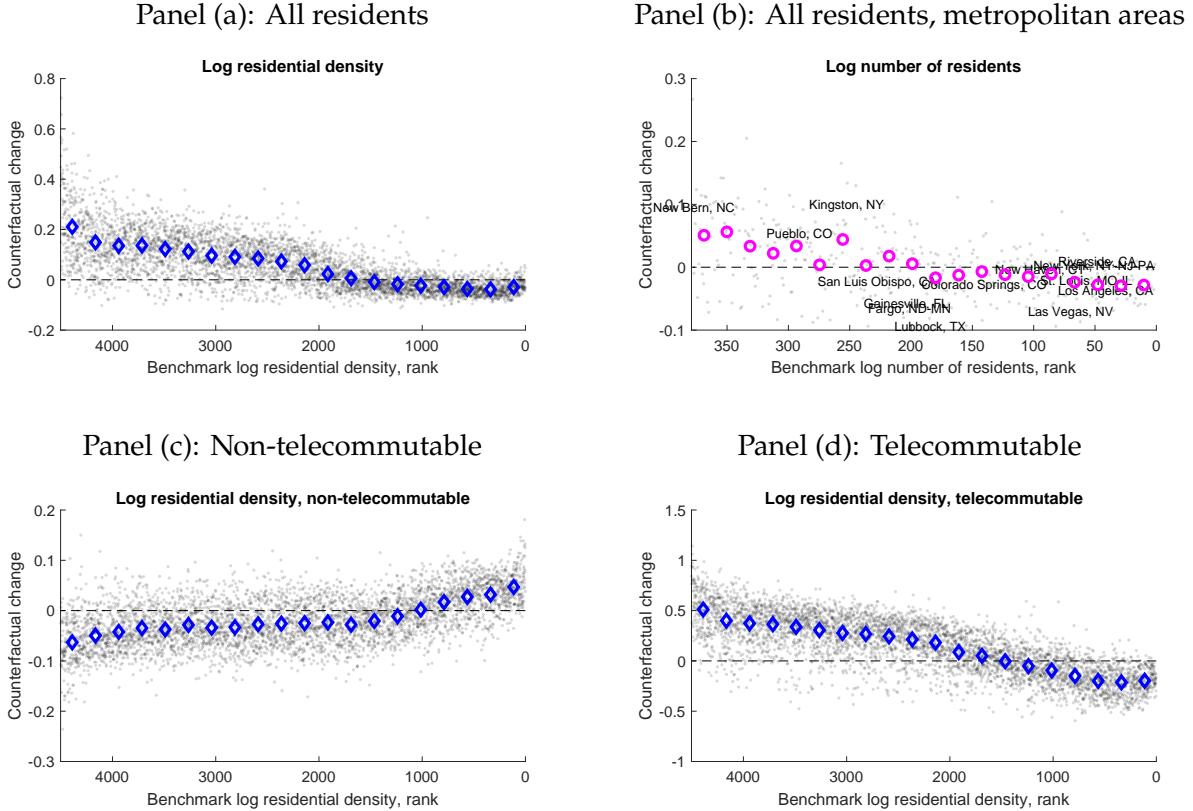
Description	Variable	Benchmark	Counterfactual
non-college, non-tradable	$\zeta_S^L$	3.0565	1.1273
non-college, tradable	$\zeta_G^L$	2.9367	1.0738
college, non-tradable	$\zeta_S^H$	3.1087	1.8517
college, tradable	$\zeta_G^H$	2.9130	1.6963

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

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

Table 6 shows the change in the aversion for remote work that was necessary to achieve the targeted increases in telecommuting. Non-college workers in both sectors see large drops in their aversion, while college workers see smaller drops, ending up with higher levels of aversion than their non-college counterparts. One possible interpretation of this result is that even once the technological and cultural barriers to telework are removed, college workers have some reasons to come to the office—possibly information sharing and networking—that may be less important for non-college workers. In Appendix Section I.2, we study a counterfactual 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 7: Change in Residents



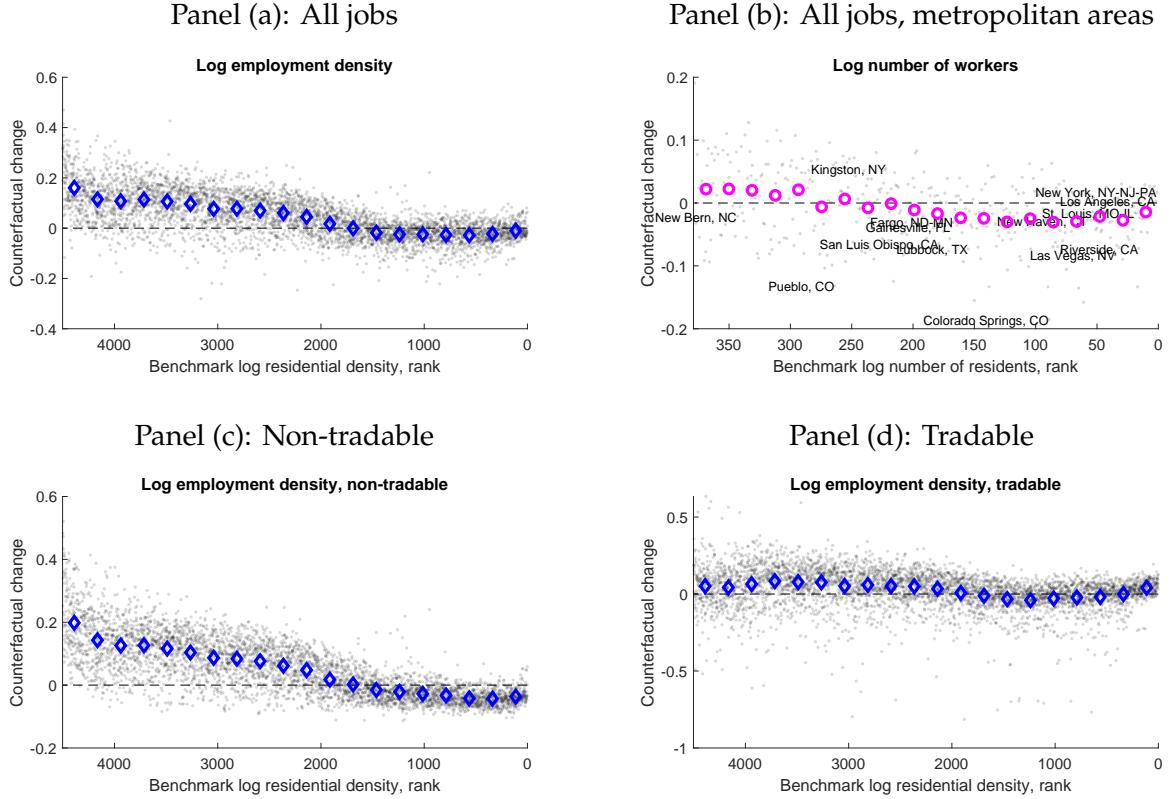
Note: Panel (a) shows the relationship between residential density rank for model locations and change in log residential density. Panel (b) shows the relationship between total resident rank for metro areas and change in log total residents. Panels (c) and (d) repeats the exercise for non-telecommutable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

## 5.2 Residents, Jobs and Real Estate Prices

**Distribution of residents.** We predict a net reallocation of residents across model locations equivalent to 5% of the population—about one-third of which is due to within-metro-area moves, and two-thirds due to moves across metro areas. These calculations are described in Appendix Section D. As panels (a) and (b) in Figure 7 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.

Among the five largest metro areas, New York’s population grows 0.5%, Chicago’s shrinks by slightly less than half a percent, and Los Angeles, Dallas and Houston each lose a bit more than 3%. Appendix Table J.1 provides details for changes in residents in 25 largest metro areas, and Appendix Figure J.1 displays predicted changes on a map.

Figure 8: Change in Employment

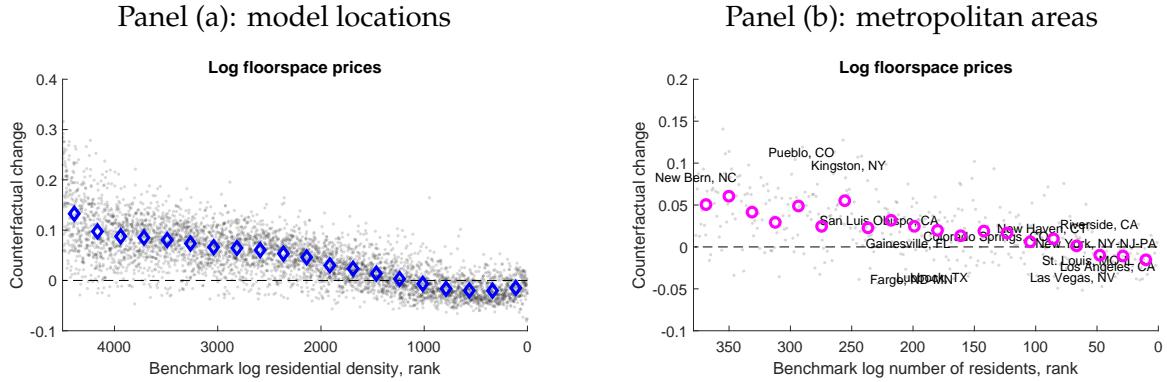


Note: Panel (a) shows the relationship between residential density rank for model locations and the change in log job density. Panel (b) shows the relationship between total resident rank for metro areas and the change in log total jobs. Panels (c) and (d) repeat the exercise for non-tradable and tradable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

While panel (d) of Figure 7 shows that telecommutable residents take advantage of increased remote work opportunities to move away from density, panel (c) shows that this is partially counteracted by a smaller movement of non-telecommutable residents back towards dense areas. This is because workers who cannot work remotely take advantage of falling prices in city centers and larger cities to relocate closer to better-paying jobs.

**Distribution of jobs.** We predict a net reallocation of jobs across model locations equivalent to 4.7% of the population. Similar to the reallocation of residents, about one-third is due to within-metro-area shifts, and two-thirds due to shifts across metro areas. In contrast to the reallocation of residents, job movements are not entirely monotonic in residential density. As panel (a) in Figure 8 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 metro area level, as shown in panel (b). Appendix Table J.1 provides details for jobs

Figure 9: 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 metro areas and the change in floorspace prices. Scatterplots in gray show individual model locations or MSAs, while diamonds or circles represent averages by ventile: i.e. below the 5<sup>th</sup> percentile, from the 5<sup>th</sup> to the 10<sup>th</sup>, etc.

changes in 25 largest metro areas, while Appendix Figure J.2 maps predicted changes.

Panel (c) shows that non-tradable jobs monotonically follow the source of their demand, residents, to less dense locations.<sup>32</sup> 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.<sup>33</sup> As a result, the densest 5% of locations increase employment by an average of over 4%.

**Real estate prices.** As a result of reallocation of many residents and some jobs to less dense locations, changes in floorspace prices show a clear negative slope in initial density, as can be seen in Figure 9. Prices decrease in most top-quartile locations and increase in most locations below the top quartile. Both the location-level and metro-level patterns are consistent with the shift of residents and non-tradable jobs to less dense locations driving up floorspace demand.<sup>34</sup> Appendix Figure J.3 displays predicted price changes on a map.

A case study of our model predictions for the New York metro area can be found in Appendix Section F, and an interactive visualization model predictions for the entire U.S. can be accessed online at [https://mattdelventhal.com/project/telecommute\\_viz/](https://mattdelventhal.com/project/telecommute_viz/).

<sup>32</sup>Althoff, Eckert, Ganapati, and Walsh (2022) provide empirical evidence for this mechanism during the pandemic.

<sup>33</sup>The correlation between log productivity in the tradable sector and log residents per square km is 0.66.

<sup>34</sup>Rappaport (2022) investigates the effect of remote work on housing supply.

### 5.3 Model Validation: Residents and Real Estate Prices, 2019–2022

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

**Residents.** We find that our model’s counterfactual residential relocations are a robust predictor of observed migration between December 2019 and December 2022, both within and across metro areas. We use Safegraph data derived from tracking cell phones to measure migration across model locations.<sup>35</sup> We then regress observed migration on model-predicted migration, and report the results in Table 7, panel A.

Column (1) corresponds to a specification with no controls, and shows a positive and statistically significant relationship between our model predictions and the observed changes. Moreover, this correlation does not merely pick up the negative relationship between initial residential density and the change in population.<sup>36</sup> As Column (2) shows, even after controlling for residential density in 2012–2016 our model predictions retain positive and significant correlation with the data. This suggests that structural reasons beyond density, such as commuter market access, can explain migration patterns during the pandemic.

Columns (3) and (4) introduce fixed effects for commuting zones (CZ), so that we only evaluate the match between our predictions and observed shifts *within* metro areas. Again our model predictions are strongly significantly correlated with observed changes, and again this is not only due to its prediction of an overall shift away from density. In Columns (5) and (6), we aggregate to the level of CZs, and see that our model is a good predictor of shifts *across* metro areas, as well.

**Real estate prices.** Our model’s counterfactual changes in floorspace prices are also a predictor of observed changes in real estate prices between December 2019 and December 2022, although mostly within CZs. We use Zillow data to construct a measure of residential price changes and regress this on our model’s predictions. We use the same sequence of specifications as we did for migration, and report the results in Table 7, panel B.

Column (1) shows that our model predictions have a positive and statistically significant

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<sup>35</sup>Details can be found in Appendix Section A.7.

<sup>36</sup>Althoff, Eckert, Ganapati, and Walsh (2022) and Haslag and Weagley (2022) previously documented a reallocation of residents from the densest to the least dense locations during the pandemic and, as Figure 7 shows, our model also predicts a movement to locations with low density.

Table 7: Changes in residents and house prices during Covid-19, model vs. data

	Panel A: Residents					
	(1)	(2)	(3)	(4)	(5)	(6)
Log chg residents, model	1.659 (0.0369)	0.302 (0.0437)	1.177 (0.0466)	0.235 (0.0573)	0.931 (0.0611)	0.559 (0.0773)
Log density, data		-0.0788 (0.00179)		-0.0629 (0.00251)		-0.0270 (0.00364)
Level of obs.	ML	ML	ML	ML	CZ	CZ
CZ fixed effects	no	no	yes	yes	–	–
Observations	4502	4502	4453	4453	723	723
R-squared	0.310	0.517	0.731	0.769	0.244	0.297

	Panel B: House prices					
	(1)	(2)	(3)	(4)	(5)	(6)
Log chg prices, model	0.314 (0.0327)	-0.0132 (0.0493)	0.472 (0.0403)	0.231 (0.0601)	0.0124 (0.110)	0.255 (0.149)
Log density, data		-0.0101 (0.00114)		-0.00759 (0.00141)		0.00928 (0.00388)
Level of obs.	ML	ML	ML	ML	CZ	CZ
CZ fixed effects	no	no	yes	yes	–	–
Observations	4449	4449	4389	4389	716	716
R-squared	0.0203	0.0372	0.662	0.665	0.0000179	0.00799

Note: In panel A, the dependent variable is the log change in residents between Dec. 2019 and Dec. 2022 constructed from Safegraph. In panel B, the dependent variable is the log change in house prices between Dec. 2019 and Dec. 2022 constructed from Zillow. Standard errors are in parentheses. The regressions are estimated at the level of model locations (“ML”), with or without CZ fixed effects, or at the level of CZs (“CZ”). Regressions at the model location level with CZ fixed effects have fewer observations because some CZs correspond to model locations.

relationship with house price changes across model locations 2019–2022, although as column (2) shows the predictive power of our model largely relies on the relationship between initial density and price growth.<sup>37</sup> 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 2019–2022. 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.<sup>38</sup>

<sup>37</sup>The relationship between initial density and price growth during the pandemic has been previously documented. Gupta, Mittal, Peeters, and Van Nieuwerburgh (2022) and Liu and Su (2021) find a “flattening” of the relationship between prices and distance to the center in major metro areas for residential real estate; Rosenthal, Strange, and Urrego (2021) report a similar relationship for commercial real estate.

<sup>38</sup>Haslag and Weagley (2022) show that in 2020 and 2021, Covid-related reasons accounted for up to 20%

Figure 13 below confirms that, while our model predicts a convergence of metro-level prices in the counterfactual economy, in the data metro areas with higher prices in 2019 did not experience lower price growth between 2019 and 2021.

## 5.4 Commuting and Welfare

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

**Commuting.** The average worker lives 52% farther, in terms of commuting time, from their workplace, but spends 20.5% less time commuting, because the average frequency of work from home has increased by 0.9 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, 17.7% of workers live and work in different metro areas. In the counterfactual economy, this number goes up to 23.9% as remote work increases the average distance between residence and workplace.

**Income and inequality.** Workers' income rises by 1.6%, averaging larger gains by those who can work from home against smaller gains or even losses by those who cannot. A major reason for this disparity is that, in our calibration, for most workers telework is more productive; therefore, more frequent remote work boosts their incomes. We examine the implications of this feature in Appendix Section I.4 where we eliminate productivity differences between on-site and remote work for all types, and show that with equal productivity income would fall by 0.7% and welfare gains would be smaller.

Among non-telecommutable workers, those without a college degree experience a 0.6% income growth, while college graduates see a 1.7% decline in income. This happens 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 by more than the incomes of their non-college counterparts, which means the overall college wage gap increases (Katz and Murphy, 1992).

**Prices.** The average price of floorspace drops by 0.8%, due to the net movement of residents and jobs to peripheral locations with lower building costs. Telecommutable workers pay between 2 and 4% less for housing, as they relocate to more affordable areas. Non-telecommutable workers move to denser locations, and end up paying slightly more

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of interstate migration, and reasons related to local restrictions or infection rates played an important role.

Table 8: Aggregate results

	non-college				college		
	all workers	all	non-tel.	tel.	all	non-tel.	tel.
Average time to work, % chg	52.0	50.7	-0.4	152.6	54.8	-0.7	77.5
Time spent commuting, % chg	-20.5	-18.0	-0.4	-86.6	-27.0	-0.7	-47.6
Average WFH days/week, chg	0.9	0.8	—	3.5	1.2	—	2.9
Income, % chg	1.6	0.9	0.6	1.8	2.8	-1.7	5.3
Floorspace prices, % chg	-0.8	-0.5	0.6	-4.3	-1.3	0.2	-2.4
Non-tradables prices, % chg	3.5	3.6	3.6	3.4	3.4	3.5	3.4
Welfare, % chg							
consumption only	-0.8	-1.5	-2.2	0.2	0.6	-4.2	3.2
+ commuting	0.8	0.0	-2.0	6.0	2.2	-3.9	5.7
+ amenities	0.8	0.0	-0.7	2.1	1.9	-1.7	4.0
total welfare	7.2	4.0	-1.5	46.9	20.5	-3.4	28.0

*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.

for housing on average—even though prices fall on average in central locations, the slope of the price gradient from city center to periphery remains negative.

Non-tradable prices increase by around 3.5%. 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.<sup>39</sup>

**Workers’ welfare and landowners’ income.** In Table 8, we break down welfare gains by incrementally considering the effects of consumption, commuting, and amenities. Welfare decomposition is described in Appendix Section E. Consumption goes up for telecommuters and down for non-telecommuters, declining by 0.8% on average. This is the net result of the 1.6% increase in income and the 0.8% fall in floorspace prices, outweighed by the 3.5% increase in the price of non-tradables. The reduction in time commuting yields small gains for non-telecommutable workers and large gains for the remote-capable.<sup>40</sup> 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 7.2%. This is the net result of large gains for telecommutable workers and

<sup>39</sup>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.

<sup>40</sup>Since our model does not allow for endogenous reduction in traffic due to less frequent commuting, these welfare gains may be understated.

smaller losses for the rest.<sup>41</sup> 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. 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 goes up by 1.9%. This demand is allocated to places with higher supply elasticity (and, therefore, lower land share), and *floorspace* prices decline. Nevertheless, due to the combination of fixed land and higher demand for floorspace, average land prices, and thus landlord income, go up by 1%.

## 5.5 The Role of Real Estate Supply, Amenities, and Knowledge Spillovers

To assess the roles of various mechanisms, we run a series of alternative counterfactuals in which some variables do not adjust. Appendix Section G contains full details and discussion for these and other exercises.

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 residential and commercial real estate prices moving in opposite directions, with residential increasing by 16% and commercial decreasing by the same amount. 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 respond to changes in residential and employment density. 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 we 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 especially for non-telecommutable workers.

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<sup>41</sup>Because we do not take a position on whether the calibrated "aversion to telecommuting" parameters,  $\varsigma_m^s$ , reflect genuine worker preferences or other kinds of non-pecuniary barriers to remote work, we exclude the shift in these parameters from all welfare change calculations.

## 5.6 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. Nevertheless, in our baseline exercise we choose to hold relative productivity constant and model the change as a pure shock to preferences. As a robustness check and also as a way to evaluate the relative importance of each explanation, we also conduct an exercise in which the increase in remote work is driven purely by technology. From this, we have two important findings. First, the main qualitative results of our model hold regardless. Second, in each of the three productivity-driven counterfactual exercises our model makes predictions that are contradicted by the data in some important way.

In the productivity-based scenario, we calibrate the baseline as described above, and instead of shifting preference parameters to target the change in remote work frequency, we change the relative productivity parameters. This results in very (implausibly) large wage gains for remote capable workers. Also, while the predictions of this scenario are qualitatively similar to those of our main exercise, they are poor predictors of the observed migration and real estate price changes that were the subject of Section 5.3. This scenario described in Appendix Section H.<sup>42</sup>

## 6 The Great Re-Convergence

The “Great Divergence” is a much-remarked-upon and consequential trend in the decades following the 1980s.<sup>43</sup> 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 sort of re-convergence, as newly-freed laptop workers disperse to greener pastures and increase their geographic proximity to the proverbial “main street America.”

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<sup>42</sup>Neither of these two defects are remedied in another scenario, in which we forgo matching observed relative wages of remote workers in the baseline, and instead assume that relative productivity is 8% lower for remote work across all types (Mas and Pallais (2017) estimate that workers would be willing to give up 8% of wages in exchange for the opportunity to work from home). Finally, we construct a scenario in which all groups face zero aversion, and baseline rates of remote work are targeted using productivity parameters alone. This yields parameters which imply that full-time remote workers should earn on average only one-third the wage of a similar, full-time office-based worker. We do not believe there is a way to reconcile such a large initial penalty with the data, which show comparable wage levels.

<sup>43</sup>The “Great Divergence” was first summarized in Moretti (2012). The period from 1980s follows decades of regional convergence, as documented in Blanchard and Katz (1992).

Figure 10: Reversal of the sorting across metro areas

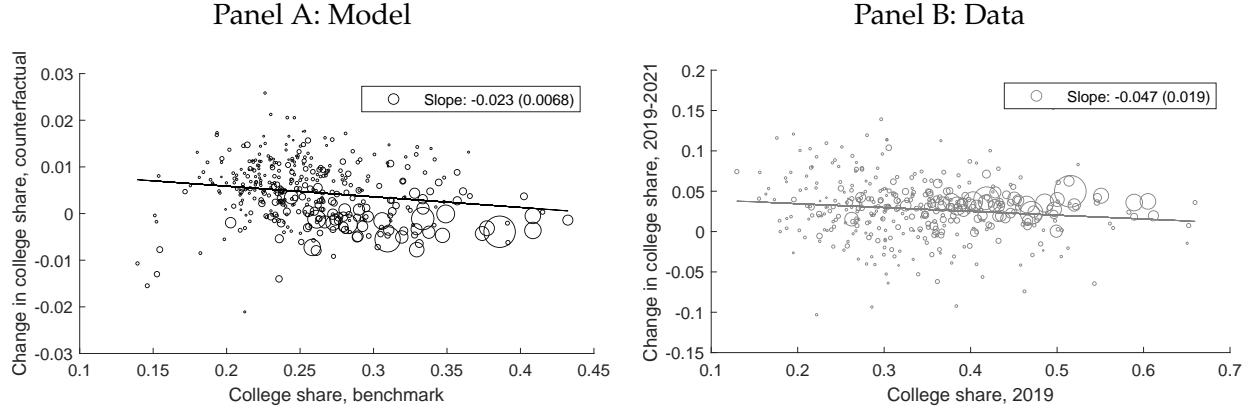
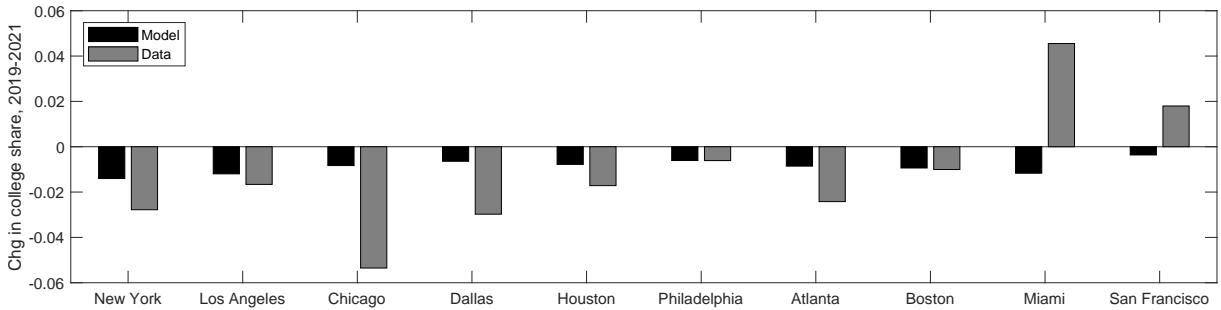


Figure 11: Reversal of the urban revival



Note: The figure shows the percentage-point change in the college share in a 10 km ring around centers of ten largest metro areas in the counterfactual economy (black bars) and in the data between 2019 and 2021 (gray bars). Data changes are adjusted to account for the nationwide increase in the college share. Center of a metro area is defined as the location of the city hall of the largest municipality.

In this section we will explore our model's predictions for a "re-convergence" within and across metro areas. Where possible, we will compare these with data on the changes that took place between 2019 and 2022.

## 6.1 Skill Sorting

Panel A of Figure 10 shows our model's predictions for the sorting of college-educated workers across metro areas. 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 as early as 2021. We estimate college shares at the MSA level from the ACS in 2019 and 2021 and find that cities with higher college shares in 2019 saw a slower growth in college shares 2019–2021.<sup>44</sup>

Our model also predicts that education will become less concentrated in city centers. Couture and Handbury (2020) documented growing concentration of college graduates around the centers of U.S. cities since 2000 and linked this yuppie-led 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 predominantly college-educated remote workers out of the urban centers. Combined with less frequent commuting, this makes city centers less attractive for college graduates. Figure 11 demonstrates that college graduates might have already started leaving the centers of eight out of ten largest metro areas, according to the comparison of 2019 and 2021 ACS data at the PUMA level.<sup>45</sup>

## 6.2 Income Inequality

Our model predicts that differences across MSAs in the average wage paid to individuals who *work* there will not change much, as demonstrated in Panel A of Figure 12. Cities that were more productive before the pandemic will continue offering high incomes to their workers.<sup>46</sup> However, as telecommuting improves access to jobs in high-paying locations, the disparities in across MSAs in the wage of the average *resident* will fall significantly, as shown in Panel B.<sup>47</sup> 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) *inter alia*. Panel C provides evidence that this reversal has already started happening. Using 2019 and 2021 ACS, we find a negative correlation between average wages earned by MSA residents in 2019 and wage growth 2019–21.<sup>48</sup>

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<sup>44</sup>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 2021, while our model is calibrated to 2012–2016.

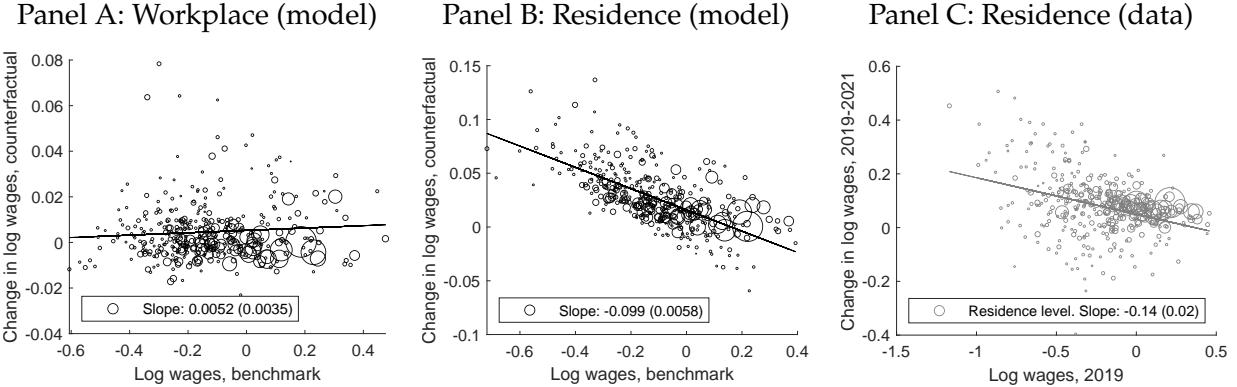
<sup>45</sup>City center is defined as the 10km ring around the location of the city hall of the largest municipality. Miami and San Francisco are two outliers that experienced increases in college shares in city centers, and reasons outside our model could explain these two cases. For example, anecdotal evidence suggests that during the pandemic several tech companies moved to Miami. At the same time, strict lockdowns could have disproportionately lowered employment of non-college workers in San Francisco.

<sup>46</sup>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.

<sup>47</sup>The results in panel C 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 C compares 2019 with 2021, while our model is calibrated to 2012–2016.

<sup>48</sup>We cannot build a data counterpart to Panel A because ACS does not report the place of employment precisely enough. Data with more reliable workplace-level wage data, such as LODES or County Business Patterns, has not been yet released for 2021 or 2022.

Figure 12: Changes in wage inequality across metro areas



Note: Panel A shows the relationship between demeaned log average wages paid to individuals who work in a given MSA in the benchmark economy and the log change in wages in the counterfactual. Panel B shows the same relationship for wages earned by individuals who live in a given MSA. Panel C shows the relationship for wages earned by residents of an MSA in the 2019 ACS sample and the change in wages in the 2021 ACS sample. Circle size is proportional to MSA population in the benchmark. The legend shows best-fit slope coefficients and their standard errors.

### 6.3 House Price Dispersion

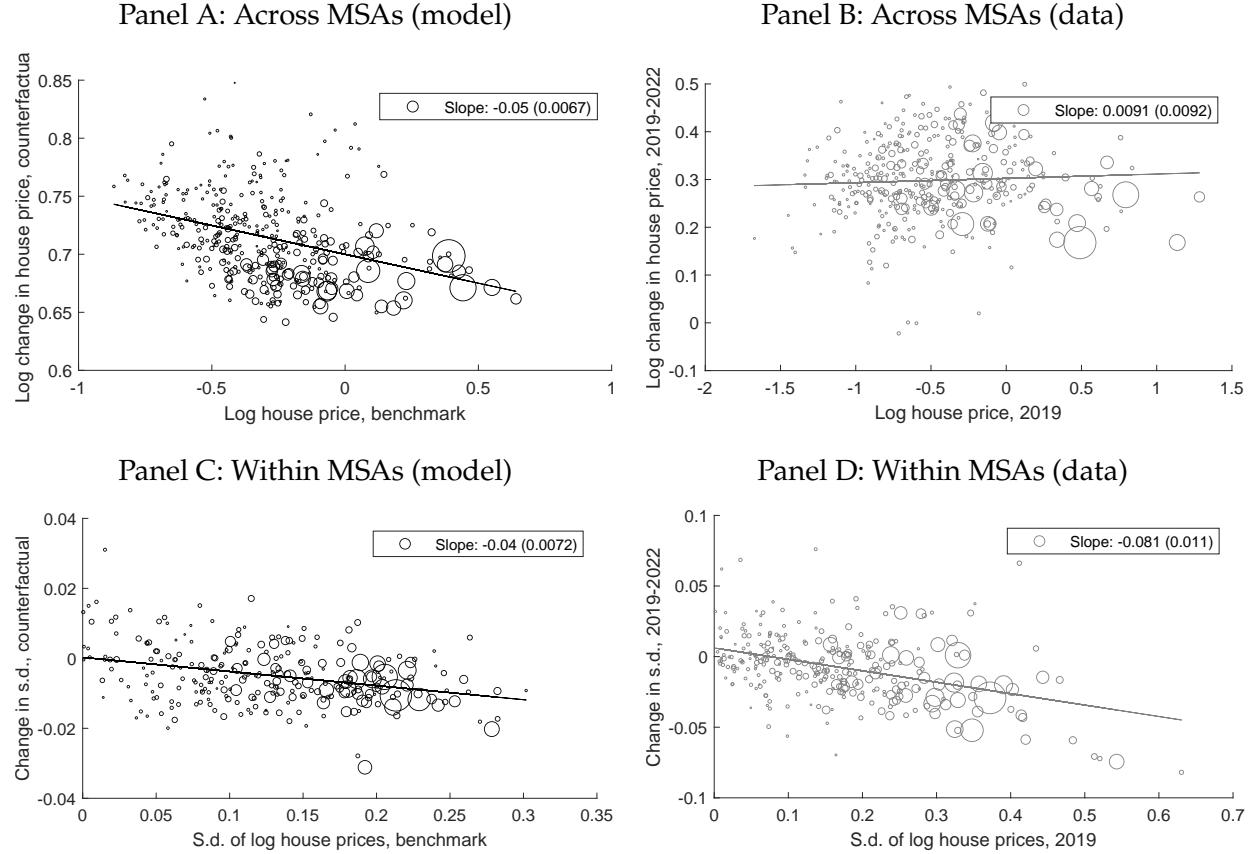
Previous work by [Van Nieuwerburgh and Weill \(2010\)](#) and [Albouy and Zabek \(2016\)](#) has documented increased dispersion of house prices both across and within cities in the decades leading up to 2020. In our model the decline in skill concentration and income inequality lead to more balanced distribution of housing demand across space, and thus presage a reduction in real estate price dispersion both across and within metro areas. Panel A of Figure 13 shows that metro areas with high average prices in the benchmark model will see a decline in prices, while more affordable MSAs will experience price increases. Panel C shows that the dispersion of prices across locations within MSAs will also fall.

We find evidence that house price dispersion has not fallen across metro areas, in spite of the fact that price growth in most large MSAs was slower than elsewhere, as can be seen in panel B of Figure 13.<sup>49</sup> At the same time, we document a large reduction of within-city price variance, as can be seen in panel D.<sup>50</sup> These trends suggest that telecommuting could change the geography of housing affordability, especially so within metropolitan areas. 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.

<sup>49</sup>The results in panels B and D have somewhat different magnitudes than model predictions for at least two reasons. First, they use Zillow data, while our model uses ACS data. Second, panels B and D compare 2019 with 2021, while our model is calibrated to 2012–2016.

<sup>50</sup>These findings are consistent with the trends documented in [Gupta, Mittal, Peeters, and Van Nieuwerburgh \(2022\)](#) and [Althoff, Eckert, Ganapati, and Walsh \(2022\)](#), *inter alia*.

Figure 13: Reversal of house price divergence



Note: Panel A shows the relationship between demeaned log average house prices at the MSA 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 Dec. 2019 and the change between Dec. 2019 and Dec. 2022. Panel C shows the relationship between the population-weighted standard deviation of log house prices across model locations within an MSA in the benchmark and the change in the st. dev. in the counterfactual. Panel D shows the same relationship using prices from Zillow in Dec. 2019 and Dec. 2022. Circle size is proportional to MSA population in the benchmark. The legend shows best-fit slope coefficients and their standard errors.

## 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 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.

## Bibliography

- ACS (2016): American Community Survey, U.S. Census Bureau. <https://usa.ipums.org/usa/>. Accessed through IPUMS USA, September 2020.
- AGRAWAL, D. R., AND J. K. BRUECKNER (2022): “Taxes and Telework: The Impacts of State Income Taxes in a Work-from-Home Economy,” Working Paper.
- AHLFELDT, G. M., AND E. PIETROSTEFANI (2019): “The economic effects of density: A synthesis,” *Journal of Urban Economics*, 111, 93–107.
- AHLFELDT, G. M., S. J. REDDING, D. M. STURM, AND N. WOLF (2015): “The Economics of Density: Evidence From the Berlin Wall,” *Econometrica*, 83(6), 2127–2189.
- ALBOUY, D., AND G. EHRLICH (2018): “Housing productivity and the social cost of land-use restrictions,” *Journal of Urban Economics*, 107, 101 – 120.
- ALBOUY, D., AND M. ZABEK (2016): “Housing Inequality,” Working Paper 21916, National Bureau of Economic Research.
- ALLEN, T., C. ARKOLAKIS, AND X. LI (2020): “On the Equilibrium Properties of Network Models with Heterogeneous Agents,” Working Paper 27837, National Bureau of Economic Research.
- ALLEN, T., AND D. DONALDSON (2020): “Persistence and Path Dependence in the Spatial Economy,” Working Paper 28059, National Bureau of Economic Research.
- ALTHOFF, L., F. ECKERT, S. GANAPATI, AND C. WALSH (2022): “The Geography of Remote Work,” *Regional Science and Urban Economics*, 93, 103770.
- BARRERO, J. M., N. BLOOM, AND S. J. DAVIS (2021): “Why Working from Home Will Stick,” Working Paper 28731, National Bureau of Economic Research.
- BARTIK, A. W., Z. B. CULLEN, E. L. GLAESER, M. LUCA, AND C. T. STANTON (2020): “What Jobs are Being Done at Home During the Covid-19 Crisis? Evidence from Firm-Level Surveys,” NBER Working Paper 27422.

- BAUM-SNOW, N., AND L. HAN (2021): "The Microgeography of Housing Supply," Working Paper.
- BEHRENS, K., S. KICHO, AND J.-F. THISSE (2021): "Working from Home: Too Much of a Good Thing?" Working Paper.
- BERRY, C. R., AND E. L. GLAESER (2005): "The divergence of human capital levels across cities\*," *Papers in Regional Science*, 84(3), 407–444.
- BICK, A., AND A. BLANDIN (2021): "Real Time Labor Market Estimates During the 2020 Coronavirus Outbreak," Working paper.
- BICK, A., A. BLANDIN, AND K. MERTENS (2021): "Work from Home Before and After the COVID-19 Outbreak," Working paper.
- BLANCHARD, O., AND L. KATZ (1992): "Regional Evolutions," *Brookings Papers on Economic Activity*, 23(1), 1–76.
- BLOOM, N., R. HAN, AND J. LIANG (2022): "How Hybrid Work from Home Works Out," Working paper.
- BLOOM, N., J. LIANG, J. ROBERTS, AND Z. J. YING (2015): "Does working from home work? Evidence from a Chinese experiment," *The Quarterly Journal of Economics*, 130(1), 165–218.
- BROWN, J. P., AND C. TOUSEY (2023): "The Shifting Expectations for Work from Home," *Kansas City Fed Economic Review*, 108 (2).
- BRUECKNER, J., M. E. KAHN, AND G. C. LIN (2021): "A New Spatial Hedonic Equilibrium in the Emerging Work-from-Home Economy?" NBER Working Paper 28526.
- CARD, D. (2009): "Immigration and Inequality," *American Economic Review*, 99(2), 1–21.
- CHOUDHURY, P., T. KHANNA, C. MAKRIDIS, AND K. SCHIRRMANN (2022): "Is hybrid work the best of both worlds? Evidence from a field experiment," Working Paper.
- COUTURE, V., J. I. DINGEL, A. GREEN, J. HANDBURY, AND K. R. WILLIAMS (2021): "JUE Insight: Measuring movement and social contact with smartphone data: a real-time application to COVID-19," *Journal of Urban Economics*.
- COUTURE, V., AND J. HANDBURY (2020): "Urban revival in America," *Journal of Urban Economics*, 119(C), S0094119020300383.
- CTPP (2016): Census Transportation Planning Products, American Association of State Highway and Transportation Officials. <https://ctpp.transportation.org/ctpp-data-set-information/>. Accessed September 2020.
- DALTON, M., M. DEY, AND M. LOEWENSTEIN (2022): "The impact of remote work on local employment, business relocation, and local home costs," Working Paper.
- DAVIS, M. A., A. C. GHENT, AND J. M. GREGORY (2022): "The Work-at-Home Technology Boon and its Consequences," NBER Working Paper 28461.
- DAVIS, M. A., AND F. ORTALO-MAGNÉ (2011): "Household Expenditures, Wages, Rents," *Review of Economic Dynamics*, 14(2), 248 – 261.
- DE FRAJA, G., J. MATHESON, AND J. ROCKEY (2021): "Zoomshock: The geography and local labour market consequences of working from home," Working paper.
- DELVENTHAL, M. J., E. KWON, AND A. PARKHOMENKO (2022): "JUE Insight: How do cities change when we work from home?," *Journal of Urban Economics*, 127, 103331, JUE Insights: COVID-19 and Cities.

- DIAMOND, R. (2016): "The Determinants and Welfare Implications of US Workers' Diverging Location Choices by Skill: 1980-2000," *American Economic Review*, 106(3), 479–524.
- DINGEL, J. I., AND B. NEIMAN (2020): "How Many Jobs Can Be Done at Home?," *Journal of Public Economics*, 189, 104235.
- DINGEL, J. I., AND F. TINELNOT (2020): "Spatial Economics for Granular Settings," Working Paper.
- ELLEN, I. G., AND K. HEMPSTEAD (2002): "Telecommuting and the Demand for Urban Living: A Preliminary Look at White-collar Workers," *Urban Studies*, 39(4), 749–766.
- EMANUEL, N., E. HARRINGTON, AND A. PALLAIS (2022): "The Power of Proximity," Working Paper.
- GAMBER, W., J. GRAHAM, AND A. YADAV (2023): "Stuck at home: Housing demand during the COVID-19 pandemic," *Journal of Housing Economics*, 59, 101908, COVID-19's Impacts on Housing Markets.
- GASPAR, J., AND E. GLAESER (1998): "Information Technology and the Future of Cities," *Journal of Urban Economics*, 43(1), 136–156.
- GAUBERT, C., P. KLINE, D. VERGARA, AND D. YAGAN (2021): "Trends in U.S. Spatial Inequality: Concentrating Affluence and a Democratization of Poverty," NBER Working Paper 28385.
- GIANNONE, E. (2022): "Skill-Biased Technical Change and Regional Convergence," Working Paper.
- GIBBS, M., F. MENDEL, AND C. SIEMROTH (2022): "Work from Home and Productivity: Evidence from Personnel and Analytics Data on IT Professionals," Working Paper.
- GLAESER, E., AND G. PONZETTO (2007): "Did the Death of Distance Hurt Detroit and Help New York?," NBER Working Papers 13710, National Bureau of Economic Research, Inc.
- GRAHAM, M. R., M. J. KUTZBACH, AND B. MCKENZIE (2014): "Design Comparison of LODES and ACS Commuting Data Products," Discussion Paper 14-38, U.S. Census Bureau.
- GUPTA, A., V. MITTAL, J. PEETERS, AND S. VAN NIEUWERBURGH (2022): "Flattening the curve: Pandemic-Induced revaluation of urban real estate," *Journal of Financial Economics*, 146(2), 594–636.
- GUPTA, A., V. MITTAL, AND S. VAN NIEUWERBURGH (2022): "Work From Home and the Office Real Estate Apocalypse," Working Paper 30526, National Bureau of Economic Research.
- HASLAG, P. H., AND D. WEAGLEY (2022): "From L.A. to Boise: How Migration Has Changed During the COVID-19 Pandemic," Working paper.
- HEBLICH, S., S. J. REDDING, AND D. M. STURM (2020): "The Making of the Modern Metropolis: Evidence from London," *Quarterly Journal of Economics*, 135(4), 2059–2133.
- HOWARD, G., J. LIEBERSOHN, AND A. OZIMEK (2022): "The Short- and Long- Run Effects of Remote Work on U.S. Housing Markets," Working Paper.
- KATZ, L., AND K. M. MURPHY (1992): "Changes in Relative Wages, 1963–1987: Supply and Demand Factors," *The Quarterly Journal of Economics*, 107(1), 35–78.
- KYRIAKOPOULOU, E., AND P. M. PICARD (2021): "The Zoom City: Working From Home and Urban Land Structure," Working paper.
- LARSON, W., AND W. ZHAO (2017): "Telework: Urban form, energy consumption, and greenhouse gas implications," *Economic Inquiry*, 55(2), 714–735.

- LEE, E. (2020): "Trade, inequality, and the endogenous sorting of heterogeneous workers," *Journal of International Economics*, 125, 103310.
- LENNOX, J. (2020): "More working from home will change the shape and size of cities," Working Paper.
- LI, W., AND Y. SU (2021): "The Great Reshuffle: Residential Sorting During the COVID-19 Pandemic and Its Welfare Implications," Working paper.
- LIU, S., AND Y. SU (2021): "The impact of the COVID-19 pandemic on the demand for density: Evidence from the U.S. housing market," *Economics Letters*, 207, 110010.
- (2023): "The Effect of Working from Home on the Agglomeration Economies of Cities: Evidence from Advertised Wages," Working Paper.
- LODES (2016): Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics, U.S. Census Bureau. <https://lehd.ces.census.gov/data/>. Accessed September 2020.
- MAS, A., AND A. PALLAIS (2017): "Valuing alternative work arrangements," *American Economic Review*, 107(12), 3722–59.
- (2020): "Alternative Work Arrangements," *Annual Review of Economics*.
- MONDRAGON, J. A., AND J. WIELAND (2022): "Housing Demand and Remote Work," Working Paper 30041, National Bureau of Economic Research.
- MONGEY, S., L. PILOSSOPH, AND A. WEINBERG (2020): "Which Workers Bear the Burden of Social Distancing?," Working Paper 27085, National Bureau of Economic Research.
- MONTE, F., C. PORCHER, AND E. ROSSI-HANSBERG (2023): "Remote Work and City Structure," Working Paper.
- MONTE, F., S. J. REDDING, AND E. ROSSI-HANSBERG (2018): "Commuting, Migration, and Local Employment Elasticities," *American Economic Review*, 108(12), 3855–90.
- MORETTI, E. (2012): *The New Geography of Jobs*. Houghton Mifflin Harcourt, New York.
- (2013): "Real Wage Inequality," *American Economic Journal: Applied Economics*, 5(1), 65–103.
- NHTS (2017): National Household Transportation Survey, Federal Highway Administration, U.S. Department of Transportation. <https://nhts.ornl.gov/> Accessed May 2021.
- OZIMEK, A. (2020): "Remote Workers on the Move," Upwork Economist Report.
- RAMANI, A., AND N. BLOOM (2021): "The Donut Effect of Covid-19 on Cities," Working Paper 28876, National Bureau of Economic Research.
- RAPPAPORT, J. (2022): "Hybrid Working, Commuting Time, and the Coming Long-Term Boom in Home Construction," *Kansas City Fed Economic Review*, 107 (4).
- RHEE, H.-J. (2008): "Home-based telecommuting and commuting behavior," *Journal of Urban Economics*, 63(1), 198–216.
- ROSENTHAL, S. S., W. C. STRANGE, AND J. A. URREGO (2021): "JUE insight: Are city centers losing their appeal? Commercial real estate, urban spatial structure, and COVID-19," *Journal of Urban Economics*, p. 103381.
- SAFIROVA, E. (2003): "Telecommuting, traffic congestion, and agglomeration: a general equilibrium model," *Journal of Urban Economics*, 52(1), 26–52.
- SAIZ, A. (2010): "The Geographic Determinants of Housing Supply\*," *The Quarterly Journal*

- of Economics*, 125(3), 1253–1296.
- SIPP (2018): Survey of Income and Program Participation, U.S. Census Bureau. <https://www.census.gov/programs-surveys/sipp/data/datasets/2018-data/2018.html>. Accessed September 2020.
- SPEAR, B. D. (2011): *NCHRP 08-36, Task 098 Improving Employment Data for Transportation Planning*. American Association of State Highway and Transportation Officials.
- STANTON, C. T., AND P. TIWARI (2021): “Housing Consumption and the Cost of Remote Work,” Working Paper 28483, National Bureau of Economic Research.
- TSIVANIDIS, N. (2019): “The Aggregate and Distributional Effects of Urban Transit Infrastructure: Evidence from Bogotá’s TransMilenio,” Working Paper.
- VALENTINYI, A., AND B. HERRENDORF (2008): “Measuring factor income shares at the sectoral level,” *Review of Economic Dynamics*, 11(4), 820–835.
- VAN NIEUWERBURGH, S. (2023): “The remote work revolution: Impact on real estate values and the urban environment: 2023 AREUEA Presidential Address,” *Real Estate Economics*, 51(1), 7–48.
- VAN NIEUWERBURGH, S., AND P.-O. WEILL (2010): “Why Has House Price Dispersion Gone Up?,” *Review of Economic Studies*, 77(4), 1567–1606.
- VEUGER, S., P. G. HOXIE, AND L. BROOKS (2023): “Working from Density,” Working Paper.
- WALLS, M., E. SAFIROVA, AND Y. JIANG (2006): “What Drives Telecommuting? The Relative Impact of Worker Demographics, Employer Characteristics, and Job Types,” Discussion papers, Resources For the Future.
- ZHU, P. (2012): “Are telecommuting and personal travel complements or substitutes?,” *The Annals of Regional Science*, 48(2), 619–639.

# Appendix

## A Data

### A.1 Telecommuting Frequencies

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

### A.2 Work-from-Home Wage Premia

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

### A.3 Local Wage Indices

Our sources of wage data is the Census Transportation Planning Products ([CTPP](#)), aggregated at the Census tract level, and microdata from the American Community Survey ([ACS](#)). We use the data reported for the period from 2012 to 2016. We use the variable “earnings in the past 12 months (2016 \$), for the workers 16-year-old and over,” which is based on the respondents’ workplace locations. The variable provides the estimates of the number of people in each of the several earning bins in each workplace tract.<sup>51</sup>

We calculate mean labor earnings for tract  $k$  as  $\bar{w}_k = (\sum_b N_{b,k} \bar{w}_b) / \sum_b N_{b,k}$ , where  $N_{b,k}$  is the number of workers in bin  $b$  in tract  $k$ , and  $\bar{w}_b$  is mean earnings in bin  $b$  for each PUMA, calculated from the ACS microdata. Next, to control for possible effects of workers’

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<sup>51</sup>The bins are  $\leq \$9,999$ ;  $\$10,000\text{--}\$14,999$ ;  $\$15,000\text{--}\$24,999$ ;  $\$25,000\text{--}\$34,999$ ;  $\$35,000\text{--}\$49,999$ ;  $\$50,000\text{--}\$64,999$ ;  $\$65,000\text{--}\$74,999$ ;  $\$75,000\text{--}\$99,999$ ; and  $\geq \$100,000$ .

heterogeneity on tract-level averages, we estimate

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

where  $age_k$  is the average age;  $sexratio_k$  is the proportion of males to females in local labor force;  $race_{r,j}$  is the share of race  $r \in \{\text{Asian, Black, Hispanic, White}\}$ ;  $ind_{d,k}$  is the share of jobs in industry  $d$ ; and  $occ_{o,k}$  is share of jobs in occupation  $o$  in tract  $k$ .<sup>52</sup> The estimated tract-level wage index is the sum of the estimated constant and the tract fixed effect:  $\hat{w}_k^0 \equiv \hat{\alpha} + \hat{\epsilon}_k$ . We then construct wage indices for each location  $j$ ,  $\hat{w}_j^0$ , as the employment-weighted average of the values of  $\hat{w}_k^0$  for each tract  $k$  that pertains to model location  $j$ .

Then, using microdata from the American Community Survey (ACS), we calculate average wage premia for college over non-college workers, and tradable industry over non-tradable industry workers, separately at the place-of work public-use microdata area (POWPUMA) level, and assume that they are uniform across all model locations belonging to a single POWPUMA.<sup>53</sup> Let the college wage premium for model location  $j$  be designated  $\phi_j^H$ , and for the sake of concision of presentation let us also define a non-college wage “premium”  $\phi_j^L = 1$ . Let the tradable industry premium for model location  $j$  be defined as  $\rho_j^G$ , while the non-tradable “premium” is  $\rho_j^S = 1$ .

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

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<sup>52</sup>We use the following *industry* categories: Agricultural; Armed force; Art, entertainment, recreation, accommodation; Construction; Education, health, and social services; Finance, insurance, real estate; Information; Manufacturing; Other services; Professional scientific management; Public administration, Retail. We use the following *occupation* categories: Architecture and engineering; Armed Forces; Arts, design, entertainment, sports, and media; Building and grounds cleaning and maintenance; Business and financial operations specialists; Community and social service; Computer and mathematical; Construction and extraction; Education, training, and library; Farmers and farm managers; Farming, fishing, and forestry; Food preparation and serving related; Healthcare practitioners and technicians; Healthcare support; Installation, maintenance, and repair; Legal; Life, physical, and social science; Management; Office and administrative support; Personal care and service; Production; Protective service; Sales and related.

<sup>53</sup>POWPUMAs are larger than PUMAs and even in dense urban areas often correspond to counties.

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

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

## A.4 Telecommuters' Distance to Job Sites

To study the relationship between the propensity to work at home and the distance between home and job site, we use data from the 2017 National Household Transportation Survey ([NHTS](#)). We focus on full time workers in the 48 contiguous United States and Washington, D.C. Bins for each commuting frequency are constructed as follows: 5 days per week telecommuters reported working from home more than 90% of the days in a 21.67-day average work month; 4 days—between 90% and 70%, 3 days—between 70% and 50%, etc. The sample comprises 83,512 observations. The distance between home and job site is great circle distance as reported in the database. Those who reported working from home over 22 days a month are excluded.

## A.5 Local Rent Indices

We measure local rents by constructing hedonic rent indices at the level of PUMAs. In cases when a PUMA contains more than one model location we assign the same index to all. We use the 2016 5-year ACS sample tabulated by the IPUMS ([ACS, 2016](#)).<sup>54</sup> To construct local rent indices, we use self-reported rents and estimate the following regression,

$$\ln \mathbf{q}_{i,it} = \beta_0 + \boldsymbol{\beta}_1 \mathbf{X}_{i,it} + \varphi_i + \varphi_t + \varepsilon_{i,it}, \quad (\text{A.3})$$

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

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<sup>54</sup>We keep only household heads to ensure that the analysis is at the level of a residential unit. We exclude observations who live in group quarters; live in farm houses, mobile homes, trailers, boats, tents, etc.; are younger than 18 years old; and live in a dwelling that has no information on the year of construction.

characteristics listed before and idiosyncratic effects, and is given by  $\mathbf{Q}_i \equiv \exp(\beta_0 + \varphi_i)$ .

## A.6 Estimation of Travel Times

We follow the practice recommended by Spear (2011) and use LODES data as a measure of commuting flows and Census Transportation Planning Products (CTPP) data to provide information on commute times. The CTPP database reports commuting time data for origin-destination pairs of Census tracts across the contiguous United States for 2012–2016, and is tabulated using American Community Survey (ACS) data.<sup>55</sup> Travel times are reported for a little over 4 million trajectories, a small fraction of all possible bilateral trajectories, because most pairs of tracts are far enough apart that the ACS survey does not observe anyone commuting between them. We process this data in the following steps.

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

Second, to prevent “breaks” in the network, we check to see if any location does not have an estimated travel time to its 5 nearest neighbors. If any are missing, we project a one using estimated coefficients of a regression of average location-to-location travel times on average great circle distance and an indicator of origin = destination. This procedure adds  $\approx 10,000$  additional links, out of 20,268,004 possible location-to-location trajectories.

Finally, we take the  $\approx 34,000$  primitive connections, the travel times for which we have calculated as detailed above, as the first-order connections in a transport network. We use Dijkstra’s algorithm to find the least possible travel times through this network between each pair of model locations.

## A.7 Safegraph Location Data

Safegraph tracks and collects information from approximately 20 million of mobile devices in the US, and uses this information to construct geographical location data. Home locations are determined based on where mobile devices are detected at nighttime. To obtain an estimate of the change in the residence patterns between 2019 and 2022, we take

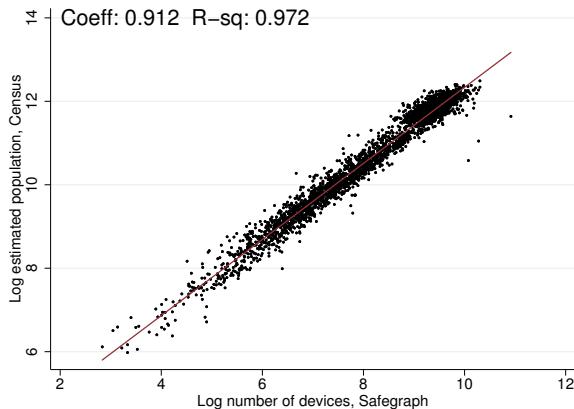
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<sup>55</sup>The CTPP data divides commuting times into 10 bins: less than 5 minutes, 5 to 14 minutes, 15 to 19 minutes, 20 to 29 minutes, 30 to 44 minutes, 45 to 59 minutes, 60 to 74 minutes, 75 to 89 minutes, 90 or more minutes, and work from home.

the number of devices in each Census block group in both December 2019 and December 2022. We aggregate these counts up to the level of model locations, and calculate the share of devices in each location.

How accurate is the Safegraph data as a proxy of local population? [Couture, Dingel, Green, Handbury, and Williams \(2021\)](#) show that cell phone data provides reliable estimates of local population levels at the county level. To assess the validity of Safegraph data at the level of our model locations which are typically smaller than counties, we compute population estimates for each location using Census estimates at the tract level for the year 2019. Similarly, for each location we compute the number of mobile devices from Safegraph. Figure A.1 shows that the correlation between Safegraph and Census population estimates is nearly one. At the same time, the regression coefficient of slightly lower than one suggests that Safegraph somewhat oversamples locations with larger population.

Figure A.1: Comparison of Census and Safegraph population counts



*Note:* The figure shows the relationship between population estimates for each model location based on the Census data and the number of mobile devices in each location from the Safegraph data in 2019.

## B Existence and Uniqueness of an Equilibrium

Consider a simplified version of our model with fixed floorspace supply, single industry, no heterogeneity in education, and no externalities in residential amenities. Also, let all workers have an occupation that allows telecommuting. Without telework, this model corresponds to a version of [Ahlfeldt, Redding, Sturm, and Wolf \(2015\)](#) for which [Allen, Arkolakis, and Li \(2020\)](#) derive sufficient conditions for existence and uniqueness.

The simplified model's equilibrium can be written as a system of  $I \times 3$  equations in

floorspace prices, supply of on-site work days, and productivity as

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

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

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

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

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

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

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

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

That is, existence and uniqueness may depend on location-specific outcomes; however, we can check the domain of  $\{\tilde{Q}_{ij}^1/\tilde{Q}_{ij}, Q_{ij}^1/Q_{ij}, Q_{ji}^2/\tilde{Q}_{ji}, Q_{ji}^2/Q_{ji}\}$  to obtain maximum absolute values of (B.4) and (B.5), given values of  $\alpha, \gamma, \epsilon, \zeta, \lambda, \kappa$ , and  $\nu$  from our calibrated model (see Tables 3 and 5).<sup>56</sup> We do so by noticing that  $t_{ij} \in [0, \infty)$  and  $q_i \in (0, \infty)$ . Thus, the matrix of cross-elasticites  $\max_{i,j} \{|\mathcal{E}_{ij}(X_h X_{h'})|\}$  for  $h \in \{q, N_{WC}, A\}$  is

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

<sup>56</sup>Our calibrated model has multiple values of  $\nu$  and  $\zeta$  depending on education and industry. We use weighted-average values of each parameter.

**Existence and uniqueness.** According to Theorem 1 in [Allen, Arkolakis, and Li \(2020\)](#), if  $\mathcal{A}$  has a spectral radius less than 1, then the equilibrium exists and is unique. For the parameter values in our calibrated model, the spectral radius of  $\mathcal{A}$  is 1.0084, marginally greater than 1. That is, in the *simplified version* of our model the equilibrium is not guaranteed to exist and, if it does, multiple equilibria exist.

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

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

To confirm this reasoning, we found that when  $\lambda < 0.084$ , the spectral radius of  $\mathcal{A}$  is less than 1. We also shut down the ability to telecommute by setting  $\zeta = 0$  and  $\nu = 0$ . In this case, even with  $\lambda = 0.086$ , the spectral radius is 0.82, and there exists a unique equilibrium. Since we assumed that in this version of the model all workers can telecommute, even though in the data only 34% of workers can work remotely, the latter result is highly relevant and, all else equal, makes the uniqueness of an equilibrium in our quantitative model a likely outcome.

## C Model Inversion and Calibration

### C.1 Inversion and Calibration Algorithm

In order to obtain the values of location-specific fundamentals  $\tilde{a}_{mi} \equiv a_{mi}\Lambda_i^{-\lambda}$ ,  $\tilde{x}_{mi}^s \equiv x_{mi}^s\Lambda_i^{-\lambda}$ ,  $\tilde{\phi}_i \equiv \phi_i\Lambda_i$ ,  $X_{mi}$ ,  $X_i^s$ ,  $E_{mj}$ ,  $E_j^s$ , and  $\omega_{mj}$ , as well as economy-wide parameters  $\nu_m^s$ ,  $\varsigma_m^s$ ,  $\zeta_m^s$ ,  $\tau$ , and  $\beta$ , we invert the model using the following sequence of steps.

1. Guess the values of  $X_{mi}$ ,  $X_i^s$ ,  $E_{mj}$ ,  $E_j^s$ ,  $\nu_m^s$ ,  $\varsigma_m^s$ ,  $\zeta_m^s$ ,  $\tau$ , and  $\beta$ .
2. Perform the following sequence:
  - (a) Solve for industry and location choice probabilities,  $\pi_{mij}^{so}$ , using equation (3.3)

and compute residential population and employment by education and industry as follows:  $N_{Rmi} = \sum_s \sum_o \sum_j \pi_{mij}^{so}$ ,  $N_{Ri}^s = \sum_o \sum_m \sum_j \pi_{mij}^{so}$ ,  $N_{Wmj} = \sum_s \sum_o \sum_i \pi_{mij}^{so}$ , and  $N_{Wj}^s = \sum_o \sum_m \sum_i \pi_{mij}^{so}$ .

- (b) Solve for optimal commuting frequency,  $\theta_{mij}^{so}$ , using equation (3.11) and find the average for each  $(m, s)$  type:  $\bar{\theta}_m^s \equiv (\sum_o \sum_i \sum_j \pi_{mij}^{so} \theta_{mij}^{so}) / (\sum_o \sum_i \sum_j \pi_{mij}^{so})$ .
- (c) Compute the variance of commuting frequencies for each  $(m, s)$  for the interval  $\theta \in [0.2, 0.8]$ :  $\text{Var}(\theta_s^m | \theta \in [0.2, 0.8])$ .
- (d) Compute the average distance between residence and job site for “commuters” ( $\theta > 0.9$ ) and “telecommuters” ( $\theta \leq 0.9$ ), and then calculate the ratio of the two numbers.
- (e) Solve for optimal effort  $\Omega_{mij}^{so}$  and commuting costs, as a function of optimal commuting frequency,  $d_{mij}^{so}$ , using equations (3.10) and (3.2), respectively.
- (f) Solve for wages and disposable income: (i) convert wages observed in the tradable sector in the data to the measure of wages used in the model using equation (A.2); (ii) find disposable income using equation (3.9).<sup>57</sup>
- (g) Combine equations (3.14) and (3.17) to find  $\omega_{mj}$ :

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

- (h) Solve for labor productivity in the non-tradable sector using the data on prices of non-tradables and equation (3.20).
- (i) Compute the ratio between mean wages in tradable/non-tradable sectors.
- (j) Compute for each industry/education pair the ratio between mean wages for telecommutable workers with  $\theta > 0.8$ , and those with  $\theta < 0.2$ .
- (k) Update  $\bar{X}_{mi}$ ,  $\bar{X}_i^s$ ,  $\bar{E}_{mj}$ ,  $\bar{E}_j^s$ : increase  $\bar{X}_{mi}$  if the value of  $N_{Rmi}$  in the model is lower than in the data, reduce it otherwise; increase  $\bar{X}_i^s$  if the value of  $N_{Ri}^s$  in the model is lower than in the data, reduce it otherwise; increase  $\bar{E}_{mj}$  if the value of  $N_{Wmj}$  in the model is lower than in the data, reduce it otherwise; increase  $\bar{E}_j^s$  if the value of  $N_{Wj}^s$  in the model is lower than in the data, reduce it otherwise.
- (l) Update the work-from-home aversion  $\varsigma_m^s$ : increase  $\varsigma_m^s$  if the average  $\theta$  of type  $(m, s)$  in the data is greater than the value of  $\bar{\theta}_m^s$ ; reduce  $\nu_m^s$  otherwise.

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<sup>57</sup>As discussed in Section C.2, our model is overidentified because employment amenities determine both local employment by industry and education and the college wage premium in the non-tradable sector. Thus, we take wages in the tradable sector directly from the data, while wages in the non-tradable sector are determined within the model.

- (m) Update the work-from-home productivity  $\nu_m^s$ : increase  $\nu_m^s$  if the wage ratio between telecommutable workers with  $\theta < 0.1$  to those with  $\theta > 0.9$  is lower than the wage gap between those who work from home full-time to those who commute full time in the data; reduce  $\nu_m^s$  otherwise.
  - (n) Update  $\tau$ : increase  $\tau$  if the ratio of average distance between residence and job site for “commuters” to “telecommuters” is higher in the model than its data counterpart; reduce  $\tau$  otherwise.
  - (o) Update the non-tradables expenditure share  $\beta$ : increase  $\beta$  if the ratio between mean wages in tradable/non-tradable sectors is lower in the model than in the data; decrease  $\beta$  otherwise.
  - (p) Return to step (2a) and repeat the sequence, unless moments computed in steps (2a), (2b), (2c), (2d), (2i), and (2j) in the model are equal to their counterparts in the data within a tolerance limit.
3. Construct education-industry amenities as  $X_{mi}^s = X_{mi}X_i^s$  and  $E_{mj}^s = E_{mj}E_j^s$ .
  4. Compute the exogenous part of amenities,  $\tilde{x}_{mi}^s \equiv x_{mi}^s \Lambda_i^{-\chi}$ , using equation (3.25) as follows:  $\tilde{x}_{mi}^s = X_{mi}^s / (N_{Ri})^\chi$ , where  $N_{Ri}$  and  $N_{WTj}$  are constructed using probabilities computed in step (2a).
  5. Compute the exogenous part of productivity,  $\tilde{a}_{mi} \equiv a_{mi} \Lambda_i^{-\lambda}$ , using equation (3.24) as follows:  $\tilde{a}_{mi} = A_{mj} / (N_{WCj} + \psi N_{WTj})^\lambda$ , where  $N_{WCj}$  and  $N_{WTj}$  are constructed from choice probabilities computed in step (2a), and commuting frequencies computed in step (2b).
  6. Compute floorspace demand  $H_i$  and then compute construction sector productivities,  $\tilde{\phi}_i \equiv \phi_i \Lambda_i$ , using equations (3.22) and (3.23) as follows:  $\tilde{\phi}_i = H_i q_i^{-\frac{1}{\eta_i}} (1 - \eta_i)^{-\frac{1-\eta_i}{\eta_i}}$ .

## C.2 Proof of Proposition 1: Existence and Uniqueness of Inversion

In what follows we prove that there exists a unique set of parameters consistent with the data being an equilibrium of the model.<sup>58</sup> These parameters are  $\tilde{a}_{mi} \equiv a_{mi} \Lambda_i^{-\lambda}$ ,  $\tilde{x}_{mi}^s \equiv x_{mi}^s \Lambda_i^{-\chi}$ ,  $\tilde{\phi}_i \equiv \phi_i \Lambda_i$ ,  $X_{mi}$ ,  $X_i^s$ ,  $E_{mj}$ ,  $E_j^s$ , and  $\omega_{mj}$ .

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

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<sup>58</sup>The proof follows closely Ahlfeldt, Redding, Sturm, and Wolf (2015) (see Propositions S.3 and S.4 in their appendix) but requires extra steps due to the nature of our model and data. When appropriate, we refer to lemmas and equations in their proof.

amenities as a function of amenities per se and wages:

$$\hat{E}_{mj}\hat{E}_j^s = E_{mj}E_j^s w_{mj}^s. \quad (\text{C.2})$$

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

$$D_{Wj}^L(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S) \equiv N_{Wj}^L - \sum_i N_{Ri}^L \sum_o \left[ \frac{(\hat{E}_{Sj}\hat{E}_j^L\Phi_{Sij}^{Lo})^\epsilon}{\sum_{j'}(\hat{E}_{Sj'}\hat{E}_{j'}^L\Phi_{Sij'}^{Lo})^\epsilon} n_{RSi}^{Lo} + \frac{(\hat{E}_j^L\Phi_{Gij}^{Lo})^\epsilon}{\sum_{j'}(\hat{E}_{j'}^L\Phi_{Gij'}^{Lo})^\epsilon} n_{RGi}^{Lo} \right] = 0, \quad (\text{C.3})$$

$$D_{Wj}^H(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S) \equiv N_{Wj}^H - \sum_i N_{Ri}^H \sum_o \left[ \frac{(\hat{E}_{Sj}\hat{E}_j^H\Phi_{Sij}^{Ho})^\epsilon}{\sum_{j'}(\hat{E}_{Sj'}\hat{E}_{j'}^H\Phi_{Sij'}^{Ho})^\epsilon} n_{RSi}^{Ho} + \frac{(\hat{E}_j^H\Phi_{Gij}^{Ho})^\epsilon}{\sum_{j'}(\hat{E}_{j'}^H\Phi_{Gij'}^{Ho})^\epsilon} n_{RGi}^{Ho} \right] = 0, \quad (\text{C.4})$$

$$D_{WSj}(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S) \equiv N_{WSj} - \sum_i N_{RSi} \sum_o \left[ \frac{(\hat{E}_{Sj}\hat{E}_j^L\Phi_{Sij}^{Lo})^\epsilon}{\sum_{j'}(\hat{E}_{Sj'}\hat{E}_{j'}^L\Phi_{Sij'}^{Lo})^\epsilon} n_{RSi}^{Lo} + \frac{(\hat{E}_{Sj}\hat{E}_j^H\Phi_{Sij}^{Ho})^\epsilon}{\sum_{j'}(\hat{E}_{Sj'}\hat{E}_{j'}^H\Phi_{Sij'}^{Ho})^\epsilon} n_{RSi}^{Ho} \right] = 0, \quad (\text{C.5})$$

where  $\Phi_{mij}^{so} \equiv \frac{1}{g_{ij}d_{mij}^{so} p_i^\beta q_i^\gamma} \Omega_{mij}^{so}$  and  $n_{Rmi}^{so} \equiv N_{Rmi}^{so}/N_{Rmi}$ .<sup>59</sup> Note that  $d_{mij}^{so}$  and  $\Omega_{mij}^{so}$  are functions of observed floorspace prices and the productivity of telework. Each of these conditions are of the form of the market clearing condition (S.43) in Ahlfeldt, Redding, Sturm, and Wolf (2015). Thus, using the same steps as in their Lemma S.6, we can show that function  $D_{Wj}^s(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S)$  is continuous, homogeneous of degree zero, and exhibits gross substitution in  $\hat{\mathbf{E}}^s$  for all  $s \in \{L, H\}$ . Similarly, function  $D_{WSj}(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S)$  is continuous, homogeneous of degree zero, and exhibits gross substitution in  $\hat{\mathbf{E}}^S$ . Moreover,  $\sum_j D_{Wj}^s(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S) = 0$  and  $\sum_j D_{WSj}(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S) = 0$  for all  $s \in \{L, H\}$ ,  $j \in \mathcal{I}$ , and  $\{\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\} \in \mathbb{R}_+^I \times \mathbb{R}_+^I \times \mathbb{R}_+^I$ .

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

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<sup>59</sup>Even though employment shares  $n_{Rmi}^{so}$  are unobserved, their presence does not change the properties of market clearing conditions that are required for the set of employment amenities to exist and be unique.

the proof of Lemma S.7 in Ahlfeldt, Redding, Sturm, and Wolf (2015).

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

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

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

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

$$D_{Rj}^L(\mathbf{X}^L, \mathbf{X}^H, \mathbf{X}_S) \equiv N_{Rj}^L - \sum_j N_{Wj}^L \sum_o \left[ \frac{(X_{Si} X_i^L \Phi_{Sij}^{Lo})^\epsilon}{\sum_{i'} (X_{Si'} X_{i'}^L \Phi_{Si'j}^{Lo})^\epsilon} n_{WSj}^{Lo} + \frac{(X_i^L \Phi_{Gij}^{Lo})^\epsilon}{\sum_{i'} (X_{i'}^L \Phi_{Gi'j}^{Lo})^\epsilon} n_{WGj}^{Lo} \right] = 0, \quad (\text{C.6})$$

$$D_{Rj}^H(\mathbf{X}^L, \mathbf{X}^H, \mathbf{X}_S) \equiv N_{Rj}^H - \sum_j N_{Wj}^H \sum_o \left[ \frac{(X_{Si} X_i^H \Phi_{Sij}^{Ho})^\epsilon}{\sum_{i'} (X_{Si'} X_{i'}^H \Phi_{Si'j}^{Ho})^\epsilon} n_{WSj}^{Ho} + \frac{(X_i^H \Phi_{Gij}^{Ho})^\epsilon}{\sum_{i'} (X_{i'}^H \Phi_{Gi'j}^{Ho})^\epsilon} n_{WGj}^{Ho} \right] = 0, \quad (\text{C.7})$$

$$D_{RSj}(\mathbf{X}^L, \mathbf{X}^H, \mathbf{X}_S) \equiv N_{RSj} - \sum_j N_{WSj} \sum_o \left[ \frac{(X_{Si} X_i^L \Phi_{Sij}^{Lo})^\epsilon}{\sum_{i'} (X_{Si'} X_{i'}^L \Phi_{Si'j}^{Lo})^\epsilon} n_{WSj}^{Lo} + \frac{(X_{Sj} X_i^H \Phi_{Sij}^{Ho})^\epsilon}{\sum_{i'} (X_{Sj} X_{i'}^H \Phi_{Si'j}^{Ho})^\epsilon} n_{WSj}^{Ho} \right] = 0. \quad (\text{C.8})$$

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

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

*Proof.* The proof is identical to the proof of Lemma C.1.  $\square$

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

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

*Proof.* Note, by inspection of the indirect utility function (3.1) and choice probability (3.3), that uniqueness of  $\{\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\}$  and  $\mathbf{X}_m^s$  implies that choice probabilities are also unique, conditional on observables. Here each element of  $\mathbf{X}_m^s$  is  $X_{mi}^s = X_i^s X_{mi}$ . This means that there is a unique mapping between education-industry-specific wages in the tradable sector observed in the data,  $\hat{w}_{Gj}^s$ , and their model counterpart,  $w_{Gj}^s$ , as given by equation (A.2). Once wages are known, we can solve for  $E_j^s = \hat{E}_j^s/w_{Gj}^s$ , where we used the fact that  $\hat{E}_G = 1$ .

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

$$\frac{w_{Sj}^H}{w_{Sj}^L} = \frac{\hat{E}_j^H \hat{E}_{Sj}}{\hat{E}_j^L \hat{E}_{Sj}} \frac{\hat{E}_j^L}{\hat{E}_j^H}, \quad (\text{C.9})$$

since both ratios on the right-hand side are identified.  $\square$

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

**Lemma C.4.** Given the parameters  $\{\epsilon, \kappa, \tau, \alpha, \zeta_m^s, v_m^s, \varsigma_m^s\}$ , observables  $\{\mathbf{N}_{Wm}, \mathbf{N}_{Rm}, \mathbf{q}, \mathbf{p}, \mathbf{t}, \hat{\mathbf{w}}_G^s\}$ , employment amenities in the tradable sector  $\mathbf{E}_G^s$ , college wage premium in the non-tradable sector  $w_{Sj}^H/w_{Sj}^L$ , and residential amenities  $\mathbf{X}_m^s$ , there exist unique vectors  $\omega_m \in \mathbb{R}_{++}^I$  and  $\mathbf{A}_m \in \mathbb{R}_{++}^I$  for each  $m \in \{G, S\}$ , and a unique vector  $\tilde{\phi} \in \mathbb{R}_{++}^I$ .

*Proof.* There is sufficient information to construct a unique matrix of choice probabilities. Thus, the results follow immediately from equation (C.1), the zero-profit condition (3.19), and the land and floorspace market clearing conditions, (3.22) and (3.23).  $\square$

**Wages in the non-tradable sector.** Note that our model is overidentified because employment amenities determine both local employment by industry and education and, as shown in equation (C.9), the college wage premium in the non-tradable sector. Thus, while our quantitative model takes wages in the tradable sector directly from the data, wages in the non-tradable sector are determined within the model. To identify wages in the non-tradable sector, we use the values of  $\mathbf{A}_m$  and  $\omega_m$ , and equation (3.13).

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

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

*Proof.* The results follow immediately from equations that determine local productivity and amenities, (3.24) and (3.25).  $\square$

## D Measuring Relocation of Residents and Jobs

Since our model is static, direct measures of migration of residents do not exist. As a proxy for migration, we measure the magnitude of shifts in the distribution of residents between our benchmark and counterfactual economies as follows. The measure of type- $(s, o, m)$  workers who have chosen residential location  $i$  in the benchmark economy is  $\pi_{mi}^{so} = \sum_j \pi_{mij}^{so}$ . The corresponding measure in the counterfactual economy is  $\tilde{\pi}_{mi}^{so}$ . If  $\tilde{\pi}_{mi}^{so} > \pi_{mi}^{so}$ , then it must be the case that some workers “moved” to location  $i$  from other locations. If  $\tilde{\pi}_{mi}^{so} < \pi_{mi}^{so}$ , then some workers “moved” out of location  $i$ . Therefore, the magnitude of the relocation of type- $(s, o, m)$  workers to/from location  $i$  is  $\Delta\pi_{mi}^{so} \equiv \tilde{\pi}_{mi}^{so} - \pi_{mi}^{so}$ . Then, the economy-wide *residential relocation index* is equal to

$$\frac{1}{2} \sum_s \sum_o \sum_m \sum_i |\Delta\pi_{mi}^{so}|,$$

where we divided by 2 in order to adjust for the double-counting of movers. We can also define the relocation index at the level of MSAs in the same way. This approach only measures net migration and cannot account for gross migration. Therefore, it understates the overall number of moves across locations between the benchmark and the counterfactual economies.

We calculate that the residential relocation index is 5% at the level of model locations and 3.3% at the level of MSAs. That is, about two-thirds of relocations between the benchmark and the counterfactual economies are relocations across metro areas and the remaining one-third are relocations within metro areas. Using the same approach, we calculate the *job relocation index* to be 4.7%. As with residents, about two-thirds of relocations are across metro areas and one-third are within.

## E Measuring Welfare Changes

**Overall welfare.** Our measure of worker's welfare is  $V^{so}$ , given by (3.7). Since indirect utility  $v_{mij}^{so}$  is proportional to optimal composite consumption,  $\tilde{w}_{mij}^{so} p_i^{-\beta} q_i^{-\gamma}$ , the percentage change in consumption-equivalent welfare is equal to the percentage change in  $V^{so}$ . To find the economy-wide change in welfare, we compute the percentage change in the weighted-average of  $V^{so}$ , i.e.,  $V \equiv \sum_s \sum_o l^{so} V^{so}$ . In our calculations, we adjust the counterfactual disutility of commuting,  $d_{mij}^{so}$ , to reflect changes in commuting frequencies. But because we do not take a position on whether the calibrated work-from-home aversion reflects genuine worker preferences or other kinds of non-pecuniary barriers to remote work, we do not adjust the changes in  $\zeta_m^s$  when computing welfare gains.

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

$$V_C^{so} = \sum_m \sum_i \sum_j \pi_{mij}^{so} \tilde{w}_{mij}^{so} p_i^{-\beta} q_i^{-\gamma}. \quad (\text{E.1})$$

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

$$V_{CC}^{so} = \sum_m \sum_i \sum_j \pi_{mij}^{so} \tilde{w}_{mij}^{so} p_i^{-\beta} q_i^{-\gamma} / d_{mij}^{so}. \quad (\text{E.2})$$

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

$$V_{CCA}^{so} = \sum_m \sum_i \sum_j \pi_{mij}^{so} X_{mi}^s E_{mj}^s \tilde{w}_{mij}^{so} p_i^{-\beta} q_i^{-\gamma} / (g_{ij} d_{mij}^{so}). \quad (\text{E.3})$$

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

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

$$\sum_i \eta_i q_i H_i. \quad (\text{E.4})$$

## F In focus: New York Metropolitan Area

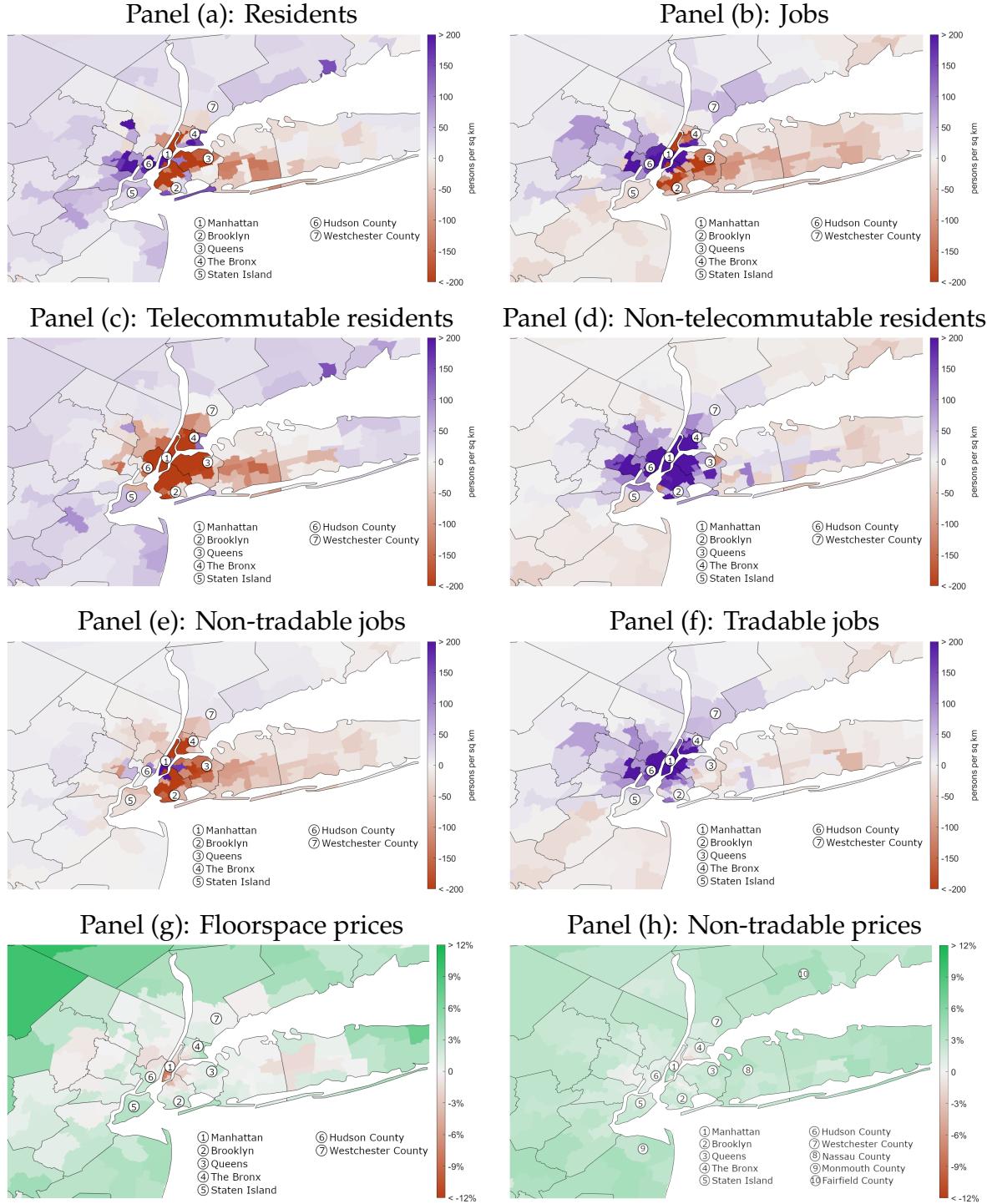
A closer look at the New York metro area gives us a more concrete idea of how predicted changes in jobs and residents play out at the intra-city level. In panel (a) of Figure F.1 we see that there is a large predicted movement of residents out of most of Manhattan, Brooklyn, and Queens. The Bronx, Staten Island, and isolated locations in Manhattan and Queens see significant inflows. Counties in New Jersey and Connecticut and outlying counties in New York state gain residents. This donut-shaped pattern is consistent with the nationwide patterns we reviewed earlier as well as with migration evidence during the Covid-19 pandemic ([Ramani and Bloom, 2021](#)).

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

On the aggregate, the residential population of the New York metropolitan area increases by 0.5% while employment goes up by 1.7% (see Appendix Table J.1). Job gains exceed population gains because, with more common remote work, more workers can access the attractive New York's labor market without having to live there. These workers tend to live in nearby metro areas where housing is more affordable. For example, Philadelphia's residential population barely changes, declining only 0.1%, even though the number of jobs in the metro area falls by 0.8%.

As panel (c) makes clear, workers with telecommutable occupations overwhelmingly leave central areas and move to peripheral areas—the same pattern we see countrywide. In panel (d), we see workers with non-telecommutable occupations move downtown in significant numbers, off-setting much of the telecommutable exodus.

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



*Note:* The maps show absolute changes in the number of residents (panel a); jobs (panel b); telecommutable residents (panel c); non-telecommutable residents (panel d); non-tradable jobs (panel e); and tradable jobs (panel f); per square kilometer in the main counterfactual exercise. Panel (g) shows percentage changes in floorspace prices and panel (h) shows percentage changes in non-tradable goods prices.

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

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

## G Further Discussion of Alternative Counterfactuals

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

Table G.1 reports results for each scenario. In counterfactual (1), we see that average welfare rises as soon as remote work becomes more accessible, even before workers can move and floorspace supply can change. However, gains are only experienced by telecommutable workers. These enjoy higher income from a more productive combination of at-home and on-site time, and less time spent commuting. Among those who cannot work from home, non-college workers see essentially no change while college workers have 1.7% lower welfare. This can be attributed to the impact of general equilibrium labor supply changes on income for each group. A larger proportion of college workers are remote-capable, and they are slightly more productive working at home. In the counterfactual this leads to an aggregate increase in the supply of college-educated labor. This bolsters the wages of non-college workers, their complements; and puts downward pressure on the wages of non-telecommutable college workers, who compete directly.

In counterfactual (2), when workers are allowed to choose new jobs and residences but floorspace allocations remain the same, non-telecommutable workers are able to in-

Table G.1: Aggregate results, alternative counterfactuals

	WFH aversion falls:	✓	✓	✓	✓	✓
	Residents and jobs reallocate:	—	✓	✓	✓	✓
	Floorspace adjusts:	—	—	✓	✓	✓
	Residential amenities adjust:	—	—	—	✓	✓
	Labor productivity adjusts:	—	—	—	—	✓
	Telecommuters add to productivity:	—	—	—	—	✓
	(1)	(2)	(3)	(4)	(5)	(6)
Income, % chg						
all workers	2.9	5.7	3.6	3.6	1.6	3.6
non-college, non-telecommutable	0.5	6.3	2.5	2.6	0.6	2.7
non-college, telecommutable	7.5	2.2	3.9	3.9	1.8	4.0
college, non-telecommutable	-1.1	4.5	0.2	0.2	-1.7	0.1
college, telecommutable	6.7	7.7	7.4	7.3	5.3	7.2
Floorspace prices, % chg						
residential	1.6	16.0	1.1	0.4	-0.8	-0.1
commercial	-5.2	-16.5	—	—	—	—
Non-tradable goods prices, % chg	0.4	2.7	3.5	3.4	3.5	3.3
Average time to work, % chg	0.0	46.4	51.5	52.2	52.0	52.9
Time spent commuting, all workers, % chg	-17.4	-19.3	-20.6	-20.4	-20.5	-20.2
Time spent commuting, commuters ( $\theta = 1$ ), % chg	0.0	-0.6	-0.7	-0.3	-0.4	0.0
Distance traveled, all workers, % chg	-17.5	-19.9	-21.4	-20.9	-21.1	-20.5
Average WFH days/week, chg	0.7	0.9	0.9	0.9	0.9	0.9
Welfare, % chg						
all workers	7.6	7.5	8.9	9.1	7.2	9.2
non-college, non-telecommutable	0.0	0.8	0.1	0.2	-1.5	0.3
non-college, telecommutable	48.9	39.9	49.1	49.6	46.9	50.1
college, non-telecommutable	-1.7	-0.5	-1.6	-1.8	-3.4	-1.8
college, telecommutable	21.3	22.7	30.0	30.3	28.0	30.5
Landlord income, % chg	2.1	25.5	3.1	2.9	1.0	2.7
due to change in demand	2.2	28.1	3.9	3.9	1.9	3.9
due to reallocation to low $\eta_i$	0.0	-2.6	-0.7	-1.0	-0.8	-1.2

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

crease their income by moving into jobs in central locations left behind by remote workers. Non-telecommutable workers also take advantage of reduced floorspace demand in central areas to move slightly closer to their jobs, reducing their time spent commuting by 0.6%. We also see a gap emerge between the income gains of college remote-capable workers, and the gains of their non-college counterparts. This can be attributed to an industry composition effect: a greater proportion of college workers are employed in the

tradable sector, and are thus able to take advantage of easier remote work to match with more productive job sites. Non-tradable employment, however, follows residents to less productive locations, as evidenced by the increase in non-tradable prices. This reduces income gains for non-college remote workers. This counterfactual also leads to the most extreme shifts in floorspace prices of any of the scenarios we consider—under-utilized, centrally located commercial floorspace faces deep price cuts, while surging demand for residential floorspace drives steep price increases.<sup>60</sup>

In counterfactual (3), allowing floorspace supply to adjust sharply cuts income gains by non-telecommutable workers, as center-city offices are downsized and more employment shifts to less central locations. This also brings double-digit shifts in floorspace prices and land income down to a 1.1% and a 3.1% increase, respectively. The main impact of allowing residential amenities adjust in counterfactual (4) is to cause non-telecommutable workers to choose residences that are slightly farther away from their jobs, as some of the amenities have now followed remote workers out to the suburbs. In counterfactual (5), our main counterfactual, we see the impact of reduced agglomeration externalities from having workers out of the office. Income gains are cut by 2 percentage points across the board, in each category of worker.

In counterfactual (6) working at home contributes to productive externalities in the main job site as much as working on site ( $\psi = 1$ ). This could happen if remote interaction technology advances to the point that it can fully simulate the experience of being co-located with one's collaborators thus eliminating any disadvantage remote work has in sparking spontaneous spillovers.<sup>61</sup> Comparing columns 6 and 4 of Table G.1, we can see that income losses from reduced productivity are neatly reversed under this alternative assumption.

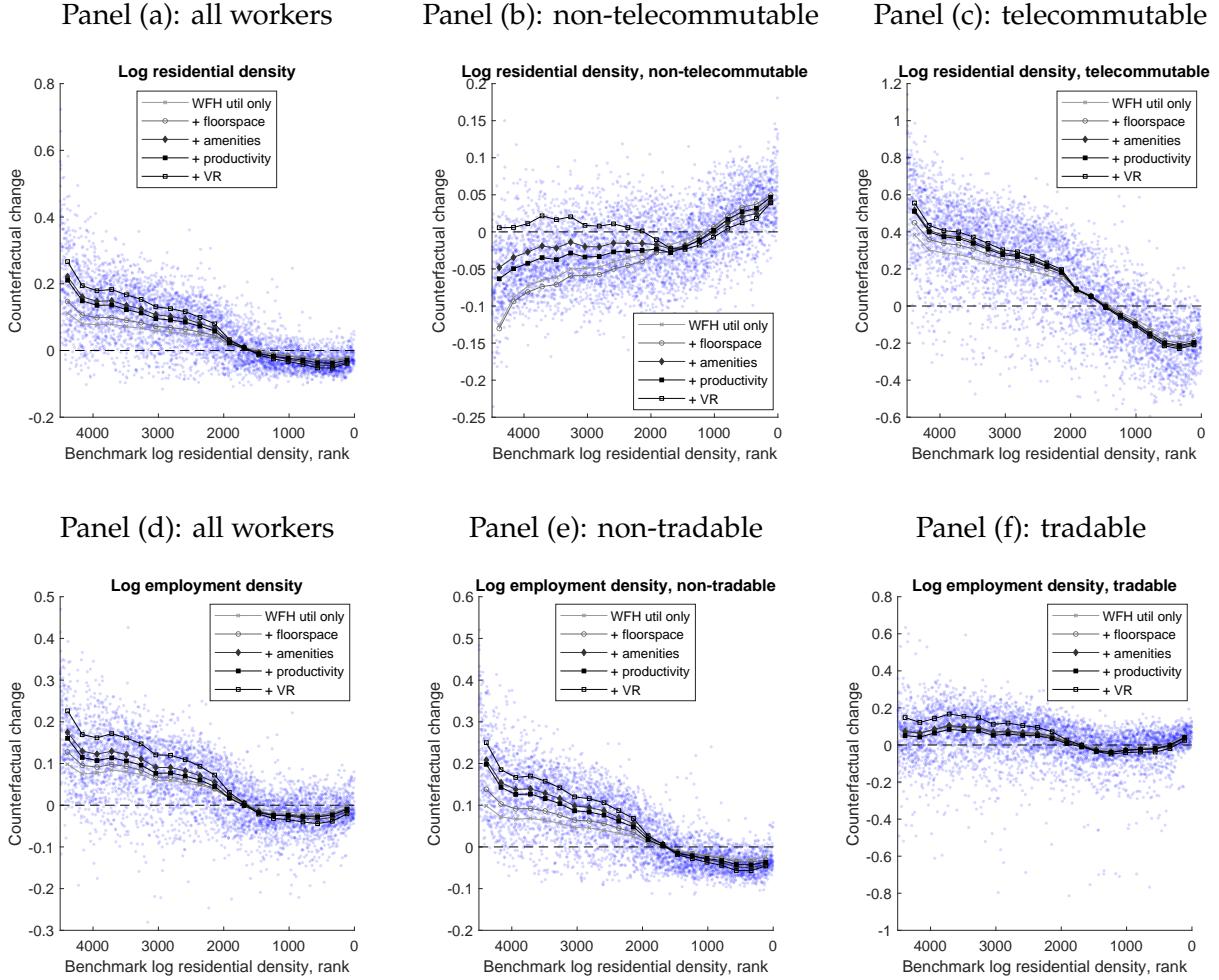
The top three panels in Figure G.1 plot reallocations of residents across counterfactuals (2) through (6). Obviously, in the first counterfactual, there is no reallocation of residents. Panel (a) shows the overall reallocation. Here, we see that each step accentuates the initial pattern—a net movement of residents from denser to less dense locations. Panels (b) and (c) break this down by occupation type, and reveal a heterogeneous pattern. For workers who can work from home in panel (c), things look similar to the overall average—each successive step accentuates reallocation from center to periphery. For workers who cannot work from home, in panel (b), the opposite happens—the reallocation from periphery to center is strongest in the second and third counterfactuals. In the fourth and fifth counterfactuals

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<sup>60</sup>We are able to distinguish between commercial and residential prices because in this counterfactual floorspace supply is fixed.

<sup>61</sup>The “holodeck” from *Star Trek: The Next Generation* also comes to mind.

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



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

the reallocation into the city is smaller, as the telecommuting workers end up carrying a part of the city's amenities out with them. Finally, in the sixth counterfactual, increased productivity in the periphery draws additional non-telecommutable workers out. In this scenario, non-telecommutable workers move out of medium-density locations, into both peripheral and central locations.

The bottom three panels in Figure G.1 show reallocations of jobs across the second through sixth counterfactuals. As with residents, each successive step accentuates the main pattern of reallocation towards less dense locations. Glancing at panel (e), it is clear

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

Description	Variable	Benchmark	Counterfactual	% change
non-college, non-tradable	$v_S^L$	0.9734	2.8520	192.99%
non-college, tradable	$v_G^L$	1.1351	3.3519	69.48%
college, non-tradable	$v_S^H$	1.0114	1.7141	195.29%
college, tradable	$v_G^H$	1.2054	2.1614	79.31%

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

this is mostly driven by non-tradable sector jobs following the movement of residents. Looking at panel (f), it is interesting to note that the variations between counterfactuals (2), (3), (4), and (5) have very little effect on the reallocation of tradable jobs. Reallocations of labor in the tradable sector are driven by the broadening of the labor market which is already fully operative by counterfactual (2). In counterfactual (6), however, less-dense locations see a significant jump in competitiveness, as remote workers begin contributing to local TFP.

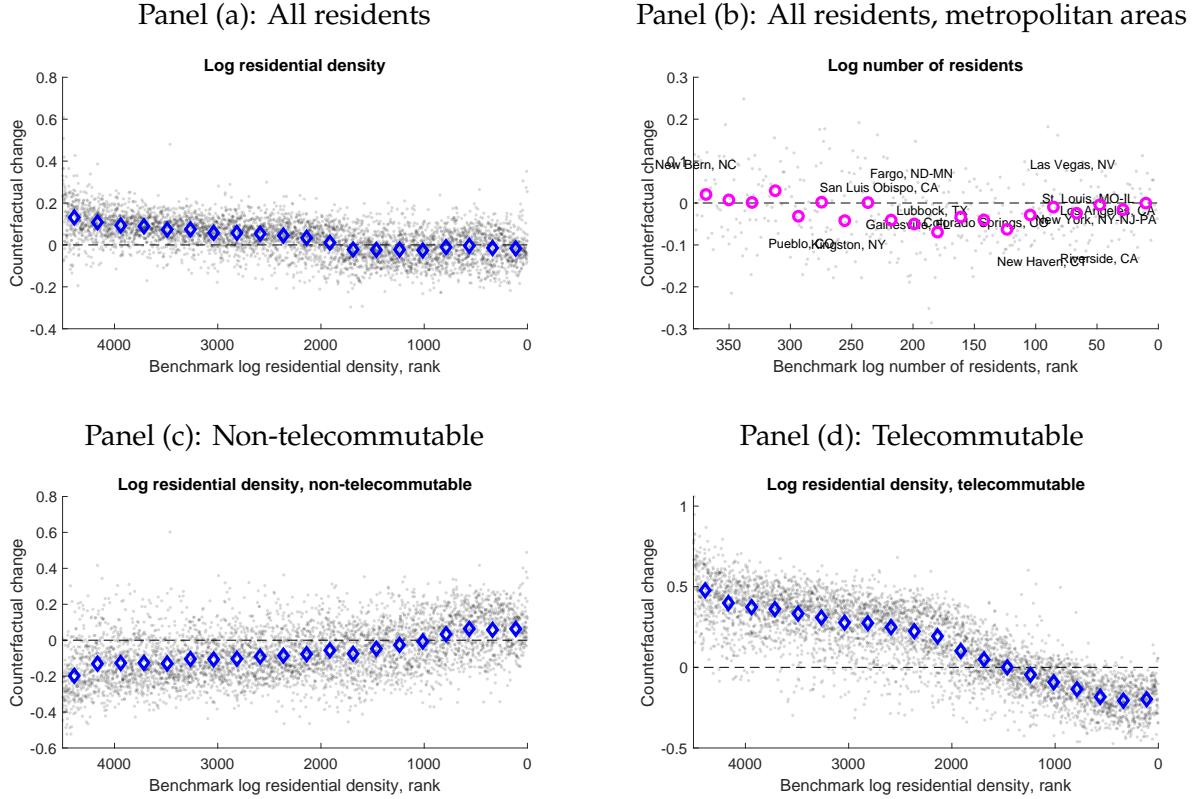
## H Counterfactual: Increased Productivity of Remote Work

In this section we consider a counterfactual in which increased working from home is due solely to increased productivity, rather than solely to changes in preferences as in the baseline counterfactual. While many of the patterns are similar to those seen in the baseline, it produces unrealistic increases in the wages of telecommuters, and performs poorly in predicting migration and changes in house prices during the pandemic. Table H.1 reports the changes in productivity of work from home required to attain the predicted increase in work from home frequency. The productivity of remote work must go up by 69–195% depending on the type of worker.

**Distributions of residents and jobs.** Figure H.1 shows changes in residents. Comparing it with Figure 7, we can see that the overall patterns are similar, except that the pattern of decentralization of residents among the densest locations and largest metro areas is more mixed. Next, comparing Figure H.2 with Figure 8, we can see that as with residents, the overall patterns of job reallocation are similar between this and the baseline counterfactual. The main driving force for the shifts in residents and jobs is greater attractiveness of work from home, whether due to lower aversion to it or due to its higher productivity.

**Aggregate results and welfare effects.** Table H.2 reports aggregate results from this counterfactual. Comparing with Table 8, we can see that changes in aggregate commuting behavior are similar. This is not surprising, as the same changes in average telecommuting

Figure H.1: Change in Residents

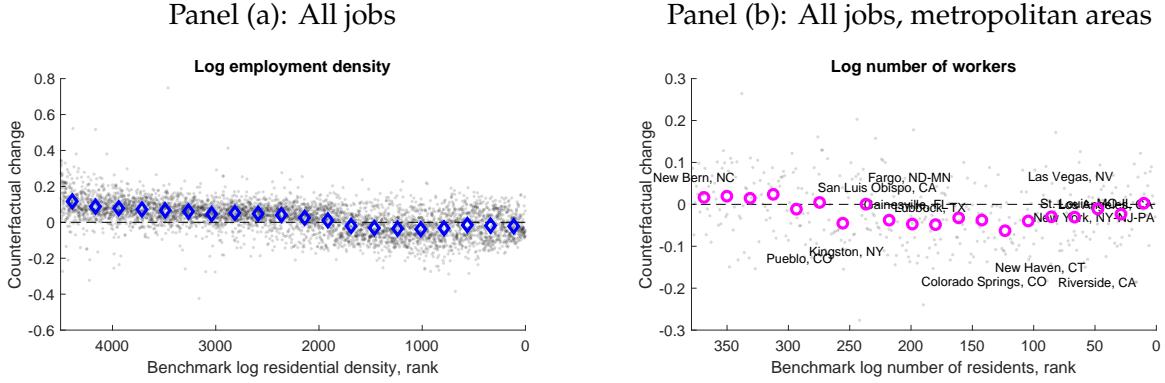


*Note:* Panel (a) shows the relationship between residential density rank for model locations and counterfactual change in log residential density. Panel (b) shows the relationship between total resident rank for metro areas and the counterfactual change in log total residents. Panel (c) repeats the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

frequencies are targeted in the calibration. However, the predictions for changes in income are very different. An average worker earns 50% more, with the increase driven entirely by telecommutable workers. Among these, college workers earn 69% more, while non-college workers earn over 219% more. We find it hard to call the prediction of such increases in the wages of telecommutable professions, due solely to technological changes in the year or so after March 2020, anything but very unrealistic.

**Evidence during Covid-19.** Finally, we compare this counterfactual's predictions about reallocations of residents and changes in floorspace prices with observed migration and changes in housing rents and prices between 2019 and 2022, as we did in Section 5.3. Comparing column (1) in Table H.3 with column (1) in Table 7, we see that when it is assumed that increased work from home is driven only by productivity, the model is a much poorer predictor of observed shifts in residential population: the  $R^2$  falls from 0.31

Figure H.2: Change in Employment



Note: Panel (a) shows the relationship between residential density rank for model locations and counterfactual change in log job density. Panel (b) shows the relationship between total resident rank for metro areas and the counterfactual change in log total jobs. Scatterplots in gray show individual model locations or MSAs, while diamonds or circles represent averages by ventile: i.e. below the 5<sup>th</sup> percentile, from the 5<sup>th</sup> to the 10<sup>th</sup>, etc.

Table H.2: Aggregate results

	non-college				college		
	all workers	all	non-tel.	tel.	all	non-tel.	tel.
Average time to work, % chg	57.6	53.5	-1.8	163.8	66.3	-1.9	94.2
Time spent commuting, % chg	-20.5	-18.8	-1.8	-84.7	-25.0	-1.9	-43.1
Average WFH days/week, chg	0.9	0.8	-	3.5	1.2	-	2.9
Income, % chg	50.7	54.1	-3.5	219.0	44.7	2.1	68.8
Floorspace prices, % chg	31.2	32.0	33.3	27.5	29.4	31.5	28.0
Non-tradables prices, % chg	10.8	10.9	10.9	11.0	10.4	10.4	10.4
Welfare, % chg							
consumption only	32.2	34.8	-16.3	179.7	27.3	-10.9	48.7
+ commuting	29.8	33.8	-15.7	180.9	22.2	-10.2	41.3
+ amenities	29.1	33.6	-12.2	170.0	22.1	-5.0	38.2
total welfare	30.1	21.9	-15.1	310.6	64.2	-9.3	87.5

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

to 0.14. Once initial density is controlled for (columns 2, 4, and 6), model projections have much weaker or zero correlation with actual changes. This is in contrast to the baseline counterfactual, which is a significant predictor of actual changes, even after density controls. Comparing the results for real estate prices in Table H.3 with those in Table 7, we see that assuming that the increase in remote work is due to productivity

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

	Panel A: Residents					
	(1)	(2)	(3)	(4)	(5)	(6)
Log chg residents, model	1.262 (0.0464)	0.0658 (0.0405)	0.590 (0.0478)	-0.0434 (0.0458)	0.746 (0.0764)	0.269 (0.0811)
Log density, data		-0.0863 (0.00148)		-0.0704 (0.00208)		-0.0386 (0.00330)
Level of obs.	ML	ML	ML	ML	CZ	CZ
CZ fixed effects	no	no	yes	yes	—	—
Observations	4502	4502	4453	4453	723	723
R-squared	0.141	0.512	0.697	0.768	0.117	0.257

	Panel B: House prices					
	(1)	(2)	(3)	(4)	(5)	(6)
Log chg prices, model	0.264 (0.0224)	0.0941 (0.0355)	0.352 (0.0267)	0.237 (0.0365)	-0.0234 (0.0797)	0.165 (0.118)
Log density, data		-0.00738 (0.00119)		-0.00593 (0.00128)		0.00916 (0.00421)
Level of obs.	ML	ML	ML	ML	CZ	CZ
CZ fixed effects	no	no	yes	yes	—	—
Observations	4450	4450	4390	4390	716	716
R-squared	0.0302	0.0385	0.665	0.667	0.000121	0.00670

*Note:* In panel A, the dependent variable is the log change in residents between Dec. 2019 and Dec. 2022 constructed from Safegraph. In panel B, the dependent variable is the log change in house prices between Dec. 2019 and Dec. 2022 constructed from Zillow. Standard errors are in parentheses. The regressions are estimated at the level of model locations (“ML”), with or without CZ fixed effects, or at the level of CZs (“CZ”). Regressions at the model location level with CZ fixed effects have fewer observations because some CZs correspond to model locations.

changes does not improve the predictive power of the model.

One of the reasons for the inability of this counterfactual to predict observed shifts in population becomes clear when comparing Figures H.1 and 7: non-telecommutable workers move more strongly away from the periphery to central locations, dampening the net pattern of core-periphery reallocation. This is also a consequence of gigantic remote worker wage increases—they use their higher incomes to rent more floorspace, pricing non-remote workers out of the rural and suburban real estate markets.

# I Robustness

## I.1 No Penalty for Living Far from Job Site

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

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

## I.2 Equal Reduction in Work-from-Home Aversion

In our main counterfactual, we calibrated somewhat larger reductions in work-from-home aversion for non-college workers. This gives this group of workers a boost to counterfactual welfare gains. How sensitive are our results to the differences in calibrated changes in dislike for telework?

We recalibrate the post-Covid economy so that the aggregate reduction in work-from-home aversion is the same for all workers in all industries by targeting the overall, not education-industry specific, increase in work from home. The calibrated fall in the aversion parameter,  $\zeta_m^s$ , is 49% for all types of workers. Column 3 of Table I.1 compares the results of this counterfactual to the main counterfactual (column 1). Overall, the results are similar. The welfare gains of telecommutable college graduates become larger and the losses of non-telecommutable college graduates become smaller. At the same time, for non-college graduates the gains turn smaller and the losses larger. This implies that the gap in welfare gains between college and non-college workers would be even greater if we assumed the same reduction in work from home aversion for all worker types.

## I.3 Equal Floorspace Supply Elasticities

In our quantitative model, we use estimates of floorspace supply elasticities from Baum-Snow and Han (2021). To our knowledge, these are the only estimates at a sufficiently high level of resolution (Census tracts) that can be applied to our model locations. At the

Table I.1: Aggregate results, robustness counterfactuals

	(1) Main CF	(2) $\tau = 0$	(3) Same chg $\varsigma_m^s$	(4) Same $\eta_i$	(5) $v_m^s = 1$
Income, % chg					
all workers	1.6	1.1	2.0	1.5	-0.7
non-college, non-telecommutable	0.6	0.8	0.4	0.7	-0.5
non-college, telecommutable	1.8	1.5	4.9	1.8	-2.6
college, non-telecommutable	-1.7	-0.2	-1.4	-2.0	-1.9
college, telecommutable	5.3	2.2	5.2	4.9	1.1
Floorspace prices, % chg					
residential	-0.8	-1.7	-0.8	-1.6	-2.4
commercial	0.0	0.0	0.0	0.0	0.0
Non-tradable goods prices, % chg	3.5	3.6	3.5	3.1	1.9
Average time to work, % chg	52.0	193.2	51.2	53.3	52.5
Time spent commuting, all workers, % chg	-20.5	-19.9	-20.5	-20.2	-20.6
Time spent commuting, commuters ( $\theta = 1$ ), % chg	-0.4	-0.2	-0.3	0.1	-0.4
Distance traveled, all workers, % chg	-21.1	-21.1	-20.8	-20.0	-21.2
Average WFH days/week, chg	0.9	0.9	0.9	0.9	0.9
Welfare, % chg					
all workers	7.2	30.1	7.7	7.3	6.7
non-college, non-telecommutable	-1.5	-1.5	-1.9	-1.5	-1.2
non-college, telecommutable	46.9	110.6	40.6	47.8	44.9
college, non-telecommutable	-3.4	-2.3	-3.0	-3.8	-2.3
college, telecommutable	28.0	63.0	37.2	28.2	24.7
Landlord income, % chg	1.0	0.1	1.4	1.8	-1.3
due to change in demand	1.9	1.4	2.3	1.8	-0.5
due to reallocation to low $\eta_i$	-0.8	-1.3	-0.9	0.0	-0.8

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

same time, these elasticities are significantly lower than those estimated in prior literature (see the discussion in Section 4.2.1).

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

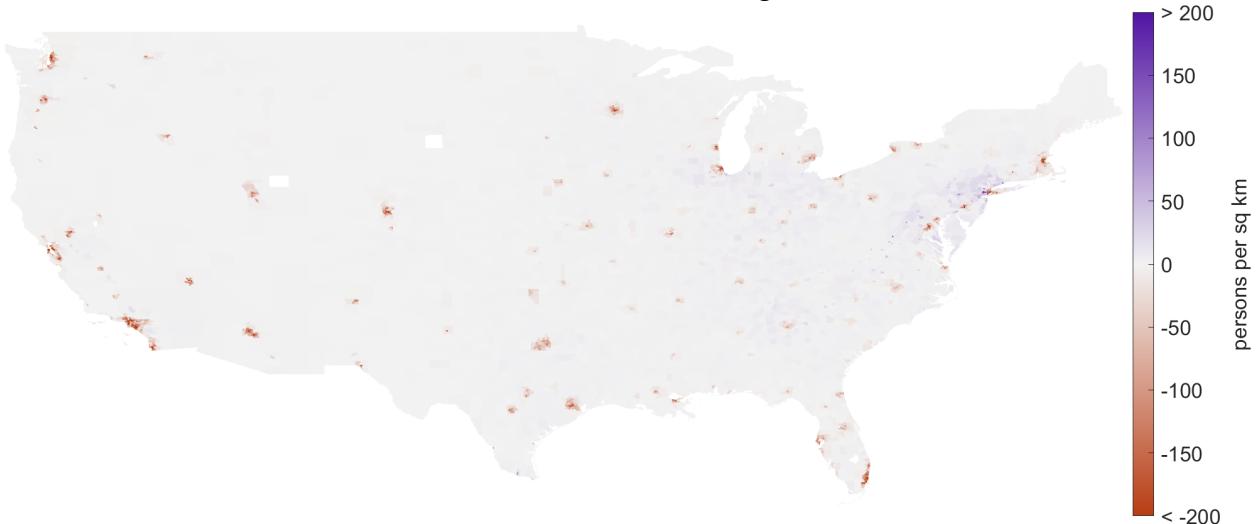
## I.4 Equal Productivity of Remote Work

Our counterfactual results depend, to some extent, on the calibrated values of the relative productivity of remote work. In particular, many workers can increase their income by working from home more often because for most of the worker types remote work is more productive (see Table 5). To understand the role of exogenous productivity differences between on-site and remote work effort, we fix  $v_m^s = 1$  for all types, recalibrate the model, and rerun the main counterfactual. The results in column 5 of Table I.1 show that, if remote work was as productive as on-site work, most workers would experience income losses and welfare gains would be less pronounced.

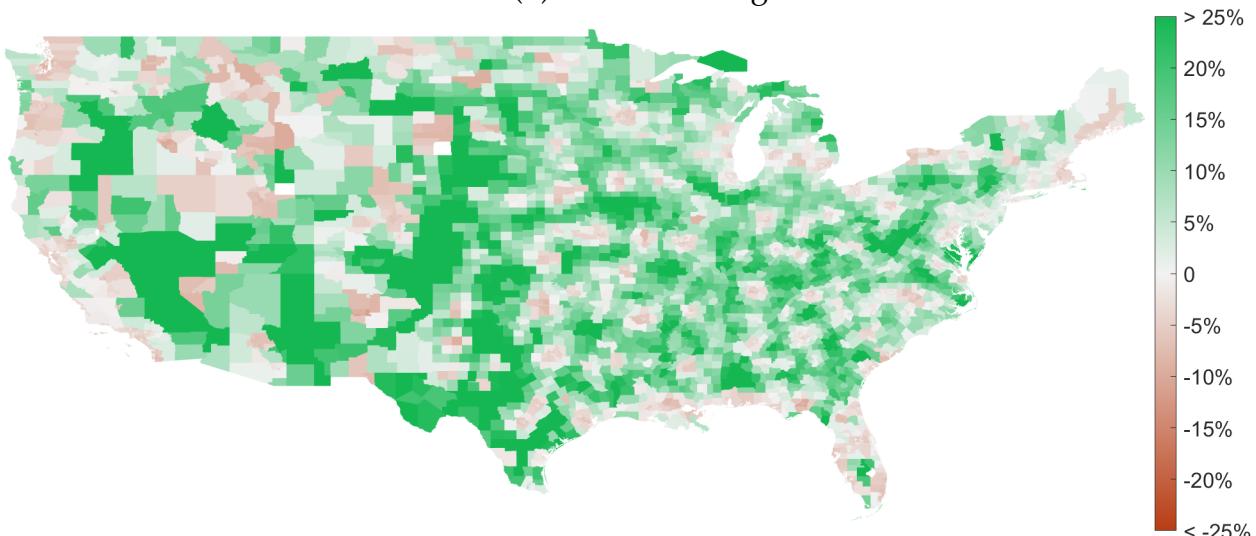
## J Additional Figures, Tables, and Maps

Figure J.1: Density of residents

Panel (a): absolute changes



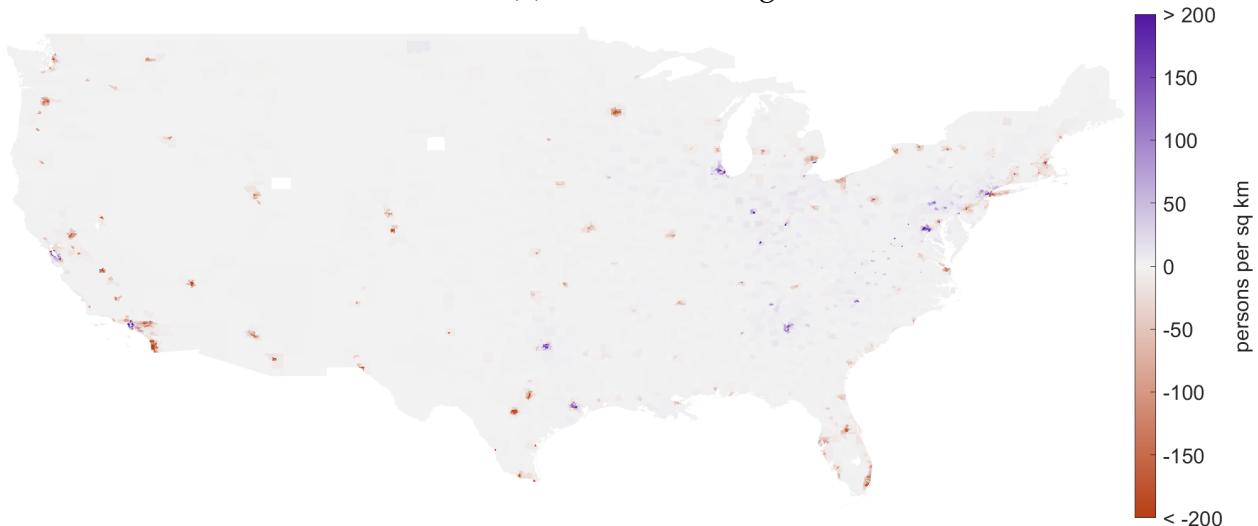
Panel (b): relative changes



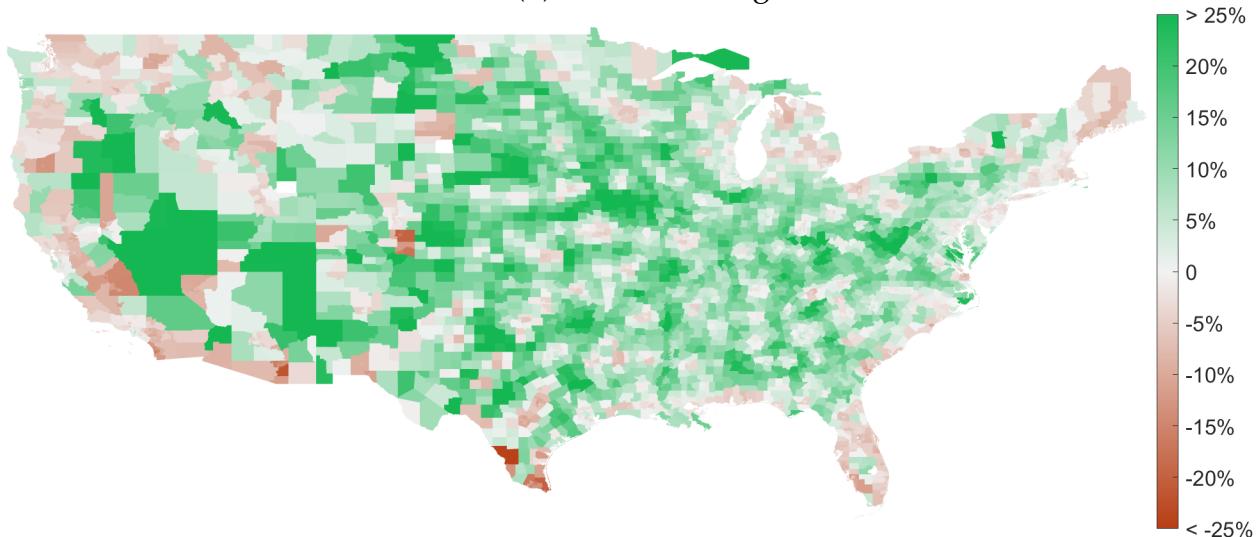
Note: Panel (a) shows absolute changes in the number of residents per square kilometer in each model location in the main counterfactual where the aversion for work from home falls and all endogenous variables adjust. Panel (b) shows percentage changes.

Figure J.2: Density of jobs

Panel (a): absolute changes

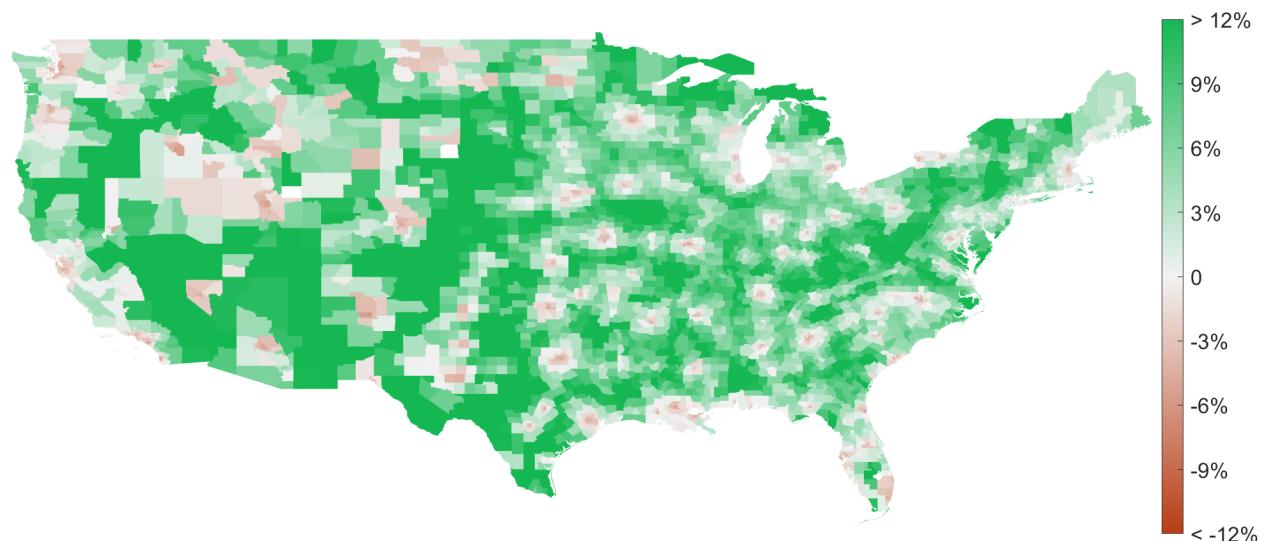


Panel (b): relative changes



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

Figure J.3: Floorspace prices, percentage changes



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

Table J.1: Changes in residents and jobs in 25 largest MSAs

Panel (a): Residents

MSA	all residents % '000	non-coll. '000	coll. '000	non-trad. '000	trad. '000	non-telec. '000	telec. '000	
New York-Newark-Jersey City, NY-NJ-PA	0.5	42	60	-18	-22	64	128	-86
Los Angeles-Long Beach-Anaheim, CA	-3.5	-199	-107	-92	-177	-22	136	-335
Chicago-Naperville-Elgin, IL-IN-WI	-0.4	-19	-8	-11	-45	26	104	-122
Dallas-Fort Worth-Arlington, TX	-3.1	-99	-64	-35	-93	-6	123	-222
Houston-The Woodlands-Sugar Land, TX	-3.4	-96	-67	-28	-96	1	85	-181
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	-0.1	-3	-2	-1	5	-9	-27	23
Atlanta-Sandy Springs-Alpharetta, GA	-0.4	-10	-3	-7	-34	24	50	-60
Boston-Cambridge-Newton, MA-NH	-3.2	-77	-37	-40	-57	-20	35	-111
Miami-Fort Lauderdale-Pompano Beach, FL	-5.8	-139	-87	-52	-96	-43	70	-209
San Francisco-Oakland-Berkeley, CA	-4.1	-89	-52	-37	-90	1	41	-130
Washington-Arlington-Alexandria, DC-VA-MD-WV	0.2	4	9	-5	-16	19	24	-20
Detroit-Warren-Dearborn, MI	-2.5	-47	-17	-30	-17	-29	30	-77
Phoenix-Mesa-Chandler, AZ	-5.7	-106	-73	-32	-93	-13	62	-167
Minneapolis-St. Paul-Bloomington, MN-WI	-3.8	-70	-38	-33	-32	-38	36	-106
Seattle-Tacoma-Bellevue, WA	-5.9	-102	-57	-45	-84	-18	63	-165
Riverside-San Bernardino-Ontario, CA	1.0	16	6	10	14	2	-50	66
San Diego-Chula Vista-Carlsbad, CA	-4.8	-67	-39	-28	-11	-55	-8	-58
Denver-Aurora-Lakewood, CO	-5.6	-74	-44	-30	-66	-9	52	-127
St. Louis, MO-IL	-2.0	-26	-17	-9	-21	-6	25	-51
Baltimore-Columbia-Towson, MD	-1.4	-18	-13	-4	-21	3	-12	-6
Tampa-St. Petersburg-Clearwater, FL	-4.4	-53	-39	-14	-29	-24	22	-75
Pittsburgh, PA	-2.0	-22	-17	-6	-9	-14	-7	-15
Charlotte-Concord-Gastonia, NC-SC	0.5	5	5	-0	3	2	21	-16
Portland-Vancouver-Hillsboro, OR-WA	-4.9	-54	-33	-21	-29	-24	22	-75
Orlando-Kissimmee-Sanford, FL	-3.6	-38	-29	-9	-15	-23	14	-52

Panel (b): Jobs

MSA	all jobs % '000	non-coll. '000	coll. '000	non-trad. '000	trad. '000	non-telec. '000	telec. '000	
New York-Newark-Jersey City, NY-NJ-PA	1.7	156	70	86	-21	177	123	32
Los Angeles-Long Beach-Anaheim, CA	0.3	18	16	2	-109	127	120	-102
Chicago-Naperville-Elgin, IL-IN-WI	2.7	123	87	36	-27	150	105	18
Dallas-Fort Worth-Arlington, TX	1.9	65	58	7	-57	122	126	-61
Houston-The Woodlands-Sugar Land, TX	1.3	37	37	-0	-55	92	85	-48
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	-0.8	-24	-22	-2	-7	-17	-23	-1
Atlanta-Sandy Springs-Alpharetta, GA	2.7	68	51	17	-14	82	51	17
Boston-Cambridge-Newton, MA-NH	-1.0	-27	-15	-13	-42	15	35	-63
Miami-Fort Lauderdale-Pompano Beach, FL	-4.6	-113	-80	-34	-97	-16	66	-179
San Francisco-Oakland-Berkeley, CA	1.4	33	25	8	-36	69	31	2
Washington-Arlington-Alexandria, DC-VA-MD-WV	2.9	63	37	26	11	51	24	39
Detroit-Warren-Dearborn, MI	-2.3	-44	-28	-16	-36	-9	27	-72
Phoenix-Mesa-Chandler, AZ	-2.5	-47	-25	-23	-61	13	59	-107
Minneapolis-St. Paul-Bloomington, MN-WI	-4.5	-84	-49	-36	-54	-30	38	-123
Seattle-Tacoma-Bellevue, WA	-2.3	-43	-20	-23	-56	14	65	-108
Riverside-San Bernardino-Ontario, CA	-7.0	-93	-74	-19	-23	-70	-36	-57
San Diego-Chula Vista-Carlsbad, CA	-12.5	-169	-111	-58	-48	-121	-9	-160
Denver-Aurora-Lakewood, CO	-1.6	-23	-8	-15	-45	23	51	-74
St. Louis, MO-IL	-1.5	-20	-12	-8	-21	1	24	-44
Baltimore-Columbia-Towson, MD	-0.5	-6	-6	-1	-10	3	-10	4
Tampa-St. Petersburg-Clearwater, FL	-4.1	-52	-34	-17	-38	-14	20	-72
Pittsburgh, PA	-2.1	-24	-18	-7	-10	-14	-6	-19
Charlotte-Concord-Gastonia, NC-SC	2.6	30	22	7	-5	34	22	7
Portland-Vancouver-Hillsboro, OR-WA	-5.6	-63	-38	-25	-35	-28	24	-87
Orlando-Kissimmee-Sanford, FL	-5.2	-61	-44	-17	-27	-34	16	-77

*Note:* The table shows counterfactual results for changes in residents (panel a) and jobs (panel b) aggregated to the metropolitan statistical area (MSA) level for the largest 25 MSAs, ranked according to number of residents 2012–2016. The first two columns show percentage and absolute overall changes. The next two show absolute changes by education level. The next two show absolute changes by industry. The last two columns show absolute changes by occupation.