Winners and Losers from the Work-from-Home Technology Boon*

Morris A. Davis
Rutgers University
Rutgers Business School

Andra C. Ghent
University of Utah
David Eccles School of Business

Jesse Gregory
University of Wisconsin-Madison

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Abstract

We model how an increase in Work-from-Home (WFH) productivity differentially affects workers using a framework in which some workers cannot work offsite, some are hybrid, and some are completely remote. The improvement in WFH productivity increases housing demand and thus housing prices since housing is inelastically supplied. Because workers in non-telecommutable occupations must consume housing but their total factor productivity does not increase, the rise in house prices reduces their welfare. The welfare decline is equivalent to 1-9% of consumption, depending on how substitutable WFH is with onsite work, and it arises despite measured income of all workers increasing.

Remote work. Housing affordability. WFH. Skill-biased technological change.

JEL codes: G12, O33, O41, R12, R33.

*Davis: mdavis@business.rutgers.edu; Ghent: andra.ghent@eccles.utah.edu.; Gregory: jmgregory@ssc.wisc.edu. We thank Derek Hoff and seminar participants at the AREUEA Virtual Seminar, ASU, London Business School, the SIEPR Implications of Remote Work Conference, the University of Miami, and the University of Utah for helpful comments on an earlier draft.

1 Introduction

The improvement in the productivity of Work-from-Home (WFH) wrought by the pandemic dramatically changed the nature of work for workers in telecommutable occupations. Workers in such occupations now spend less time commuting and enjoy their increased locational flexibility. However, less than half of US workers work in an occupation that permits any WFH. In this paper, we study the consequences of the improvement in WFH productivity for those that can WFH for the welfare of workers that cannot WFH.

We extend the model of Davis, Ghent, and Gregory (2024) (DGG) along two dimensions and quantify the change in welfare for workers in different occupations and of different education levels. As in DGG, some workers cannot work off-site all and some workers can choose to work a hybrid schedule, under which they still need to live in the same city as their employer is located (hybrid workers). In contrast to DGG's model, another subset of workers can work entirely remotely (remote workers). Additionally, unlike DGG, where all workers live in one representative city, in this paper all workers choose one of many possible cities in which to live along with where to live within that city. We calibrate the model to match worker choices of city, location within a city, and, for workers in occupations that can be done entirely remotely, the share of workers that choose to be remote.

The key factor driving welfare changes is that housing is inelastically supplied in many places. Housing is an important capital input for workers that WFH and, after the increase in WFH productivity, workers in WFH-feasible occupations demand additional housing for production. Further, the increase in productivity increases income for workers in WFH-feasible occupations leading them to demand more housing. Both forces put upward pressure on house prices.[1] As housing is inelastically supplied, the increase in demand for housing from workers in telecommutable occupations drives up the price of housing for everyone, including those that cannot WFH and experience little or no change in income. This reduces the amount of housing that workers who cannot WFH rent, which reduces their welfare despite being able to relocate to locations with cheaper housing. The decline in welfare is entirely because housing is inelastically supplied; when we consider a counterfactual simulation

[1] All studies of which we are aware show that the increase in WFH increases housing prices (see, for example, Delventhal and Parkhomenko, 2022; Gupta, Mittal, Peeters, and Van Nieuwerburgh, 2022; Howard, Liebersohn, and Ozimek, 2023; Van Nieuwerburgh, 2023; Richard, 2024).

in which housing is nearly perfectly elastically supplied in all locations, all workers benefit from the change in productivity of WFH.

The magnitudes of the welfare changes we report depend critically on how substitutable WFH is with work on-site for hybrid workers. In our benchmark calibration, we find a long run welfare decline equivalent to 4% of non-housing consumption for workers who cannot telecommute. The greatest increase in welfare is for fully remote workers, who experience an increase in welfare equivalent to 21% of consumption despite their incomes only rising by 3%. However, when WFH is more substitutable with work at the office than in our benchmark calibration, such that the increase in Total Factor Productivity (TFP) required to generate a fourfold increase in hybrid WFH is smaller, the decline in welfare for workers who cannot WFH is equivalent to only 1-3% of consumption.

Though all workers in non-telecommutable occupations are harmed by the technological progress, quantitatively, the model predicts that the welfare loss is larger for college educated workers than for non-college educated workers. Although non-college educated households have a higher expenditure share on housing, and are thus more affected by the increase in home prices, college-educated households in non-telecommutable occupations experience a reduction in their TFP because agglomeration economies in production decline. The decline in agglomeration occurs because skilled workers work in-person less frequently as WFH becomes more productive and therefore persistent.

Our welfare calculations depend critically on housing being inelastically supplied. Reassuringly, our model replicates the observed increase in residential rents and the decrease in office rents in the data, moments we did not target in calibration. In the data, real listing prices for homes increased by 14% between 2019 and 2023, while our model implies an increase in rents of 16% in the long run, after supply has had a chance to adjust. Our model implies a real decline in office rents of 12% in the short run and 13% in the long run. Data on office rents adjusted for lease characteristics and location shows a 12-13% decrease in real office rents between 2019 and 2022. We also replicate the empirical flattening of the residential bid-rent gradient shown in Gupta et al. (2022) and Howard et al. (2023).

In our model, a set of workers have the ability to work for employers that allow fully remote work. The share of workers choosing to be remote increases more than fourfold between 2019 and 2022 in the data, and the model requires a large increase in the productivity of remote work to match this increase. Remote workers disproportionately increase housing demand, and therefore housing prices, because they do all their work at home. Our model predicts that the share of remote workers will rise by an additional 25 percentage points in the long run relative to our calibration target for 2022. However, because remote-capable workers constitute less than 10% of the labor force in almost every city, the increase in *hybrid* work remains an important part of how WFH has changed the US economy.

Our paper contributes to two distinct literatures. A long literature has documented the tendency of skill-biased technology to exacerbate income inequality (Krussel, Ohanian, Rios-Rull, and Violante, 2000; Violante, 2008; Beaudry, Doms, and Lewis, 2010), but ours is the first paper to document that an improvement in productivity can harm some types of workers in absolute terms rather than merely worsen their relative position. The features of the model that generate this result are that 1) an inelastically supplied good, housing in this case, must be consumed by all households; and 2) the productivity improvement can be largely consumed by the same households whose productivity increases. We model the increase in WFH as arising from an improvement in the TFP of WFH; in complementary work, Richard (2024) similarly finds welfare losses for workers in non-telecommutable occupations in a setting where an increase in WFH arises from an increase in the preference for WFH.

We also contribute to the modeling of WFH on the labor market and the spatial allocation of workers. DGG, Behrens et al. (2024), and Delventhal and Parkhomenko (2022) model only hybrid WFH, while Brueckner, Kahn, and Lin (2023) and Liu and Su (2023) model only remote workers. Monte, Porcher, and Rossi-Hansberg (2023) model both remote and hybrid work insofar as individuals in their model make a choice first of whether to do any work off-site and then, if they choose to be off-site, how much work to do off-site. However, there is no city choice in Monte, Porcher, and Rossi-Hansberg (2023) although there is a within city location choice. In contrast, in our model all workers choose in which city to live and remote-capable workers choose their city after choosing whether to work remotely. As such, our model captures any changes in the population distribution across cities due to the rise of remote work uncoupling workers from the city of their employer.

In the next section, we present the model. Section 3 describes how we parameterize the model for different cities and types of workers In Section 4, we present our findings regarding on how rents and welfare change.

2 Model

2.1 Overview

Our model extends DGG along two important dimensions. First, in DGG, no workers were allowed to work 100% remote. Instead, a subset of workers in DGG had the option to choose a firm that allowed a hybrid work schedule, by which some work could be done off-site. Here, we introduce an additional type of worker who has the option to work primarily remote. Second, DGG model one representative city. Here, we model a system of C cities. In calibration, we allow for heterogeneity across cities in occupational shares, productivities of different types of workers, the rent gradient within each city, and commuting times. We allow workers to choose the city in which they wish to live. Throughout this section, whenever possible, we take some wording directly from DGG to avoid confusing readers with different notation or verbiage to describe the same concepts. For various parts of the model that are not new, we also refer readers to DGG for additional details on the model solution.

2.2 Households

Households vary with respect to their skill and occupation. A worker's skill and occupation are pre-determined and permanent. There are two skill levels, high and low, and two types of occupations, telecommutable and not. Type 1 workers are high-skill workers working in a telecommutable occupation, type 2 are low-skill workers working in a telecommutable occupation, type 3 are high-skill workers working in a non-telecommutable occupation, and type 4 are low-skill workers working in a non-telecommutable occupation. A fifth type of worker (type 5) has the option to be fully remote in the sense that they do so little on-site work that they can live in a different city than the one in which their employer is located. We think of these workers as high-skill workers in the IT sector. These households are similar to type 1 households, except that at the beginning of each period they choose whether or not to work at a firm that allows fully remote work.

Fully remote workers may have to fly into the office once a month or quarter. However, these workers can feasibly live in any metro area. In contrast, hybrid workers must go at least one day a week to the office, such that the vast majority will have to live in the same metro area as the one in which their employer is located. Hereafter, we refer to fully remote workers as simply remote.

Households in the model make a set of choices in a given sequence to maximize expected utility. First, type 5 workers choose whether to be remote. If they choose *not* to be remote, they decide whether to be hybrid workers similar to type 1 workers. Next, all households choose which city c of C possible cities to live in. After choosing a city, all households choose where to live from one of $n = 1, \ldots, N$ locations within city c.

After choosing where to live, households that work in a teleworkable occupation (type 1, 2, and 5 workers that choose not to work for a firm that allows remote work) choose whether to work for a firm that allows hybrid work. Households that do not work in a teleworkable occupation all work at firms that do not allow WFH. Type 1, 2, 3, and 4 households choose the number of days to work at the office. Each day worked at the office involves a commute to the CBD that costs time and resources. Type 5 households that have chosen remote work also choose how many days per week to work, but this work requires no commute. All households also choose non-housing consumption and housing to rent. Type 1, 2, and 5 households who choose to work at a firm that allows hybrid work also choose days to work at home. Households that do some WFH also choose home-office equipment to rent and home-office space to rent. All households receive utility from non-housing consumption, housing, leisure, and their location. Type 1, 2, and 5 households also receive utility from their firm choice. Households maximize expected utility.

2.2.1 Type 5 remote decision

For type 5 agents, let V_6 denote the expected value of choosing to be remote. Let V_5 denote the expected value of choosing not to be remote and therefore having the same decisions to make as a type 1 agent, although possibly having different location preferences. A given household j that is type 5 decides whether to be remote by choosing the max of the following:

$$\max\left\{\nu_r\left(\hat{a} + V_6\right) + \hat{e}_{6j}, \quad \nu_r V_5 + \hat{e}_{5j}\right\} \tag{1}$$

where $\hat{e}_{6,j}$ and $\hat{e}_{5,j}$ are iid Type 1 Extreme Value shocks specific to household j, $\hat{a}$ is a preference shifter that pins down the average fraction of type 5 workers who choose remote work, and ν_r determines the elasticity of this choice with respect to changes in $[V_6 - V_5]$.

2.2.2 City location decision

We use the notation $\iota \in (1,2,3,4,5,6)$ to index workers after the remote decision has been made. Type 1 through 4 workers are indexed by $\iota = 1,2,3,4$. Type 5 workers who choose not to be remote are indexed by $\iota = 5$, and type 5 workers who choose to be remote are indexed by $\iota = 6$. We refer to ι as the individual's ilk.

Once a type 5 worker decides whether or not to be remote, type 5 agents and all other household types decide in which city to live. Denote $V_{\iota c}$ as the expected value of ilk ι living in city c. Household j of ilk ι chooses a city $c \in \{1,\ldots,C\}$ according to

$$\max_{c\in\{1,\ldots,C\}} \{\nu_c(\tilde{a}_{\iota c} + V_{\iota c}) + \tilde{e}_{\iota cj}\} \tag{2}$$

where $\tilde{e}_{\iota jc}$ is an iid Type 1 Extreme Value shock specific to household j living in city c. $\tilde{a}_{\iota c}$ pins down the average population by ilk in each metro area, and ν_c pins down the elasticity of city choice (for all ilks) in response to changes in the differential of economic fundamentals across cities. The expected value of being ilk ι, V_ι, is equal to the expected value of equation (2):

$$V_\iota = E\left[\max_{c\in\{1,\ldots,C\}} \{\nu_c(\tilde{a}_{\iota c} + V_{\iota c}) + \tilde{e}_{\iota cj}\}\right] \tag{3}$$

For $\iota = 5,6$, this determines the values of V_5 and V_6 used in equation (1).

2.2.3 Within-city location decision

Once the city c has been chosen, the location n in that city must be chosen. Denote the expected value of utility of non-housing consumption, housing, leisure, and firm choice (for ilks 1, 2, and 5) for households of ilk ι living in location n of city c as $X_{n\iota c}$. Household j living in city c, choosing to live in location n at the start of the period, receives utility equal to

$$V_{n\iota cj} = \nu(a_{n\iota c} + X_{n\iota c}) + e_{n\iota cj}. \tag{4}$$

$a_{n\iota c}$ are amenities enjoyed by all ilk ι households living in location n of city c and $e_{n\iota cj}$ are amenities from living in location n of city c by ilk ι households that are specific to household j. We assume $e_{n\iota cj}$ is drawn iid across locations n, cities c, ilks ι, and households j from the Type 1 Extreme Value distribution such that ν scales the deterministic portion of $V_{n\iota cj}$ relative to the variance of the draws of $e_{n\iota cj}$.

Household j chooses the location within the city that provides the maximum utility. The expected value of choosing city c by ilk ι is equal to the expected value of equation (4) before the values of $e_{n\iota cj}$ are realized, i.e.,

$$V_{\iota c} \quad = \quad E\left[\ \max_n V_{n\iota cj}\ \right].$$

These expected values enter into equation (2), the equation that determines the optimal city in which to live.

2.2.4 Determining $X_{n\iota c}$ for $\iota = 1, \ldots, 5$

After choosing where to live, households working in teleworkable occupations ($\iota = 1, 2, 5$) choose whether to work for a non-WFH firm or a hybrid firm. Households of ilk $\iota = 3, 4$ always work at a non-WFH firm. At a non-WFH firm, all households work in an office located in the CBD of the metro area on workdays. At a hybrid firm, households can choose full days to work at the office in the CBD and full days to work at home.

Let $\kappa = 0$ denote a non-WFH firm and $\kappa = 1$ denote a hybrid firm. A household j living in location n of city c and working for a firm of type $\kappa \in 0, 1$ receives the following utility

$$X^{\kappa}_{n\iota cj} \quad = \quad X^{\kappa}_{n\iota c} \ + \ (1/\zeta)\,\epsilon^{\kappa}_{n\iota cj}\ . \tag{5}$$

As specified, the utility of households living in location n in city c and working for a firm of type κ has two components: a deterministic one, $X^{\kappa}_{n\iota c}$, and a stochastic one, $(1/\zeta)\,\epsilon^{\kappa}_{n\iota cj}$. We will precisely define the deterministic component of utility later, but for now note that it includes utility from optimally chosen levels of consumption, housing, and leisure. $\epsilon^{\kappa}_{n\iota cj}$ is drawn IID across all locations, cities, types, and households from the Type 1 Extreme Value distribution; ζ scales the variance of those shocks relative to the deterministic component of utility.[2]

For ilks with a choice, after the values of $\epsilon^{\kappa}_{n\iota cj}$ are drawn households choose the type of firm to work for (hybrid or non-WFH) that maximizes equation (5). The expected value of this choice before the values of $\epsilon^{\kappa}_{n\iota cj}$ are drawn is

$$
\begin{aligned}
\iota &= 1,2,5 \quad & X_{n\iota c} &= E\left[\max_{\kappa=0,1} X^{\kappa}_{n\iota cj}\right] \\
\iota &= 3,4 \quad & X_{n\iota c} &= X^{0}_{n\iota c}.
\end{aligned}
\tag{6}
$$

This expected value enters into equation (4), the equation that determines the optimal location n in which to live in city c.

Utility when employed by a non-WFH firm. Households of ilk $\iota = 1, \ldots, 5$ that choose to live in n and work for a firm operating in the CBD that does not allow WFH ($\kappa = 0$) choose consumption ($c^{0}_{n\iota c}$), housing ($h^{0}_{n\iota c}$), leisure ($\ell^{0}_{n\iota c}$), and the fraction of discretionary time to spend at the office ($b^{0}_{n\iota c}$) to maximize

$$
(1-\alpha_{\iota}) \ln c^{0}_{n\iota c} + \alpha_{\iota} \ln h^{0}_{n\iota c} + \psi \ln \ell^{0}_{n\iota c}
\tag{7}
$$

subject to the budget and time constraints of

$$
\begin{aligned}
0 &= \left(w^{0}_{\iota,c} - \tau_n\right) b^{0}_{n\iota c} - c^{0}_{n\iota c} - r_{n,c} h^{0}_{n\iota c} \\
0 &= 1 - \left(1 + t_{n,c}\right) b^{0}_{n\iota c} - \ell^{0}_{n\iota c}.
\end{aligned}
\tag{8}
$$

In equations (7) and (8), the 0 superscripts denote that the household works at a non-WFH firm. $w^{0}_{\iota c}$ denotes the wage paid by non-WFH firms to ilk ι households working in city c that spend 100% of their discretionary time at work.

Households employed by a non-WFH firm must commute to the CBD each day they work. The financial commuting costs associated with a full year of commuting to the CBD are equal to τ_n and depend on location n.[3] A household of ilk ι living in location n supplying $b^{0}_{n\iota c}$ fraction of a full year of labor earns a net annual income

[2] As discussed in DGG, by including ζ in the model, we can match the elasticity of firm choice conditional on location choice. We allow this elasticity to differ from the elasticity of location choice with respect to expected utility, which is determined by ν.

[3] Although it is possible for pecuniary commuting costs to vary by city as well, particularly if the typical commute mode differs by city, in practice car commuting is the modal form of commuting in all US metro areas including New York City according to data in the 5-year 2015-2019 American Community Survey (ACS).

of $\left(w^0_{\iota,c} - \tau_n\right) b^0_{n\iota c}$. The household spends this labor income on consumption, $c^0_{n\iota c}$, and housing, $h^0_{n\iota c}$. The rental price per unit of housing in location n is $r_{n,c}$. Households also enjoy leisure. Given a total endowment of time in the year of 1, the quantity of leisure enjoyed by a household spending $b^0_{n\iota c}$ percentage of the year working is $1-(1+t_{n,c})\, b^0_{n\iota c}$, where $t_{n,c}$ is the round-trip time spent commuting from location n in city c. In DGG, we show that optimal household choices satisfy

$$\begin{aligned}
\ell^0_{n\iota c} &= \frac{\psi}{1+\psi} \\
b^0_{n\iota c} &= \left(\frac{1}{1+\psi}\right)\left(\frac{1}{1+t_{n,c}}\right) \\
c^0_{n\iota c} &= (1-\alpha_\iota)\left(w^0_{\iota,c} - \tau_n\right) b^0_{n\iota c} \\
r_{n,c} h^0_{n\iota c} &= \alpha_\iota \left(w^0_{\iota c} - \tau_n\right) b^0_{n\iota c}.
\end{aligned}$$

Denote $X^0_{n\iota c}$ as the maximized value of equation (7). $X^0_{n\iota c}$ enters into equation (5), the equation that determines optimal firm choice for $\iota = 1, 3, 5$, as well as the second line of equation (6) for $\iota = 3, 4$ corresponding to households that can only work for a firm that does not allow hybrid work.

Utility when employed by a hybrid firm. Households of ilk $\iota = 1$, $\iota = 2$, or $\iota = 5$ living in n and choosing to work at a hybrid firm also receive utility from consumption, housing, and leisure. These households choose (a) the percentage of total time in the year to work at the firm in the CBD, $l^b_{n\iota c}$, (b) the percentage of total time in the year to work at home, $l^h_{n\iota c}$, (c) the size of the home office $s^h_{n\iota c}$, and (d) the amount of equipment and software to rent for the home office, $k^h_{n\iota c}$. Notice that these four choice variables do not have a κ superscript, as these choices are only available to households working at a hybrid firm. These choices determine the gross compensation offered by a hybrid firm to the household; we denote this gross compensation function as $\omega_{\iota,c}\left(l^b_{n\iota c}, l^h_{n\iota c}, s^h_{n\iota c}, k^h_{n\iota c}\right)$.

Households of ilk ι living in n and working at a hybrid firm make choices to maximize

$$\chi_\iota + (1-\alpha_\iota)\ln c^1_{n\iota c} + \alpha_\iota \ln h^1_{n\iota c} + \psi \ln \ell^1_{n\iota c}. \tag{9}$$

The 1 superscripts denote that the household works at a WFH firm. This is the same utility function as for households choosing a non-WFH firm except that it includes an additive preference-shifter, χ_ι, which represents a number of factors affecting the desirability of working at a hybrid versus a non-WFH firm.

Households optimally choose consumption, housing, and leisure subject to budget and time constraints that are modified to account for the fact that WFH takes time and that renting a home office and home equipment is costly, i.e.,

$$\begin{array}{llll} \text{budget}: & 0 & = & \omega_{\iota,c}\left(l^b_{n\iota c}, l^h_{n\iota c}, s^h_{n\iota c}, k^h_{n\iota c}\right) - \tau_n l^b_{n\iota c} - c^1_{n\iota c} - r_{n,c}\left(h^1_{n\iota c} + s^h_{n\iota c}\right) - r^k k^h_{n\iota c} \\ \text{time}: & 0 & = & 1 - (1 + t_{n,c})\, l^b_{n\iota c} - l^h_{n\iota c} - \ell^1_{n\iota c}. \end{array}$$

Note that the compensation offered by the firm to the worker, $\omega_{\iota,c}\left(l^b_{n\iota c}, l^h_{n\iota c}, s^h_{n\iota c}, k^h_{n\iota c}\right)$, depends on the household's choices for days worked at the office, days worked from home, the city in which the worker lives, and the amounts of business equipment and home office space, all of which affect worker productivity.

Denote $X^1_{n\iota c}$ as the maximized value of equation (9). This value enters into equation (5).

2.2.5 Determining $X_{n\iota c}$ for $\iota = 6$

Fully remote households own their own firms and produce output according to

$$y_{n6c} = Z_{6,c}\left(l_{n6c}\right)^{\theta_b}\left(k_{n6c}\right)^{\theta_k}\left(s_{n6c}\right)^{\theta_s} \tag{10}$$

where l_{n6c} is days of work, k_{n6c} is capital used, and s_{n6c} is home-office space. These households choose y_{n6c}, l_{n6c}, k_{n6c}, s_{n6c}, c_{n6c}, h_{n6c}, and ℓ_{n6c} to maximize

$$(1-\alpha)\ln c_{n6c} + \alpha \ln h_{n6c} + \psi \ln \ell_{n6c} \tag{11}$$

subject to the budget constraint, the time constraint, and the remote production function, i.e.,

$$0 = \mu_c\left[y_{n6c} - c_{n6c} - r_{n,c}\left(h_{n6c} + s^h_{n6c}\right) - r^k k^h_{n6c}\right] \tag{12}$$

$$0 = \mu_l\left[1 - l_{n6c} - \ell_{n6c}\right] \tag{13}$$

$$0 = \mu_h\left[Z_{6,c}\left(l_{n6c}\right)^{\theta_b}\left(k_{n6c}\right)^{\theta_k}\left(s_{n6c}\right)^{\theta_s} - y_{n6c}\right]. \tag{14}$$

μ_c, μ_l, and μ_h are Lagrange multipliers.

The first-order conditions of this problem are

$$\begin{array}{llrcl}
(a) & y_{n6c}: & \mu_h & = & \mu_c \\
(b) & l_{n6c}: & \mu_\ell & = & \mu_h \theta_b \left(y_{n6c} / l_{n6c} \right) \\
(c) & k_{n6c}: & \mu_c r^k & = & \mu_h \theta_k \left(y_{n6c} / k_{n6c} \right) \\
(d) & s_{n6c}: & \mu_c r_{n,c} & = & \mu_h \theta_s \left(y_{n6c} / s_{n6c} \right) \\
(e) & c_{n6c}: & \mu_c & = & \left(1 - \alpha \right) / c_{n6c} \\
(f) & h_{n6c}: & \mu_c r_{n,c} & = & \alpha / h_{n6c} \\
(g) & \ell_{n6c}: & \mu_\ell & = & \psi / \ell_{n6c}.
\end{array}$$

We start by showing that leisure is a constant. FOCs (e) and (f) imply

(15) $$\mu_c \left[c_{n6c} + r_{n,c} h_{n6c} \right] = 1.$$

After imposing $\theta_b + \theta_k + \theta_s = 1$, FOCs (a), (c), and (d) imply

(16) $$\mu_c \left[r^k k_{n6c} + r_{n,c} s_{n6c} \right] = \mu_c y_{n6c} \left(1 - \theta_b \right).$$

Adding equations (15) and (16) together and imposing the budget constraint implies

(17) $$\mu_c \theta_b y_{n6c} = 1.$$

Now note that FOCs (b) and (c) imply

$$\mu_\ell l_{n6c} = \mu_c \theta_b y_{n6c} = 1$$

where the second equality uses equation (17). Finally, insert FOC (g) and use the time constraint $l_{n6c} = 1 - \ell_{n6c}$ to get the result that leisure (and time worked) are both constants, i.e.,

(18) $$\ell_{n6c} = \frac{\psi}{1+\psi} \text{ and } l_{n6c} = \frac{1}{1+\psi}.$$

To solve for the other variables in the system, note that FOCs (a), (c), and (d) imply

(19) $$k_{n6c} = \left(\frac{\theta_k}{\theta_s} \right) \left(\frac{r_{n,c}}{r_k} \right) s_{n6c}.$$

Insert equation (19) into the production function and impose $\theta_b + \theta_k + \theta_s = 1$ to get

$$
\begin{aligned}
y_{n6c} &= Z_{6,c}\left(l_{n6c}\right)^{\theta_b}\left[\left(\frac{\theta_k}{\theta_s}\right)\left(\frac{r_{n,c}}{r_k}\right)s_{n6c}\right]^{\theta_k}\left(s_{n6c}\right)^{\theta_s} \\
&= Z_{6,c}\left(l_{n6c}\right)^{\theta_b}\left[\left(\frac{\theta_k}{\theta_s}\right)\left(\frac{r_{n,c}}{r_k}\right)\right]^{\theta_k}\left(s_{n6c}\right)^{1-\theta_b}.
\end{aligned}
$$

FOCs (a) and (d) imply $r_{n,c}s_{n6c} = \theta_s y_{n6c}$, and inserting that into the above yields

$$
s_{n6c} = Z_{6,c}\left(l_{n6c}\right)^{\theta_b}\left[\left(\frac{\theta_k}{\theta_s}\right)\left(\frac{r_{n,c}}{r_k}\right)\right]^{\theta_k}\left(\frac{\theta_s}{r_{n,c}}\right)\left(s_{n6c}\right)^{1-\theta_b}
$$

which we rearrange and reduce to get

$$
s_{n6c} = Z_{6,c}^{\frac{1}{\theta_b}} l_{n6c}\left(\frac{\theta_k}{r_k}\right)^{\frac{\theta_k}{\theta_b}}\left(\frac{\theta_s}{r_{n,c}}\right)^{\frac{1-\theta_k}{\theta_b}} \tag{20}
$$

Because equation (18) determines l_{n6c}, all the variables on the right-hand side of equation (20) are known and thus s_{n6c} is known. From equation (19), once we know s_{n6c}, we know k_{n6c}, and this implies (from the production function) that we know y_{n6c}. Once we know y_{n6c}, s_{n6c}, and k_{n6c}, we know c_{n6c} and h_{n6c} from FOCs (f) and (g) and the budget constraint.

Define $X_{n\iota c}$ for $\iota = 6$ as the maximized value of equation (11). This value enters into equation (4) for these workers, the equation that determines the optimal location n in which to live in city c.

2.3 Firms and Production

Non-WFH firms. Firms that employ non-remote workers each hire one worker. Consider the problem of a non-WFH firm that employs a household of ilk ι living in location n of city c. Denote the TFP of ilk ι working at a non-WFH firm as $Z_{\iota,c}$ For any given set of wages and prices, the firm chooses its quantities of labor, $b_{n\iota c}$, and capital in the form of both equipment and software, $k_{n\iota c}$, and office space, $s_{n\iota c}$, to maximize profits defined as

$$
\begin{aligned}
& y_{n\iota c} - w_{\iota,c}b_{n\iota c} - r^k k_{n\iota c} - r^o_c s_{n\iota c} \\
\text{where} \quad & y_{n\iota c} = Z_{\iota,c} b_{n\iota c}^{\theta_b} k_{n\iota c}^{\theta_k} s_{n\iota c}^{\theta_s}.
\end{aligned} \tag{21}
$$

$w_{\iota c}$ is the prevailing wage rate for a worker of ilk ι working at a non-WFH firm, r^k is the cost per unit of equipment and software, and r_c^o is the cost per unit of office space in city c. Importantly, the productivity of each type of worker may differ across cities such that we allow $Z_{\iota,c}$ to vary across cities.[4]

The firm maximizes profits by setting

$$w_{\iota,c} b_{n\iota c} = \theta_b y_{n\iota c}, \tag{22}$$

$$r^k k_{n\iota} = \theta_k y_{n\iota c}, \tag{23}$$

$$r_c^o s_{n\iota} = \theta_s y_{n\iota c}. \tag{24}$$

After substitutions, and using the assumption of constant returns to scale ($\theta_b + \theta_k + \theta_s = 1$), firm output from employment for a household of ilk ι living in location n is equal to

$$y_{n\iota c} = \left[\left(\frac{\theta_k}{r^k} \right)^{\frac{\theta_k}{\theta_b}} \left(\frac{\theta_s}{r_c^o} \right)^{\frac{\theta_s}{\theta_b}} (Z_{\iota,c})^{\frac{1}{\theta_b}} \right] b_{n\iota c}. \tag{25}$$

Total wage compensation paid to a household of ilk ι living in location n is $\theta_b y_{n\iota c}$, implying that $w_{\iota,c}$ is equal to the term in brackets multiplied by θ_b. The quantity of equipment and software rented by the firm is $\theta_k y_{n\iota c}/r^k$ and the quantity of office space rented by the firm is $\theta_s y_{n\iota c}/r_c^o$.

Hybrid firms. A firm that hires a household living in location n of ilk $\iota = 1$, 2, or 5 supplying $l_{n\iota c}^b$ units of labor at the firm and $l_{n\iota c}^h$ units of labor at home with $s_{n\iota c}^h$ units of home office space and $k_{n\iota c}^h$ units of equipment and software at the home office produces output of

$$y_{n\iota c} = \left[\left(y_{n\iota c}^b\right)^\rho + \left(y_{n\iota c}^h\right)^\rho \right]^{1/\rho} \tag{26}$$

where $y_{n\iota c}^b$ is output produced while working at the firm and $y_{n\iota c}^h$ is output produced while WFH. The production functions determining output from WFH and work at the

[4] We use the same parameters for the shares of business capital (θ_k), space (θ_s), and labor (θ_b) in output in all production functions. Eberly et al. (2022) argue that the elasticity of output with respect to business equipment is similar for WFH and work at the office. However, future research may reveal different factor shares in production at home than in production at the office. Absent any empirical evidence or a theoretical argument against using the same shares, we keep the shares the same for work at the office and WFH.

office are

$$\begin{aligned} y^b_{n\iota c} &= A^b_{\iota,c}\left(l^b_{n\iota c}\right)^{\theta_b}\left(k^b_{n\iota c}\right)^{\theta_k}\left(s^b_{n\iota c}\right)^{\theta_s} \\ y^h_{n\iota c} &= A^h_{\iota,c}\left(l^h_{n\iota c}\right)^{\theta_b}\left(k^h_{n\iota c}\right)^{\theta_k}\left(s^h_{n\iota c}\right)^{\theta_s}. \end{aligned}$$

$k^b_{n\iota c}$ and $s^b_{n\iota c}$ are equipment and software and office space rented at the CBD by this firm for household of ilk ι living in location n.

Given $y^h_{n\iota c}$ and $l^b_{n\iota c}$, the firm chooses $k^b_{n\iota c}$ and $s^b_{n\iota c}$ to maximize $y_{n\iota c} - r^k k^b_{n\iota c} - r^o_c s^b_{n\iota c}$. The choices satisfy

$$\begin{aligned} y^{1-\rho}_{n\iota c}\left(y^b_{n\iota c}\right)^{\rho-1}\theta_k\left(y^b_{n\iota c}/k^b_{n\iota c}\right) &= r^k \\ y^{1-\rho}_{n\iota c}\left(y^b_{n\iota c}\right)^{\rho-1}\theta_s\left(y^b_{n\iota c}/s^b_{n\iota c}\right) &= r^o_c \end{aligned}$$

Assuming labor markets are competitive such that firms make zero profits, the firm pays any household supplying $l^b_{n\iota c}$, $l^h_{n\iota c}$, $k^h_{n\iota c}$, and $s^h_{n\iota c}$ the output that remains. Households know this and choose $l^b_{n\iota c}$, $l^h_{n\iota c}$, $k^h_{n\iota c}$, and $s^h_{n\iota c}$ accordingly.

2.4 Technology

Commuting speed. Denote $\mathcal{L}_{nc}$ as the aggregate quantity of work at the office by households living in zone n during the year, and define $d_{n,c}$ as the distance from location n to the CBD in city c. We define aggregate distance commuting, $\mathcal{V}_c$, as

$$\sum_{n=1}^{N} d_{n,c}\mathcal{L}_{nc}.$$

Following Couture, Duranton, and Turner (2018), travel speed, $\mathcal{S}_c$, is subject to a negative congestion externality in aggregate distance spent commuting, determined as

$$\mathcal{S}_c = \bar{\mathcal{S}}_c \mathcal{V}_c^{\gamma} \tag{27}$$

such that time spent commuting from location n is $d_{n,c}/\mathcal{S}_c$.

TFP of working at the office. Denote $\mathcal{H}_c$ as the aggregate quantity of high-skill labor worked at the office during the period in city c. This includes all days worked on-site by ilk 1, 3, and 5; remote work does not contribute to the agglomeration economy in production. For high-skill households (ilks 1, 3, and 5), TFP at the office is positively affected by $\mathcal{H}_c$ via a high-skill agglomeration externality

$$\begin{array}{llcl} \text{non-WFH firm TFP, } \iota = 1,3,5 & Z_{\iota,c} & = & \bar{Z}_{\iota,c}\mathcal{H}_c^{\delta_b} \\ \text{hybrid firm TFP while at the office, } \iota = 1,5 & A^b_{\iota,c} & = & \bar{A}^b_{\iota,c}\mathcal{H}_c^{\delta_b}. \end{array}$$

TFP at the office can change over time due to changes to the human capital externality, or due to exogenous changes in $\bar{Z}_{\iota,c}$ and $\bar{A}^b_{\iota,c}$.[5]

TFP of WFH for hybrid workers. For ilks $\iota = 1$, 2, and 5, we specify

$$A^h_{\iota,c} = \bar{A}^h_{\iota,c}\,(L_h^{max})^{\delta_{\iota,h}} \tag{28}$$

where L_h^{max} is the maximum amount of time that households in aggregate spent working at home in any previous year. Equation (28) specifies that $A^h_{\iota,c}$ can change over time due to exogenously increasing TFP, i.e., changes to $\bar{A}^h_{\iota,c}$, or changes to the adoption externality if the total amount of time that households spent working at home in any previous year increases.

TFP of remote workers. Remote workers' productivity depends in part on the city in which they locate according to

$$Z_{6,c} = \phi(\lambda Z_{1,c} + (1-\lambda)Z_1) \tag{29}$$

where Z_1 is the national average productivity of onsite type 1 workers. That is, remote workers receive a portion of the productivity of the type 1 workers who are entirely on site in that city and a portion of the national average of the on-site productivity of type 1 workers. This specification captures the notion that some agglomeration economies operate across firms rather than within firms. $\phi < 1$ is a discount factor representing the extent to which remote workers are less productive than their hybrid counterparts.

[5] Gould (2007), Rosenthal and Strange (2008), Bacolod, Blum, and Strange (2009), Roca and Puga (2016), and Rossi-Hansberg, Sarte, and Schwartzman (2019) all find evidence that agglomeration economies in production exist primarily for high-skill workers.

2.5 Equilibrium and solution

An equilibrium in this economy is a vector of prices for business capital, r^k; office space in the CBD for each city c, r_c^o; housing and home office space in locations $1, \ldots N$ for each city c, $r_{n,c}$; a wage rate for each ilk of worker $\iota = 1, \ldots, 5$ working at a non-WFH firm in each city, $w_{\iota,c}^0$; a wage function $\omega_{\iota,c}\left(l_{n\iota c}^b, l_{n\iota}^h, s_{n\iota c}^h, k_{n\iota c}^h\right)$ for each ilk of worker $\iota = 1, 2, 5$ choosing to work at a hybrid firm; and commute times $t_{n,c}$ for locations $1, \ldots N$ in each city c such that

- ilk $\iota = 3, 4$ households choose the city c and zone n in which to live and consumption, housing, and labor supply to maximize utility given all commute times, wages, and prices subject to budget and time constraints,
- ilk $\iota = 1, 2, 5$ households maximize utility by choosing the city c and zone n in which to live and whether to work at a firm that allows WFH. If they choose to work for a non-WFH firm, they then choose consumption, housing, and labor supply to maximize utility given commute times, all wages and prices, and the budget and time constraints. If they choose to work for a hybrid firm, they choose consumption, housing, labor supply at the office, labor supply at home, business capital at home, and home office space to maximize utility given the wage function, commute times, all prices, and the budget and time constraints,
- type 5 households maximize utility by choosing whether to be remote. If a type 5 household chooses to be fully remote, it becomes ilk $\iota = 6$, chooses the city c and zone n in which to live, and then chooses its optimal quantities of labor, business equipment, home-office space, consumption, and housing to maximize utility. If a type 5 household chooses not to be remote, it becomes ilk $\iota = 5$.
- non-WFH firms take all wages and prices as given and choose labor, business capital, and office space to maximize profits,
- hybrid firms take all prices and the wage function and its inputs for each type of worker and location where the worker lives as given and choose business capital at the office and office space to maximize profits,
- the total demand for housing inclusive of home office space in each location is equal to the supply of housing in each location and the total demand for office space is equal to the supply of office space, and

- quantities in each city are consistent with the externalities affecting all wages and commute times in that city.

3 Parameterization and Predictions

3.1 Data

To parameterize the model and conduct counterfactuals, we use data from nine sources: 1) the 2018 GSS; 2) the 2017-2018 LJF (ATUS 2020 as compiled by Hofferth et al. (2020)); 3) the 2019 5-year American Community Survey (ACS) as compiled by Ruggles et al. (2023), which pools data collected in 2015-2019; 4) the 2019 and 2022 1-year ACS as compiled by Ruggles et al. (2023); 5) the 2019 American Housing Survey (AHS); 6) office rents per square foot from Compstak; 7) residential listing prices per square foot by county compiled by Realtor.com, available via FRED at the Federal Reserve Bank of St. Louis; 8) the Dingel and Neiman (2020) occupation codes (ONET) classified by telecommutable status combined with Census 2010 occupation classifications as our ACS data contains only Census occupation codes; and 9) the elasticity of housing supply from Baum-Snow and Han (2024).

We select our sample of cities from the 30 most populous US cities as of 2019 not missing the county of residence for all observations. Because the county is missing for all ACS observations for the Denver metro area, we are unable to include the populous Denver metro area. The cities in our sample represent 58% of the US population.

3.2 Matching model concepts to data

We parameterize the model to the most populous US cities and assign workers to one of two residential zones. We restrict our sample to household heads working full-time who are at least 25 years old. We classify all workers who work in an IT occupation as type 5 regardless of their educational attainment.[6] We then classify the remaining workers as types 1 through 4 based on their educational attainment and whether they work in a telecommutable occupation. We define a high-skill household as one in which the household head has at least a four-year-college degree. A household is

[6] Specifically, any worker in 2010 Occupation Code 110, 1005-1108, or 1400 is a type 5 worker.

defined as working in a telecommutable occupation when its household head works in an occupation that Dingel and Neiman (2020) classify as permitting some telecommuting. We classify a type 5 worker as remote if they report that their usual commute mode is "no commute" in the ACS.

For all cities except Atlanta and NYC, Zone 1 corresponds to the county containing the CBD. For Atlanta and NYC, Zone 1 corresponds to the CBD county as well as adjacent counties given the large number of counties these MSAs encompass. Because there are no observations for Zone 2 in the 2022 release of the 5-year ACS that is our main data source for the Boston, Miami, Phoenix, and San Diego metros, in these metros, all people live in Zone 1.

3.3 Baseline Parameterization

We first parameterize the model to the period immediately before the WFH shock that occurred in 2020.

Productivity parameters. To calibrate $Z_{\iota,c}$ for $\iota \in (1,2,3,4,5)$, we first estimate hourly wages for people working full time by household ilk ι. We strip the ACS wage data of demographics by running Mincerian regressions of hourly wages on gender, age, age squared, gender interacted with age and age squared, marital status, an indicator for the presence of children under age 5, county of residence fixed effects, and type fixed effects. We then use the fitted values for a married man of age 40 with no children under age 5 for each household type.

Given values of θ_k, θ_s, θ_b, r^k, and r^c and estimates of hourly wages by ι, we use equations (25) and (22) to solve for $Z_{\iota,c}$. Denote $\widetilde{w}_{\iota,c}$ as our estimate of hourly wages of ilk ι households in city c. Given an assumed 15 hours of discretionary time each day, the model implies

$$\begin{aligned}
\widetilde{w}_{\iota,c} \cdot 15 \cdot 365 &= \theta_b \left[\left(\frac{\theta_k}{r^k}\right)^{\frac{\theta_k}{\theta_b}} \left(\frac{\theta_s}{r^c}\right)^{\frac{\theta_s}{\theta_b}} (Z_{\iota,c})^{\frac{1}{\theta_b}} \right] \\
Z_{\iota,c} &= \text{const} \cdot (\widetilde{w}_{\iota,c})^{\theta_b}
\end{aligned}$$

where the constant is equal to

$$\left[15 \cdot 365 \cdot \theta_b^{-1} \left(\frac{\theta_k}{r^k}\right)^{-\frac{\theta_k}{\theta_b}} \left(\frac{\theta_s}{r_c^o}\right)^{-\frac{\theta_s}{\theta_b}}\right]^{\theta_b}.$$

We impose $A_{1,c}^b = \mathcal{Z} Z_{1,c}$ and $A_{2,c}^b = \mathcal{Z} Z_{2,c}$ where $\mathcal{Z}$ is determined as described in DGG.

We take the remote discount from the estimate in He et al. (2021) that corresponds most closely to our model. He et al. (2021) report that workers are willing to accept a 36% wage discount to work remotely relative to 100% on site.

Lacking empirical evidence on the value of λ, we set it to 0.5. The TFP of ilk 6 workers is then determined by equation (29). The value of ϕ that generates an average wage discount of 36% given our choice for λ is 0.6265.

Other city-specific parameters. For each city in our sample, we set the city-specific parameters of the model by method of moments. The moments we use are

- Worker ilk shares $\pi_{1,c}$, $\pi_{2,c}$, $\pi_{3,c}$, $\pi_{4,c}$, $\pi_{5,c}$, and $\pi_{6,c}$,
- Effective office rents per square foot (r_c^o) in the Compstak market most closely corresponding to the CBD county for that metro,
- Residential rents per square foot in each city in each zone ($r_{n,c}$), calculated as 5% of the listing price per square foot consistent with the long-term value of the rent-price ratio documented by Davis, Lehnert, and Martin (2008),
- The time costs of commuting, $t_{1,c}$ and $t_{2,c}$, using data from the ACS on the average one-way commute time by workers commuting into Zone 1, and
- The total number of households in each city.

Table 1 shows the share of worker types in each city as well as the share of type 5 workers that are remote at the onset of the pandemic, i.e., in the 2019 5-year ACS. Although the share of workers in telecommutable occupations differs somewhat across cities, the share of type 5 workers is only 6.7% across the entire US population. Notably, only 11.7% of remote-capable workers chose to work remotely prior to the pandemic.

Table 1: Worker Type Shares as of 2019

	Type 1	Type 2	Type 3	Type 4	Type 5	Share of Type 5 Remote
Atlanta	30.5%	17.8%	12.9%	31.1%	7.7%	17.1%
Austin	36.7%	14.7%	13.8%	23.6%	11.2%	14.9%
Baltimore	34.5%	17.0%	13.8%	26.5%	8.3%	8.4%
Boston	43.8%	11.0%	16.5%	22.1%	6.5%	6.8%
Charlotte	32.6%	15.7%	13.0%	32.0%	6.8%	14.4%
Chicago	33.2%	15.0%	14.0%	31.9%	5.9%	11.2%
Cincinnati	30.1%	16.9%	14.1%	33.5%	5.4%	11.3%
Dallas	30.0%	18.1%	11.8%	32.8%	7.3%	13.5%
Detroit	25.8%	16.5%	15.5%	37.0%	5.3%	8.3%
Houston	28.4%	17.2%	12.4%	37.5%	4.6%	9.9%
Kansas City	31.3%	16.2%	14.1%	31.3%	7.1%	10.2%
LA	29.5%	17.9%	12.9%	35.2%	4.5%	8.7%
Miami	28.2%	20.2%	14.0%	33.4%	4.1%	15.2%
Minneapolis	33.4%	15.6%	14.3%	28.7%	8.0%	9.4%
Nashville	32.7%	16.5%	14.9%	30.0%	5.9%	14.7%
NYC	34.9%	15.4%	14.8%	29.2%	5.8%	7.9%
Orlando	27.6%	19.4%	14.1%	33.3%	5.6%	16.9%
Philadelphia	32.9%	17.0%	14.5%	29.6%	6.0%	11.8%
Phoenix	26.6%	20.9%	12.7%	33.5%	6.2%	15.5%
Pittsburgh	28.8%	16.0%	14.4%	35.1%	5.8%	10.1%
Portland, OR	30.3%	16.4%	16.0%	30.2%	7.1%	15.0%
Riverside	19.0%	20.8%	10.2%	47.1%	2.9%	14.4%
Sacramento	29.0%	19.9%	13.6%	30.9%	6.5%	12.2%
St. Louis	29.9%	17.1%	13.3%	33.3%	6.5%	10.2%
San Antonio	24.7%	20.0%	12.0%	38.1%	5.2%	9.6%
San Diego	30.9%	17.0%	14.2%	31.5%	6.4%	11.5%
San Francisco	40.2%	12.3%	15.1%	20.9%	11.5%	7.4%
Seattle	30.8%	15.4%	13.3%	29.4%	11.1%	7.5%
Tampa	25.5%	21.6%	12.6%	34.8%	5.5%	17.0%
Washington, DC	46.4%	12.9%	12.4%	18.2%	10.2%	8.8%
Average	31.3%	17.0%	13.7%	31.4%	6.7%	11.7%

Notes: 1) A type 5 worker is a worker in an IT occupation. 2) A remote worker is one who reports their usual commute mode as "no commute." 3) Types 1 and 2 are in telecommutable occupations other than IT occupations. 4) Types 3 and 4 are in non-telecommutable occupations. 5) Types 1 and 3 have educational attainment of a four-year degree or greater, and types 2 and 4 have lower educational attainment than a four-year degree. 6) Cities shown correspond to CBSA definitions. 7) Data is from 2019 5-year ACS, which pools data for five years up to and including 2019.

Table 2 lists our estimates of city amenity values for each type. These city amenity values are set such that (a) for each ilk, the average (non-population weighted) value across cities is zero, and (b) the model-predicted population shares of each type in each city exactly match that of the data in 2019. There is a high correlation across types prior to the pandemic in the amenity value a city provides. Dallas is the lowest amenity value city for all types, whereas Boston, New York City, and San Diego are attractive to all types. Sunny cities typically have higher amenity values for all types, while rustbelt cities such as Detroit, Cincinnati, and St. Louis have lower amenity values.

Parameters common to all cities. We take several parameters that do not vary across cities from DGG. Table 3 shows these parameters in our baseline parameterization.

We calculate housing expenditure shares by type by taking the median ratio of gross rent to family income for renting households of that type in the ACS. We find $\alpha_1 = 0.22$, $\alpha_2 = 0.27$, $\alpha_3 = 0.23$, $\alpha_4 = 0.29$, and $\alpha_5 = 0.19$. We set $\nu_c = \nu$ based on the estimates in Monte, Redding, and Rossi-Hansberg (2018). He et al. (2021) do not provide the full distribution of their estimates, and so we set $\nu_r = \frac{1}{\zeta}$.

3.4 Counterfactuals

We consider two counterfactuals: a short-run counterfactual and a long-run counterfactual. In the former, we 1) impose the WFH productivity increase necessary to generate a fourfold increase in the number of days of WFH from hybrid work, 2) impose the increase in the productivity of remote workers necessary to match the change in the number of type 5 workers choosing to be remote between 2019 and 2022, and 3) allow the city-specific amenities to change to generate the cross-sectional change in city population observed between 2019 and 2022.[7]

More specifically, in our short-run counterfactual, we increase the relative total

[7] In the data, there is a large absolute decrease in the US full-time workforce due to the effects of COVID on mortality and changes in labor force participation. There is also a change in the share of the population of each type. We keep the number of households of each type fixed between 2019 and 2022 for the economy-wide population and so calibrate the model to generate the change in the distribution of population of each type across US cities.

Table 2: City Amenity Values in Baseline

	Type 1	Type 2	Type 3	Type 4	Type 5	Pop.weighted avg.
Atlanta	0.73	0.48	0.70	0.57	0.88	0.64
Austin	0.16	-0.20	0.05	0.00	0.31	0.06
Baltimore	-1.27	-1.42	-1.35	-1.51	-1.53	-1.39
Boston	1.99	2.54	2.29	2.53	1.99	2.24
Charlotte	0.18	0.05	0.30	0.01	0.32	0.12
Chicago	0.17	0.24	0.44	0.30	0.16	0.26
Cincinnati	-0.15	-0.17	-0.27	-0.46	-0.23	-0.29
Dallas	-3.56	-3.12	-3.31	-2.68	-3.85	-3.14
Detroit	-0.96	-0.68	-0.84	-0.64	-0.87	-0.76
Houston	-0.21	0.18	-0.04	0.47	-0.17	0.17
Kansas City	-0.56	-0.45	-0.60	-0.43	-0.44	-0.49
LA	0.20	0.46	0.25	0.59	0.29	0.40
Miami	1.59	1.74	1.78	1.86	1.54	1.75
Minneapolis	-0.05	-0.47	-0.14	-0.71	0.06	-0.32
Nashville	-0.89	-1.47	-1.03	-1.93	-0.72	-1.38
NYC	1.44	1.98	1.85	2.21	1.11	1.81
Orlando	0.35	0.47	0.41	0.48	0.36	0.43
Philadelphia	-1.22	-0.96	-0.99	-1.09	-1.49	-1.11
Phoenix	1.63	1.65	1.39	1.60	1.74	1.60
Pittsburgh	-1.53	-1.36	-1.58	-1.34	-1.36	-1.43
Portland, OR	0.19	-0.26	-0.09	-0.39	0.08	-0.13
Riverside	0.62	0.67	0.41	0.55	0.59	0.57
Sacramento	0.32	0.42	-0.03	0.20	0.46	0.25
St. Louis	-1.58	-1.85	-1.49	-1.96	-1.76	-1.76
San Antonio	0.68	0.74	0.45	0.71	0.78	0.68
San Diego	1.67	1.91	1.75	2.04	1.70	1.85
San Francisco	-0.35	-0.57	-0.37	-0.31	-0.33	-0.36
Seattle	0.63	0.19	0.55	0.00	1.00	0.41
Tampa	0.16	0.04	-0.06	-0.06	0.24	0.03
Washington, DC	-0.37	-0.80	-0.42	-0.63	-0.87	-0.55
Pop. Weighted Avg.	0.16	0.22	0.25	0.29	-0.01	

Notes: 1) Table reports values of $\tilde{a}_{\iota,c}$ for ilks 1 through 4 and the weighted average of ilks 5 and 6 for type 5 and city c in the baseline calibration, which corresponds to 2019.

Table 3: Parameters taken from DGG

Parameter	Description	Value
ψ	Coefficient on Leisure in Utility	1.15
ν	Elasticity of Location Choice wrt Expected Value	3.3
$1/\zeta$	Inverse of Elasticity of Hybrid Firm Choice wrt Expected Value	0.0634
χ_1, χ_5	Additive Utility of Hybrid Firm Choice, $\iota = 1, 5$	0.158
χ_2	Additive Utility of Hybrid Firm Choice, $\iota = 2$	0.064
ρ	Determines EOS in Production, Hours WFH and Work at Office	0.719
$\mathcal{Z}$	Relative TFP of Hybrid firms (compared to non-hybrid firms)	0.889
δ_b	Size of High-Skill Human Capital Externality at Work at Office	0.04
γ	Size of Congestion Externality in Commuting Speed	-0.15
θ_k	Business Capital share of Production, WFH and Office	0.15
θ_s	Structures share of Production, WFH and Office	0.18
$\frac{A^h_{1,c}}{A^b_{1,c}}$, $\frac{A^h_{5,c}}{A^b_{5,c}}$	Relative TFP of hours WFH (compared to office) at Hybrid Firms, $\iota = 1, 5$	0.365
$\frac{A^h_{2,c}}{A^b_{2,c}}$	Relative TFP of hours WFH (compared to office) at Hybrid Firms, $\iota = 2$	0.348
τ_1	Annual financial commuting cost from zone 1 to CBD if work at office every day	\$5,417
τ_2	Annual financial commuting cost from zone 2 to CBD if work at office every day	\$13,542

factor productivities of hybrid work to

$$\begin{aligned} \iota = 1, 5 \qquad \frac{A^h_{\iota,c}}{A^b_{\iota,c}} &= 0.665 \\ \iota = 2 \qquad \frac{A^h_{\iota,c}}{A^b_{\iota,c}} &= 0.515 \end{aligned}$$

from their baseline levels of 0.365 ($\iota = 1, 5$) and 0.348 ($\iota = 2$). Because the size of the relative productivity improvement, and thus the change in incomes, depends critically on the value of ρ, in Section 4.4 we investigate how our results change as we increase or decrease ρ within the plausible range of values.

We increase ϕ in equation (29) by 20.7% from its baseline level such that the fraction of type 5 workers that choose to be remote increases from 11.7% to 50.6%, which is the change we observe in the 1-year ACS between 2019 and 2022. Finally, we change $\tilde{a}_{\iota,c}$ for each location to match the change in the distribution of population of each type between 2019 and 2022.

Our short-run counterfactual also keeps the supply of space of each type (residential and office) in each zone and city fixed. In our long-run counterfactual, residential space adjusts in accordance with the residential elasticities in Baum-Snow and Han (2024) and we set the elasticity of office supply to 0.1 in all cities.

4 Results

4.1 Rent Predictions

As current data on incomes and population flows do not capture the long-run predictions of the model, we compare the predictions of our model for commercial and residential rents. Because most office leases span many years, and we can impute the market's predictions for residential rents using home price data, markets for space better capture the expected long-run implications of the improvement in WFH technology.

Office rents. We compare the change in real effective office rents predicted by our model to office lease data from Compstak. To control for the wide variation in property and lease characteristics, we use data from individual leases to estimate regressions of the form

$$r_{i,t} \;=\; \beta_{post} * postwfhboon_{i,t} \;+\; \beta_x * X_{i,t} \;+\; \epsilon_{i,t} \tag{30}$$

where $r_{i,t}$ is the log of effective rents per square foot. In equation 30, $X_{i,t}$ contains indicator variables for the location of the property, indicator variables for the calendar quarter in which the lease was signed, an indicator for whether the lease is a renewal or new lease, indicators for whether the lease is a gross or a net lease (the omitted category are leases wherein the landlord pays only some expenses), categorical variables to capture the lease length, and controls for the building class. We include leases from 2019 and 2022 such that $postwfhboon_{i,t} = 1$ if the lease was signed in 2022, and 0 otherwise. The coefficient on $postwfhboon_{i,t}$ thus measures the percent decline in office rents pre- to post-pandemic.

Table 4: Change in Real Office Rents 2019-2022

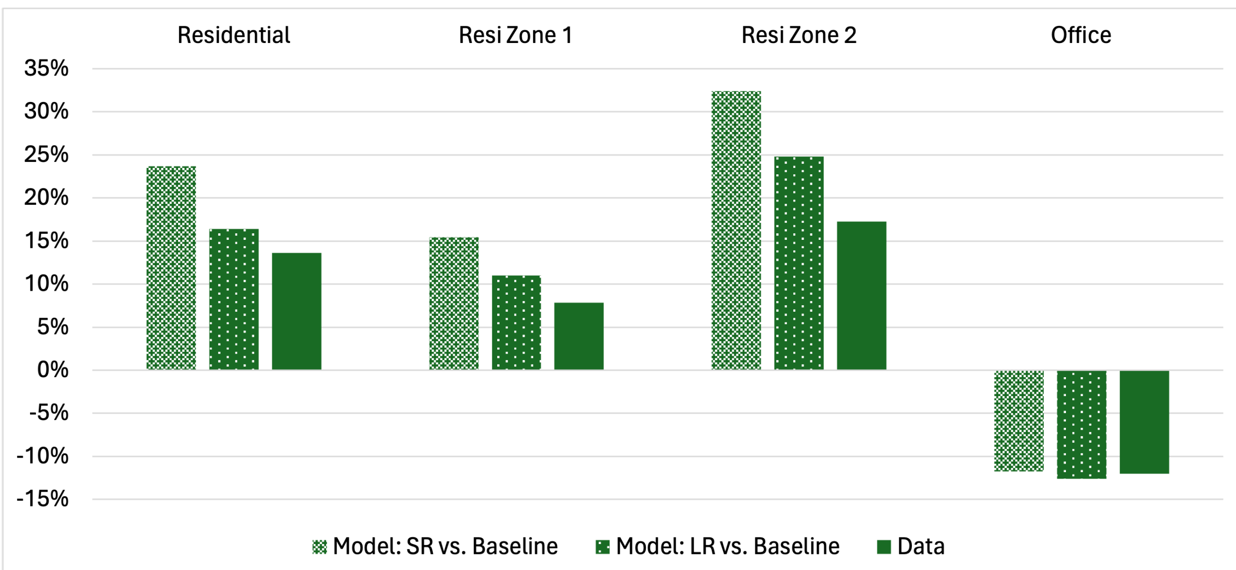
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
postwfhboon	-0.12***	-0.13***	-0.12***	-0.13***	-0.11***	-0.13***	-0.14***
	-0.0073	-0.0069	-0.0079	-0.0087	-0.018	-0.0085	-0.012
transactionsqft	2.6e-07***	2.2e-07***	2.5e-07***	3.9e-07**	0.00000021	2.8e-07***	0.00000008
	-0.0000001	-0.0000001	-0.0000001	-0.000002	-0.0000002	-0.0000001	-0.0000001
termdum1	-0.15***	-0.14***	-0.15***	-0.15***	-0.034	-0.19***	-0.057***
	-0.012	-0.011	-0.013	-0.014	-0.03	-0.014	-0.019
termdum2	-0.13***	-0.12***	-0.14***	-0.12***	-0.086***	-0.14***	-0.068***
	-0.011	-0.01	-0.012	-0.014	-0.026	-0.012	-0.02
termdum3	-0.088***	-0.083***	-0.092***	-0.061***	-0.078***	-0.091***	-0.048***
	-0.0093	-0.0087	-0.0097	-0.012	-0.021	-0.01	-0.018
Constant	3.60***	3.61***	3.63***	3.61***	3.12***	3.65***	3.51***
	-0.0084	-0.0079	-0.0088	-0.012	-0.019	-0.009	-0.017
Observations	8475	8381	6684	4242	1726	5870	2438
R^2	0.736	0.787	0.762	0.811	0.647	0.782	0.824
Building Class FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Renewal/New FEs	Yes	Yes	Yes	Yes	Yes	New Leases Only	Renewals Only
Gross/Net FEs	Yes	Yes	Yes	Only Gross	Only Net	Yes	Yes
Cal Qtr FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CBSA FEs	Yes	No	Yes	No	No	No	No
Zip Code FEs	No	Yes	No	Yes	Yes	Yes	Yes
Tenant Industry FEs	No	No	Yes	No	No	No	No

Notes: 1) Dependent variable in all specifications is log of effective rents per square foot from Compstak. 2) Data is all office leases signed in 2019 and 2022 in the 30 CBSAs described in Section 3. 3) postwfhboon takes a value of 1 for the year 2022 and 0 for 2019. 4) termdum1, termdum2, and termdum3 are indicator variables for the length of the lease. termdum1=1 if the lease is less than 36 months in length, termdum2=1 if the lease is 36-59 months in length, and termdum3=1 if the lease is 60-119 months in length.

Table 4 shows that, in the data, real office rents fell approximately 12% after controlling for lease and property characteristics. The decline is precisely estimated and does not differ substantially across specifications. When we include only CBSA fixed effects, we find a decline of 12%, while controlling for zip code fixed effects implies a decline of 13%. Similarly, when we include only gross leases, the decline is 13%, while including only net leases implies a decline of only 11%. When we include only renewals (column (6)), we find a 14% decline, while if we include only new leases, the decline is 13% (column (7)).

Figure 1 compares the predictions of the model to those from the regression presented in Table 4. The 12% decline in the data is in line with the model's prediction of an 11.7% decrease in office rents in the SR and a 12.9% decline in the LR as shown in Figure 1.

Figure 1: Rent Changes in the Model and the Data



Notes: 1) Residential rent change is calculated as the real change in residential listing prices between 2023 and 2019. 2) Office rent change is calculated as the real change in office rents between 2022 and 2019 after adjusting for lease characteristics using equation (30).

Residential rents. The much larger number of residential transactions allows us to compare the predictions of the model for each city to those in the data so far. We do so by using listing prices per square foot from Realtor.com and applying a 5%

rent-to-price ratio (Davis, Lehnert, and Martin, 2008). Figure 1 shows the average, population-weighted increase in implied rents between 2019 and 2023 and compares them to the model prediction for the SR and the LR. Relative to the data, the model slightly overpredicts the aggregate rise in residential rents. In the data, rents rise 14%, while in the model rents rise 23% in the short run and 16% in the long run. In both the data and the model, the rise in rents is much larger in Zone 2 than Zone 1 because of the increased demand for space in Zone 2 due to workers commuting to the office less frequently than in the baseline.

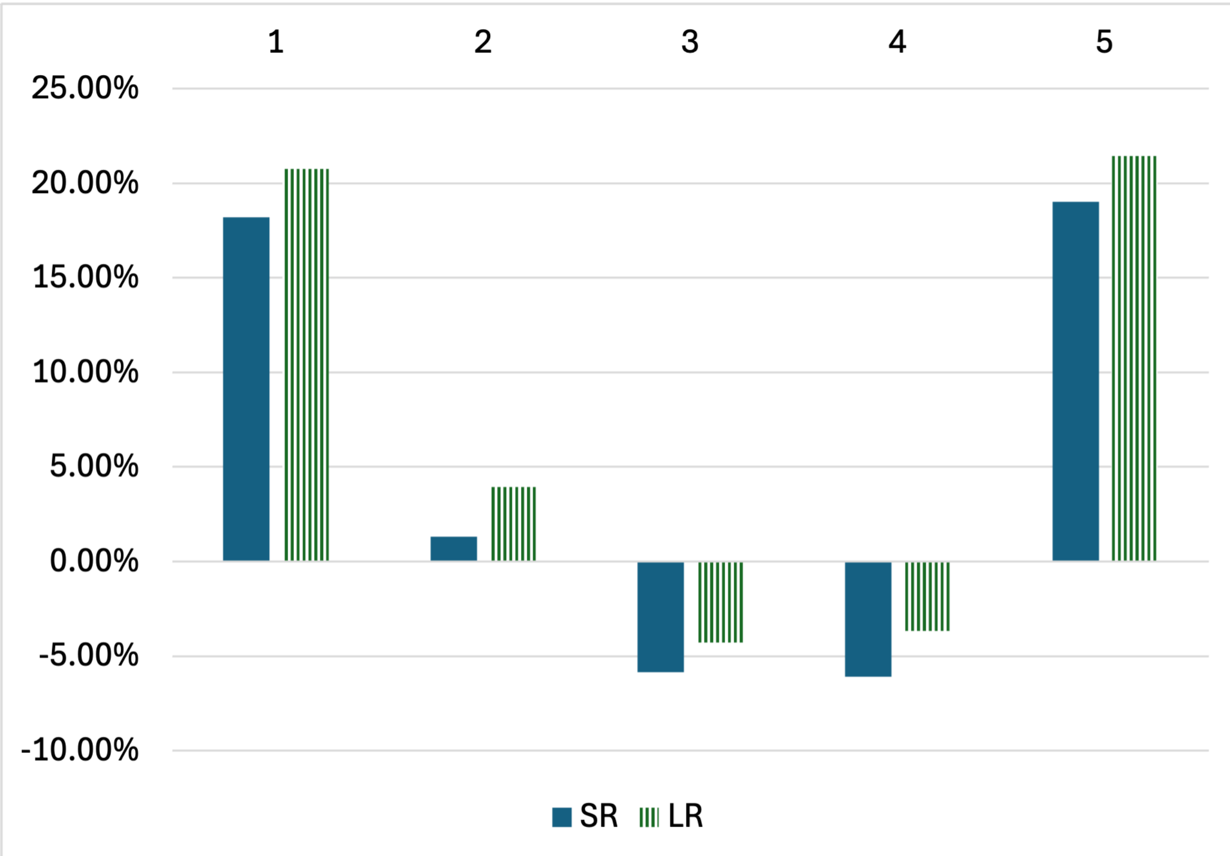
4.2 Welfare Predictions

Figure 2 shows the change in welfare by worker type as measured by the percent increase in consumption equivalent to the change in expected value. We calculate the consumption equivalent increases in welfare computationally. The biggest gainers are the type 5 workers. These workers see substantial increases in their wages and many more of them work remotely than did so prior to the pandemic. Prior to the pandemic, remote workers earned only 65% of the wages of fully in-office workers due to their lower TFP. The increase of relative TFP of 21% after the pandemic significantly increases their average wages in the SR relative to the baseline.

Type 1 households experience the next largest gains in welfare. These households see large increases in their productivity and their housing expenditure share is only 24%. Type 2 workers also see productivity improvements, but their productivity improves by less for the reasons described in DGG. Furthermore, because they have a higher housing expenditure share than type 1 workers ($\alpha_2 = 0.29$ vs. $\alpha_1 = 0.24$), the increease in house prices mitigates the benefit they see from higher wages.

Welfare improves for all worker types in the LR relative to the SR because the supply of space that can be used for housing and home offices has a chance to adjust such that rents in the LR are slightly lower than in the SR. The increase in the supply of housing allows types 1, 2, and 5 to do even more work off-site, which reduces the agglomeration benefit of being in person more in the LR than in the SR. Although this mechanism was not quantitatively important in Davis et al. (2024), the addition of remote workers to the model leads to modest reductions in the productivity of in-person work as Table 5 demonstrates. In-person productivity drops more for type 3 workers than for type 1 workers because of heterogeneity in their concentration

Figure 2: Welfare Changes in the Model by Worker Type



Notes: 1) A type 5 worker is a worker in an IT occupation. 2) Types 1 and 2 are in telecommutable occupations other than IT. 3) Types 3 and 4 are in non-telecommutable occupations. 4) Types 1 and 3 have educational attainment of a four-year degree or greater; types 2 and 4 have lower educational attainment than a four-year degree. 5) The SR corresponds to a counterfactual in which the supply of housing and office space have not yet had a chance to adjust. The LR counterfactual allows the housing supply to adjust according to the elasticities estimated by Baum-Snow and Han (2024). 6) The welfare change shown is the percent increase in non-housing consumption required to generate the increase in expected values between the counterfactual and the pre-COVID baseline. 7) The welfare change shown for type 5 workers is a lower bound because it weights ilk 5 and 6 by pre-pandemic shares of each within type 5 and the increase in welfare is slightly higher for ilk 6.

in cities and differential exposure of cities to the WFH shock. Most of the fall in productivity stems from the decline in agglomeration economies although some of it comes from workers moving to lower TFP cities between 2019 and 2022.

Table 5: Change in TFP of In-person Work Relative to Pre-pandemic Baseline

	Actual Pop. Dist.		2019 Pop. Dist. In SR and LR	
Worker Type	SR	LR	SR	LR
1	-1.43%	-1.64%	-1.12%	-1.27%
3	-1.53%	-1.71%	-1.10%	-1.25%

Notes: 1) Table presents change in population-weighted TFP for each worker type relative to pre-pandemic baseline. 2) Type 1 workers are college-educated workers who work in a telecommutable occupation. Type 3 workers are college-educated workers who work in a non-telecommutable occupation. 3) The last two columns take city-level TFP from SR and LR but weight them according to the 2019 population distribution across cities.

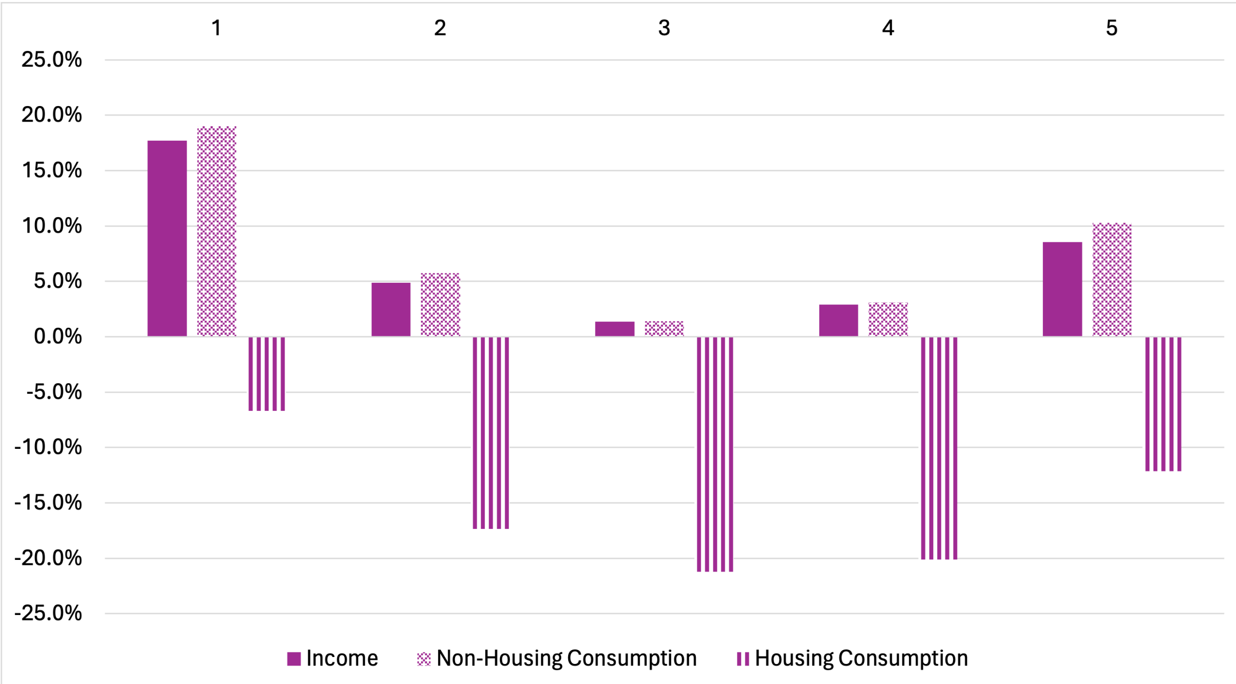
Both types 3 and 4 experience welfare decreases because they don't see any improvement in their TFP, since they work in occupations that cannot use WFH technology, but face higher housing costs. In the short run, the decline in welfare is slightly greater for type 4 than for type 3 workers because type 3 workers have lower housing expenditure shares such that they are less exposed to the increase in housing prices. However, type 3 workers also see their TFPs fall ($Z_{3,c}$) because the type 1 and type 5 workers come into the office less which reduces agglomeration spillovers for high-skill workers. In the SR, the population-weighted economywide value of $Z_{3,c}$ falls by -1.5%. In the LR, the increase in housing supply mitigates the higher house prices but, because the increased supply of residential space enables even more WFH, there is an even greater fall in the positive externality from in-person work. As such, the biggest losers from WFH in the long run are the type 3 workers.

Note that welfare decreases for type 3 and 4 workers despite their incomes rising as Figures 3 and 4 illustrate. The wages of types 3 and 4 go up slightly because they have more office space to work with, which boosts their labor productivity. They also supply slightly more labor because of a decrease in commuting time due to the fact that commuting time falls and leisure is a constant given our functional form assumptions.[8] As a result of their higher incomes, type 3 and 4 workers consume more non-housing consumption such that it may appear that they are better off. However,

[8]See Gibbs, Mengel, and Siemroth (2023) for evidence that increased WFH increases labor supply.

their housing consumption decreases dramatically because of higher house prices.

Figure 3: SR Income and Consumption Changes in the Model by Worker Type

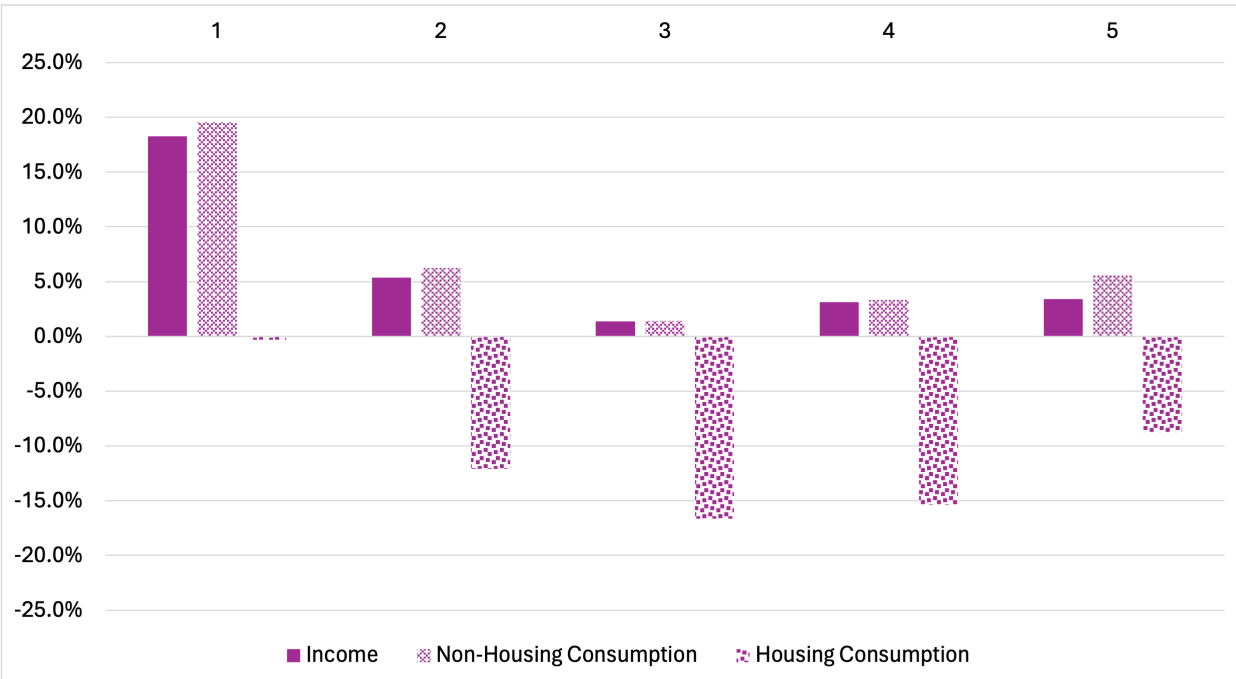


Notes: 1) A type 5 worker is a worker in an IT occupation. 2) Types 1 and 2 are in telecommutable occupations other than IT. 3) Types 3 and 4 are in non-telecommutable occupations. 4) Types 1 and 3 have educational attainment of a four-year degree or greater; types 2 and 4 have lower educational attainment than a four-year degree. 5) The SR corresponds to a counterfactual in which the supply of housing and office space have not yet had a chance to adjust. The LR counterfactual allows the housing supply to adjust according to the elasticities estimated by Baum-Snow and Han (2024).

Of all workers in telecommutable occupations, type 5 workers see the smallest income gains and yet the largest welfare gains. The reason they see large welfare gains despite only modest income gains is because so many of them switch to being remote and get the associated welfare increase. Although remote work becomes more productive between the baseline and the SR, it remains less productive on average than on-site work such that average income does not increase substantially. This is especially true in the long run when fully 76% of type 5 workers choose remote work.

The increase in non-housing consumption considerably exceeds the increase in income for types 1, 2, and 5 in both the SR and the LR. The reason is that these

Figure 4: LR Income and Consumption Changes in the Model by Worker Type



Notes: 1) A type 5 worker is a worker in an IT occupation. 2) Types 1 and 2 are in telecommutable occupations other than IT. 3) Types 3 and 4 are in non-telecommutable occupations. 4) Types 1 and 3 have educational attainment of a four-year degree or greater; types 2 and 4 have lower educational attainment than a four-year degree. 5) The SR corresponds to a counterfactual in which the supply of housing and office space have not yet had a chance to adjust. The LR counterfactual allows the housing supply to adjust according to the elasticities estimated by Baum-Snow and Han (2024).

households now spend less on pecuniary commuting costs given as they commute less frequently.

4.3 The Role of Migration and Housing Supply

To understand the roles that (a) migration and changing amenities and (b) the elasticity of housing supply play in determining welfare changes, we compute the predicted LR equilibrium after changing two sets of assumptions about the LR in the model. In the first, the "No Migration" scenario, we assume that no household can move cities, that the remote share of type 5 workers in each city does not change, and that city-level amenities remain fixed at pre-pandemic levels. In the second, the "No Migration, Constant Prices" scenario, the assumptions are the same as in the No Migration scenario, but the elasticity of housing supply in all locations in all cities is 50. In each of the two scenarios, we compute the change in welfare by ilk relative to the pre-pandemic baseline. The first scenario highlights the role that migration and changing amenities plays in determining changes to welfare; the second highlights the role of inelastically supplied housing.

The results of these scenarios are shown in Table 6. Since migration is not possible in these scenarios, we compute welfare for each ilk in all calculations in this table as $\nu_c\left(\tilde{a}_{\iota c} + V_{\iota c}\right)$; see equation (2). Comparing the change in welfare in the No Migration and Baseline columns shows that the change in city amenities and the resorting of the population between the pre-COVID and LR periods does not meaningfully affect our estimates of the change in welfare by type. In other words, if households had not been allowed to migrate, and if city-level amenities had not changed, our estimates of the impact of the change in WFH productivity on welfare by type would have been very similar.

In contrast, the right-most column shows the impact of inelastically supplied housing on welfare by type. If housing was elastically supplied everywhere, then welfare for all types would have increased after the change in WFH productivity. Even though type 4 experiences no direct change to TFP, and the TFP of ilk 3 declines due to a reduction in agglomeration, the welfare of both ilks 3 and 4 increases as a result of increased labor productivity and a small reduction in commute times from the impact of less traffic on commuting speed: see equation (27). The change in welfare is lower in the Baseline than in the No Migration, Constant Prices scenario because housing is an important component of utility, so if its relative price rises (all else equal), people are worse off. Additionally, for types 1, 2, and 5, housing is an important input in production, so if the relative price of housing rises, they use less housing in production, thus lowering WFH output relative to the scenario where the relative price of housing does not change.

Table 6: The Role of Migration and Housing Supply Elasticity

Type	Baseline	No Migration	No Migration, Constant Prices
1	20.8%	21.4%	31.7%
2	3.9%	3.7%	12.8%
3	-4.3%	-4.5%	1.2%
4	-3.7%	-4.2%	3.6%
5	21.4%	21.8%	31.6%

Notes: 1) Table lists change in welfare by type from pre-COVID to LR shown as the equivalent percent change in consumption. Welfare for every ilk in every scenario is computed as $\nu_c\left(\tilde{a}_{\iota c} + V_{\iota c}\right)$. The column labeled "Baseline" shows the change under our baseline assumptions. The column labeled "No Migration" shows the change in welfare when the distribution of ilks across cities and all values of $\tilde{a}_{\iota c}$ are unchanged from pre-COVID to LR. The column labeled "No Migration, Constant Prices" shows the change in welfare under the No Migration scenario and when the elasticity of housing supply in all zones in all cities is set to 50.0. 2) A type 5 worker is a worker in an IT occupation. 3) Types 1 and 2 are in telecommutable occupations other than IT. 5) Types 3 and 4 are in non-telecommutable occupations. 6) Types 1 and 3 have educational attainment of a four-year degree or greater; types 2 and 4 have lower educational attainment than a four-year degree.

4.4 The Role of the Elasticity of Substitution in Hybrid Work

The welfare estimates we have presented so far describe the consequences for household utility of the productivity increase required to generate a fourfold increase in WFH in our model using our baseline estimates of the model's parameters. In our benchmark analysis, we use the point estimate of ρ of 0.719. There is a large range of productivity increases consistent with a fourfold increase in WFH under alternative values for the model parameters. Because there is uncertainty in key parameters – in particular the elasticity of substitution (EOS) – there is also uncertainty about the actual size of the productivity increase. When WFH is more substitutable with work at the office, a small increase in WFH productivity can generate a substantial increase in WFH. In this section, we evaluate how sensitive our welfare results are to reasonable estimates of the EOS and the implied productivity change.

Table 7: The Importance of the Elasticity of Substitution

		Pre-COVID		SR		% Improvement	
	ρ	$\frac{A^h_{1,c}}{A^b_{1,c}}$	$\frac{A^h_{2,c}}{A^b_{2,c}}$	$\frac{A^h_{1,c}}{A^b_{1,c}}$	$\frac{A^h_{2,c}}{A^b_{2,c}}$	$\frac{A^h_{1,c}}{A^b_{1,c}}$	$\frac{A^h_{2,c}}{A^b_{2,c}}$
5th percentile	0.55	0.132	0.137	0.505	0.243	281.9%	77.2%
median (benchmark)	0.72	0.365	0.348	0.666	0.516	82.6%	48.3%
95th percentile	0.89	0.599	0.561	0.809	0.737	35.0%	31.2%

Notes: 1) Pre-COVID corresponds to the Baseline estimates of the TFP parameters. 2) SR shows the TFP necessary to generate a fourfold increase in the number of days of WFH by hybrid workers for that value of ρ.

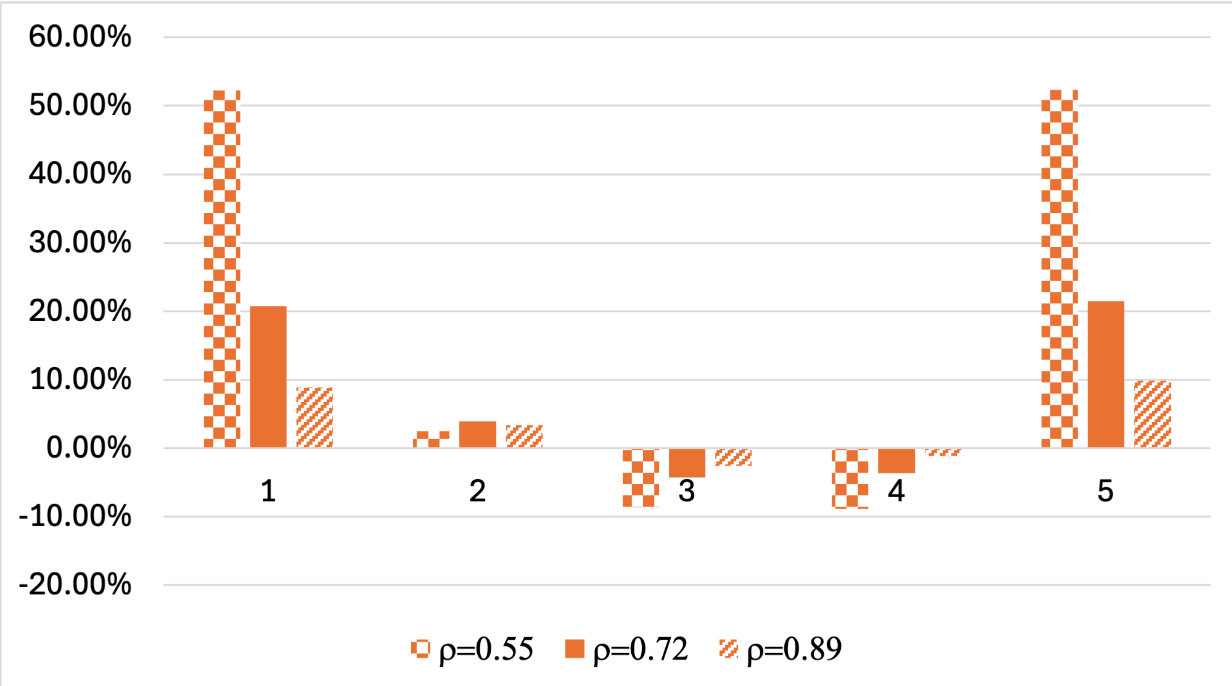
We take our benchmark value of ρ from DGG, which jointly estimates ρ along with the pre-COVID values of $\frac{A^h_{1,c}}{A^b_{1,c}}$, $\frac{A^h_{2,c}}{A^b_{2,c}}$, χ_1, χ_2, and $\mathcal{Z}$. To understand how the results change when ρ changes, we use the variance-covariance matrix of the jointly estimated parameters from DGG and draw 50,000 vectors of the jointly estimated parameters.

Table 7 reports the baseline values of $\frac{A^h_{1,c}}{A^b_{1,c}}$, and $\frac{A^h_{2,c}}{A^b_{2,c}}$ at the 5th and 95th percentiles of ρ along with the change in TFP required to get a fourfold increase in WFH for each value of ρ. The required productivity improvement is only 30-35% when WFH is more substitutable with work at the office than in the benchmark calibration. In contrast, when WFH is more complementary with work at the office, a very large increase in the TFP of WFH is necessary to generate a fourfold increase in WFH.

Figure 5 illustrates how the welfare changes between the LR and the pre-COVID baseline depend on the elasticity of substitution (EOS) of WFH with work at the office. As the EOS increases (ρ increases), the improvement in TFP falls such that the income gains of types 1 and 5 are smaller. The smaller income gains of types 1 and 5 in turn put less pressure on house prices even though the increase in WFH is the same between the baseline and the SR.[9] The gains to type 1 range from 9 to 52% of consumption while the losses to type 4 range from -1 to -9% of consumption. Type 2 sees the greatest benefit from the technology shock when ρ is at its benchmark value of 0.72. When ρ is lower, the increase in income for type 1 workers is sufficiently large that it mitigates the gains type 2 gets from the TFP shock.

[9]By construction, in all experiments we increase the relative TFP of WFH to generate a fourfold increase between the Baseline and the SR. In the LR, the quantity of WFH may differ slightly because different levels of relative productivity imply different externalities in WFH and work at the office.

Figure 5: LR Welfare Changes in the Model by Worker Type and ρ



Notes: 1) A type 5 worker is a worker in an IT occupation. 2) Types 1 and 2 are in telecommutable occupations other than IT. 3) Types 3 and 4 are in non-telecommutable occupations. 4) Types 1 and 3 have educational attainment of a four-year degree or greater; types 2 and 4 have lower educational attainment than a four-year degree. 5) The LR counterfactual allows the housing supply to adjust according to the elasticities estimated by Baum-Snow and Han (2024). 6) The elasticity of substitution between WFH and work at the office is $\frac{1}{1-\rho}$. 7) The welfare change shown is the percent increase in non-housing consumption required to generate the increase in expected values between the counterfactual and the pre-covid baseline. 8) The welfare change shown for type 5 workers is a lower bound because it weights ilk 5 and 6 by pre-pandemic shares of each within type 5 and the increase in welfare is slightly higher for ilk 6.

4.5 Sensitivity Analysis

4.5.1 Greater agglomeration in on-site production

In our benchmark parameterization, we set $\delta_b = 0.04$ based on estimates of the size of agglomeration economies at the city level. In Panel B of Table 8, we show the change in welfare, non-housing consumption, and housing consumption when we double the value of δ_b. In this case, the income of type 3 workers declines because of the decrease in their productivity. The welfare increases for types 1 and 5 are slightly lower than in the benchmark parameterization.

4.5.2 The role of remote workers

Eliminating remote workers. Panel C of Table 8 presents the changes in welfare, consumption, and income when we eliminate type 5 workers from the model such that there are no fully remote workers. The welfare results are similar to our benchmark parameterization. The main change is that the increase in housing demand is slightly more muted and the fall in office rents less severe. Because office rents don't fall by quite so much in the absence of remote workers, labor productivity rises by less for type 3 and 4 workers such that the increases in their incomes are smaller.

Increasing the number of remote workers. In Panel D of Table 8, we reassign half of the workers that were type 1s in our benchmark parameterization to be type 5s. For example, instead of 30% of workers in Dallas being type 1s and 7.3% of workers being type 5s (see Table 1), in Panel D we show the results when 15% of workers in Dallas are type 1s and 22.3% of workers are type 5s. Despite this significant increase in the share of remote workers, the welfare changes are quite similar to those in our benchmark parameterization shown in Panel A.

Locational productivity of remote workers. Panels D and E of Table 8 show the results when we change the share of productivity that remote workers get from the city in which they live. In our benchmark parameterization, we set $\lambda = 0.5$ such that 50% of the TFP of fully remote workers comes from the city in which they live and 50% comes from the national average (see equation (29)). The results for both $\lambda = 0.2$ and $\lambda = 0.8$ are quantitatively quite similar to our benchmark parameterization. When

Table 8: Sensitivity Analysis: Change from Baseline to LR

Worker Type	Welfare	Non-Housing Consumption	Housing Consumption	Income
Panel A: Benchmark Parameterization				
1	20.8%	19.6%	-0.3%	18.2%
2	3.9%	6.2%	-12.1%	5.4%
3	-4.3%	1.4%	-16.6%	1.4%
4	-3.7%	3.3%	-15.4%	3.1%
5	21.4%	5.6%	-8.7%	3.4%
Panel B: $\delta_b = 0.08$				
1	18.5%	17.5%	-0.9%	16.3%
2	4.5%	6.5%	-11.6%	5.6%
3	-6.2%	-0.4%	-17.2%	-0.4%
4	-3.1%	3.6%	-14.8%	3.4%
5	19.1%	3.9%	-9.5%	1.8%
Panel C: No Type 5 Workers				
1	21.4%	19.4%	0.9%	18.0%
2	3.7%	5.5%	-11.5%	4.6%
3	-4.4%	0.9%	-16.0%	0.8%
4	-4.2%	2.4%	-15.1%	2.2%
5				
Panel D: More Type 5 Workers				
1	19.7%	19.8%	-2.4%	18.5%
2	4.8%	8.0%	-12.8%	7.1%
3	-4.0%	2.5%	-17.6%	2.4%
4	-2.3%	5.4%	-15.5%	5.1%
5	20.4%	7.5%	-10.4%	5.5%
Panel E: $\lambda = 0.2$				
1	20.7%	19.6%	-0.4%	18.3%
2	3.9%	6.2%	-12.2%	5.3%
3	-4.3%	1.4%	-16.8%	1.3%
4	-3.7%	3.3%	-15.5%	3.1%
5	21.4%	6.3%	-7.1%	4.1%
Panel F: $\lambda = 0.8$				
1	20.8%	19.6%	-0.2%	18.2%
2	4.0%	6.3%	-11.9%	5.4%
3	-4.3%	1.4%	-16.5%	1.4%
4	-3.6%	3.3%	-15.2%	3.1%
5	21.5%	4.8%	-10.5%	2.7%

Notes: 1) In Panel B, we increase the strength of the agglomeration in productivity from in-person work from $\delta_b = 0.04$ (the benchmark parameterization) to $\delta_b = 0.08$. 2) In Panel C, we reassign all type 5 workers to be type 1 workers. 3) In Panel D, we reassign half of the type 1 workers in each city to be type 5 workers. 4) In Panels E and F, we change the share of fully remote workers' TFP that they get from the city they live in. 5) The welfare change shown is the percent increase in non-housing consumption required to generate the increase in expected values between the counterfactual and the pre-covid baseline. 6) The welfare change shown for type 5 workers is a lower bound because it weights ilk 5 and 6 by pre-pandemic shares of each within type 5 and the increase in welfare is slightly higher for ilk 6.

we decrease the share of productivity coming from the city in which they live ($\lambda = 0.2$), the income of remote workers rises slightly more.

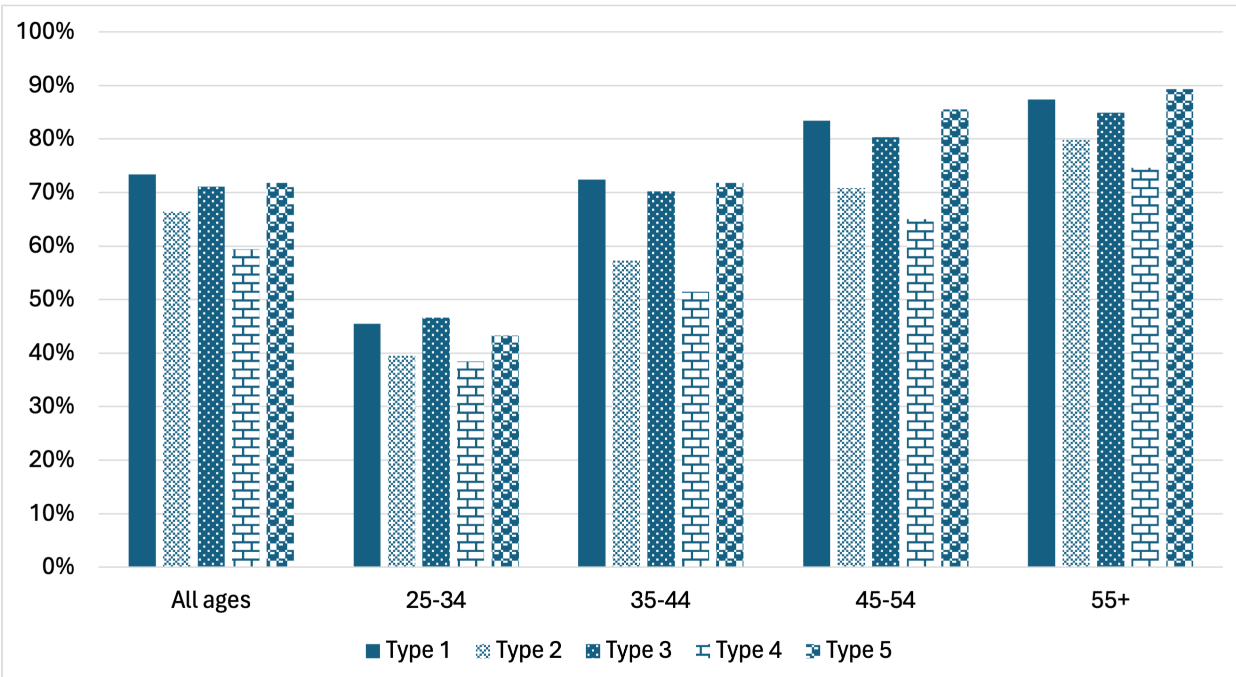
4.6 Rent Leakage

As is standard in urban economics models, households in the model have no wealth nor do they have a future liability of rents they must pay for the rest of their life (Sinai and Souleles, 2005). All households are renters. Given that an increase in home prices benefits older homeowners, who have a smaller liability of future rents, it is worth examining tenure status by worker type in the data to better understand who loses from the increase in rents. If workers in non-telecommutable occupations disproportionately own their homes, and thus see their wealth rise from the higher rents, the increase in home prices would not harm them as the model predicts.

Figure 6 shows the home ownership rate by worker type and age in the 2015-2019 5-year ACS for the sample of workers we use to calibrate the model (see Section 3). Type 4s have the lowest home ownership rate, suggesting they are most harmed by the increase in rent. Furthermore, type 3 and 4s under the age of 35 are predominantly renters and so are unambiguously hurt by the increase in rents. Given that many type 3 and 4s in older age cohorts are homeowners, and further that young households always have larger future rent liabilities, the reduction in welfare is predominantly for younger type 3 and 4s.

Though our model does not feature tenure choice, the model of Richard (2024) does. That paper finds that increased WFH creates welfare losses for workers in nontelecommutable occupations (see Table 10 of Richard (2024)). Even homeowners experience welfare losses in that model. The intuition for that result is that, although their asset appreciates in value, when housing preferences change, either locationally or due to size, homeowners must pay more for the new house and thus have less flexibility. While Richard (2024) has a simpler geography than ours, her results suggest that our finding regarding welfare loss would generalize to a model with richer geography and tenure choice.

Figure 6: Home Ownership Rates by Worker Type and Age

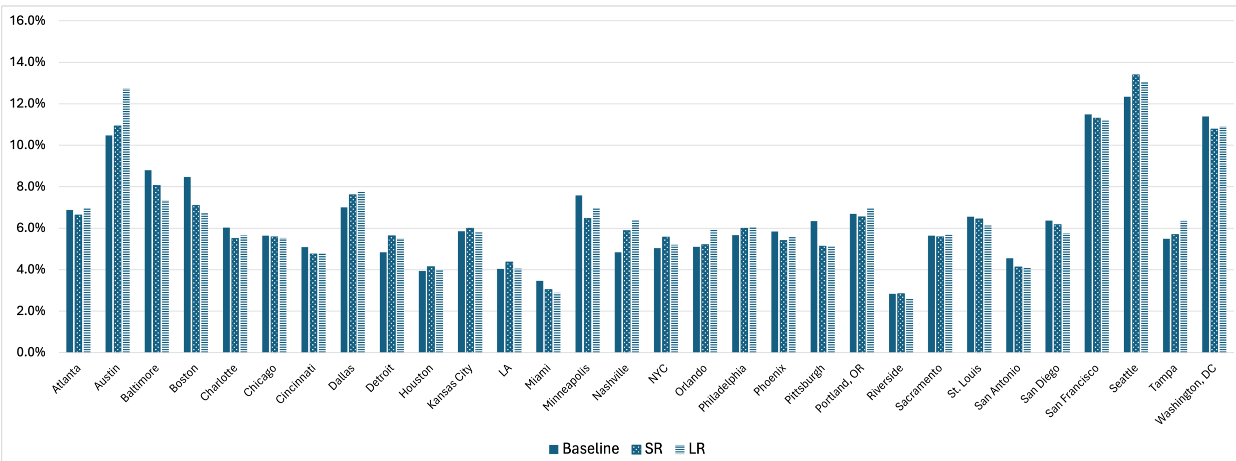


Notes: 1) A type 5 worker is a worker in an IT occupation. 2) Types 1 and 2 are in telecommutable occupations other than IT. 3) Types 3 and 4 are in non-telecommutable occupations. 4) Types 1 and 3 have educational attainment of a four-year degree or greater; types 2 and 4 have lower educational attainment than a four-year degree.

4.7 Which Cities do Type 5 Workers Choose?

The technology improvement induces a large increase in IT workers choosing to be remote such that it could cause large flows across MSAs as these workers are now free to choose a different city from the one in which their employer is located. Figure 7 shows that there are only modest changes in the share of type 5s in the population of each city between the baseline and the two counterfactuals.

Figure 7: Share of City Population Accounted for by Type 5 Workers



Notes: 1) A type 5 worker is a worker in an IT occupation. 2) Baseline is 2019 ACS data. 3) SR is 2022 ACS data. 4) LR is model projection.

Another way of considering whether the intercity relocation patterns of remote workers are quantitatively important for city population dynamics is to look at how their population patterns compare to the population as a whole. Table 9 shows the share of type 5s choosing each city in the baseline, in the SR, and the LR, along with the share of total population excluding IT workers choosing each city. Directionally, type 5 workers tend to move to and move away from the same cities that other types are moving to and from. The magnitude of the population changes is higher for IT workers however: the standard deviation of the LR from baseline change is about 0.5 percentage points for type 5s while it is 0.2 percentage points for the rest of the population. Thus, while remote workers are more mobile than the rest of the population, consistent with the findings of Bick, Blandin, Mertens, and Rubinton (2024), there are important population flows between 2022 and 2019 that cannot be accounted for by remote workers.

Table 9: Changes in City Population Shares

	Type 5 Share in City				Pop. Ex. Type 5 Share in City			
	(1) Baseline	(2) SR	(3) LR	(4) LR Change	(5) Baseline	(6) SR	(7) LR	(8) LR Change
Atlanta	4.7%	4.9%	5.3%	0.6%	4.2%	4.6%	4.7%	0.5%
Austin	2.8%	3.6%	4.4%	1.7%	1.6%	1.9%	2.0%	0.4%
Baltimore	2.7%	2.3%	2.1%	-0.6%	1.9%	1.7%	1.7%	-0.1%
Boston	4.7%	3.4%	3.1%	-1.6%	3.4%	2.9%	2.8%	-0.5%
Charlotte	1.8%	1.7%	1.7%	-0.1%	1.9%	1.9%	1.9%	0.1%
Chicago	5.9%	5.9%	5.8%	-0.1%	6.5%	6.6%	6.6%	0.1%
Cincinnati	1.2%	1.2%	1.3%	0.1%	1.5%	1.7%	1.7%	0.2%
Dallas	5.9%	6.7%	6.9%	1.0%	5.2%	5.4%	5.4%	0.2%
Detroit	2.2%	2.5%	2.5%	0.3%	2.9%	2.8%	2.8%	-0.1%
Houston	3.0%	3.1%	3.0%	0.0%	4.9%	4.8%	4.8%	-0.1%
Kansas City	1.5%	1.5%	1.4%	0.0%	1.6%	1.5%	1.5%	0.0%
LA	5.4%	5.8%	5.3%	-0.1%	8.5%	8.4%	8.3%	-0.2%
Miami	2.2%	1.9%	1.8%	-0.3%	4.1%	4.1%	4.1%	0.1%
Minneapolis	3.2%	2.8%	3.1%	-0.1%	2.6%	2.7%	2.7%	0.1%
Nashville	1.2%	1.4%	1.6%	0.4%	1.5%	1.5%	1.5%	0.0%
NYC	10.9%	11.8%	11.0%	0.1%	13.7%	13.4%	13.3%	-0.3%
Orlando	1.3%	1.6%	1.9%	0.6%	1.7%	1.9%	2.0%	0.3%
Philadelphia	3.7%	3.9%	3.9%	0.2%	4.1%	4.0%	4.0%	-0.1%
Phoenix	2.9%	2.7%	2.8%	-0.1%	3.2%	3.2%	3.2%	0.0%
Pittsburgh	1.7%	1.4%	1.5%	-0.2%	1.6%	1.8%	1.8%	0.1%
Portland, OR	1.9%	1.7%	1.8%	-0.1%	1.7%	1.7%	1.6%	-0.1%
Riverside	1.1%	1.2%	1.0%	-0.1%	2.6%	2.6%	2.6%	0.0%
Sacramento	1.3%	1.3%	1.4%	0.0%	1.5%	1.5%	1.5%	0.0%
St. Louis	2.1%	2.2%	2.1%	0.0%	2.0%	2.1%	2.2%	0.2%
San Antonio	1.1%	1.0%	1.0%	-0.1%	1.5%	1.5%	1.5%	0.0%
San Diego	2.1%	1.7%	1.5%	-0.6%	2.0%	1.7%	1.6%	-0.4%
San Fran	6.0%	5.5%	5.4%	-0.6%	3.1%	2.9%	2.9%	-0.2%
Seattle	5.8%	5.7%	5.5%	-0.2%	2.7%	2.5%	2.4%	-0.3%
Tampa	1.8%	2.0%	2.2%	0.4%	2.1%	2.2%	2.2%	0.1%
DC	8.1%	7.5%	7.8%	-0.3%	4.2%	4.1%	4.2%	0.0%
Std. Dev.				0.54%				0.23%

Notes: 1) Columns (1)-(3) show share of US population of Type 5 (IT workers) choosing each city in baseline (2019), SR (2022), and LR (model prediction). 2) Columns (5)-(7) show share of US population excluding type 5 workers choosing each city.

5 Conclusions

We examine the welfare implications of technological improvement that only increases the productivity of workers in telecommutable occupations. We find that this improvement decreases the welfare of workers in non-telecommutable occupations despite their incomes increasing slightly. Because younger workers have higher future rent liabilities due to their long expected lifespans, and they are more likely to be renters, young workers in non-telecommutable occupations incur the biggest losses.

We find that, after the pandemic, workers in non-telecommutable occupations migrate to similar cities as those in telecommutable occupations. A limitation of our quantitative model, however, is that we use changes in city-level amenities specific to each type of worker to replicate these changes in population. The increase in cross-MSA migration is an important feature of the United States post-pandemic. Empirical work suggests that increased WFH plays a role (e.g., Bick et al., 2024; Haslag and Weagley, 2024), but does not predict which cities specific worker types will move to or away from. A more microfounded explanation of the migration patterns of each city and of each type of worker is required. We leave this task to future research.

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