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

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Abstract

We model how productivity improvement in Work-from-Home (WFH) differentially affects workers using a framework in which some workers cannot work offsite at all, some workers can work hybrid work schedules, and some workers are completely remote. WFH significantly increases housing demand by workers in telecommutable occupations and, because housing is inelastically supplied, substantially increases housing prices. Because workers in non-telecommutable occupations must consume housing but their total factor productivity does not increase, technological progress worsens welfare for some workers. The fall in welfare comes despite measured income increasing slightly for the same workers whose welfare falls.

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

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

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1 Introduction

The widespread adoption of Work-From-Home (WFH) technology during the COVID-19 pandemic has major consequences for where people live and work, incomes, and rents. The most robust effect is that it increased residential housing prices by increasing the demand for residential space to produce output.[1] Further, the improvement in WFH technology directly increased the productivity only of those workers in telecommutable occupations (Behrens, Kichko, and Thisse, 2024; Davis, Ghent, and Gregory, forthcoming).

In this paper, we extend the model of Davis et al. (forthcoming) to study how this skill-biased technological improvement differentially affects workers. In particular, some workers cannot work off-site all, some can work entirely remotely (remote workers), and some workers can choose to work a hybrid schedule where they still need to live in the same city as their employer is located (hybrid workers). All workers choose both which city to live in along with where to live within a city. We calibrate the model to match the change in worker choices of city, location within a city, and, for workers in occupations that can be done entirely remotely, the change in the share of workers that choose to be remote.

The technological improvement that increases the amount of both hybrid and remote work leads to large increases in income and welfare for workers in telecommutable occupations consistent with the way an increase in total factor productivity works in most economic models. However, the technology improvements leads to a decrease in welfare for some workers because of the increase in housing prices. The productivity increase raises home prices in two ways. First, worker in telecommutable occupations increase their housing demand because their earnings increase. Second, the demand for residential space increases because of its increased use in production. With inelastic housing supply, the rise in home prices is substantial. All workers must consume housing at the higher price and this lowers expected utility for workers in non-telecommutable occupations.

While all workers in non-telecommutable occupations are harmed by the technological progress, quantitatively, the welfare loss is larger for college educated workers in the long run than for non-college educated workers. Although non-college educated

[1] See, for example, Delventhal and Parkhomenko (2022), Gupta, Mittal, Peeters, and Van Nieuwerburgh (2022), Howard, Liebersohn, and Ozimek (2023), Davis et al. (forthcoming), and the review Van Nieuwerburgh (2023) provides.

households have a higher expenditure share on housing, and are thus more affected by the rise in home prices, college-educated households in non-telecommutable occupations see a reduction in total factor productivity (TFP) because of a decrease in agglomeration economies in production. The fall in agglomeration economies happens because skilled workers work in-person less frequently as WFH becomes more productive.

Our prediction for the increase in residential rents and the decrease in office rents is well-matched by the data. 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 suggest. 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 suggests a 12-13% decrease in real office rents between 2019 and 2022.

The share of workers that choose 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 also disproportionately increase housing prices because they do all their work at home. 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 model predicts that the share of workers that are remote will rise by an additional 25 percentage points in the long run relative to what we calibrate to in 2022.

While a long literature has documented the tendency of skill-biased technology to excerbate income inequality (Krussel, Ohanian, Rios-Rull, and Violante, 2000; Violante, 2008; Beaudry, Doms, and Lewis, 2010), ours is the first paper to document that an improvement in productivity can actually harm some types of workers in absolute terms rather than merely worsen their relative position. The feature of the model that generates this result is that an inelastically supplied good, housing in this case, must be consumed by all households and yet the productivity improvement can be largely consumed by the same households whose productivity increases.

We also contribute to the modeling of WFH on the labor market and the spatial allocation of workers. Davis et al. (forthcoming), Behrens et al. (2024), and Delventhal and Parkhomenko (2022) model only hybrid WFH while Brueckner, Kahn, and Lin (forthcoming) 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 in the short- and long-run. Section 5 concludes.

2 Model

2.1 Overview

We extend the model of Davis et al. (forthcoming) to study the implications of improvement in WFH productivity for different cities. In Davis et al. (forthcoming), no workers were 100% remote. Rather, a subset of workers in Davis et al. (forthcoming) had the option to choose a firm that allowed a hybrid work schedule where some work could be done off-site. Here, we introduce a new type of worker that is primarily remote. We also allow for heterogeneity in occupational shares, productivities of different types of workers, the rent gradient, and commuting times. The remainder of this section draws heavily on Davis et al. (forthcoming). We take some wording directly from Davis et al. (forthcoming) to avoid confusing the reader with different notation or verbiage to describe the same concepts. Davis et al. (forthcoming) provides additional details on the model including the solution.

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 household 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 have to 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 these workers as simply remote.

2.2 Households

Taking their type as given, households in the model make a set of choices in a given sequence to maximize expected utility. First, type 5 workers choose whether or not to be remote. If they choose *not* to be remote, they decide whether or not 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 choosing 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 and 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 or not to be remote by choosing the max of the following:

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

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 that 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 types of workers after the remote decision has been made. Type 1 through 4 workers are indexed by $\iota = 1, 2, 3, 4$. Type 5 workers that choose not to be remote are indexed by $\iota = 5$ while type 5 workers that choose to be remote are indexed by $\iota = 6$. We refer to ι as the individual's ilk.

Once type 5 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

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

where $\tilde{e}_{\iota,j,c}$ is an iid Type 1 Extreme Value shock specific to household j living in city c. Note that for each ilk ι we have defined V_ι (as used in equation 1) as the expected value of equation (2). $\tilde{a}_{\iota,c}$ pins down the average population, by type, 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. For each ilk, we denote the expected value of this decision before the $\tilde{e}_{\iota,c,j}$ are drawn as V_ι, and this is what enters equation (1) for type 5.

2.2.3 Within-city location decision

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, choosing to live in location n at the start of the period, receives utility equal to

$$V_{n\iota cj} \;=\; \underbrace{\nu\left[a_{n,\iota,c} + X_{n\iota c}\right]}_{\equiv V_{n\iota c}} \;+\; e_{n,\iota,c,j}. \tag{3}$$

$a_{n,\iota,c}$ are amenities enjoyed by all ilk ι households living in location n of city c and $e_{n,\iota,c,j}$ are amenities from living in location n of city c by ilk ι households that are specific to household j. We assume $e_{n,\iota,c,j}$ 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 $e_{n,\iota,c,j}$.

Household j chooses the location that provides the maximum utility. Define $V_{\iota c} = \ln \sum_{n=1}^{N} e^{V_{n\iota c}}$. Before any of the values of $e_{n\iota cj}$ are realized, the probability that a household of ilk ι chooses location n', $f_{n'\iota c}$, is

$$f_{n'\iota c} \;=\; \frac{e^{V_{n'\iota c}}}{e^{V_{\iota c}}}.$$

2.2.4 Determining $X_{n\iota c}$ for Households in Telecommuting Occupations

After choosing where to live, households working in teleworkable occupations choose whether to work for a non-WFH firm or a hybrid 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 WFH firm. A household j of ilk $\iota = 1$, $\iota = 2$, or $\iota = 5$ living in location n of city c and working for a firm of type $\kappa \in 0, 1$ receives the following utility

$$X^{\kappa}_{n\iota cj} \;=\; X^{\kappa}_{n\iota c} \;+\; (1/\zeta)\, \epsilon^{\kappa}_{n\iota cj}\;. \tag{4}$$

As specified, the utility of households living in n 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, all of which may vary across type of firm κ, given location n, city c, and household type ι. $\epsilon^{\kappa}_{n\iota cj}$ 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. 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.

A household j living in location n of city c and of ilk $\iota = 1$, 2, or 5 chooses to work for the type of firm offering the highest value of $X^{\kappa}_{n\iota cj}$. Before the values of $\epsilon^{\kappa}_{n\iota cj}$ are realized, the probability that a household living in n works for a particular firm of type κ', $g^{\kappa'}_{n\iota c}$, is equal to

$$g^{\kappa'}_{n\iota c} = \frac{e^{\zeta X^{\kappa'}_{n\iota c}}}{e^{\aleph_{n\iota c}}} \quad \text{where} \quad \aleph_{n\iota c} = \ln \sum_{\kappa=0}^{1} e^{\zeta X^{\kappa}_{n\iota c}}. \tag{5}$$

The expected value of living in location n of city c after the location choice has been made but before $\epsilon^{\kappa}_{n\iota cj}$ is realized is

$$X_{n\iota c} = (1/\zeta)\left(\aleph_{n\iota c} + \Gamma\right)$$

where Γ is Euler's constant.

Utility when employed by a non-WFH firm. Households of ilk $\iota = 1$, 2, or 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

$$X^0_{n\iota c} = (1-\alpha_\iota)\ln c^0_{n\iota c} + \alpha_\iota \ln h^0_{n\iota c} + \psi \ln \ell^0_{n\iota c} \tag{6}$$

subject to the budget and time constraints of

$$\begin{aligned} 0 &= \left(w^0_{\iota,c} - \tau_n\right) b^0_{n\iota c} - c^0_{n\iota c} - r_{n,c} h^0_{n\iota c} \\ 0 &= 1 - (1 + t_{n,c})\, b^0_{n\iota c} - \ell^0_{n\iota c}. \end{aligned} \tag{7}$$

In equations (6) and (7), the 0 superscripts denote that the household works at a non-WFH firm ($\kappa = 0$), and $w_{\iota c}^0$ 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.[2] A household of ilk ι living in location n supplying $b_{n\iota c}^0$ fraction of a full year of labor earns a net annual income of $\left(w_{\iota,c}^0 - \tau_n\right) b_{n\iota c}^0$. The household spends this labor income on consumption, $c_{n\iota c}^0$, and housing, $h_{n\iota c}^0$. 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 $b_{n\iota c}^0$ percentage of the year working is $1-(1+t_{n,c})\, b_{n\iota c}^0$, where $t_{n,c}$ is the round-trip time spent commuting from location n in city c.

In Davis et al. (forthcoming), we show that optimal household choices satisfy

$$
\begin{aligned}
\ell_{n\iota c}^0 &= \frac{\psi}{1+\psi} \\
b_{n\iota c}^0 &= \left(\frac{1}{1+\psi}\right)\left(\frac{1}{1+t_{n,c}}\right) \\
c_{n\iota c}^0 &= (1-\alpha_\iota)\left(w_{\iota,c}^0 - \tau_n\right) b_{n\iota c}^0 \\
r_{n,c} h_{n\iota c}^0 &= \alpha_\iota \left(w_{\iota c}^0 - \tau_n\right) b_{n\iota c}^0.
\end{aligned}
$$

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 WFH 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, $l_{n\iota c}^b$, (b) the percentage of total time in the year to work at home, $l_{n\iota c}^h$, (c) the size of the home office, $s_{n\iota c}^h$, and (d) the amount of equipment and software to rent for use in the home office, $k_{n\iota c}^h$. Notice that these four choice variables do not have a κ superscript, as these choices are only available to households working at a WFH firm. These choices determine the gross compensation offered by a WFH firm to the household; we denote this gross compensation function as $\omega_{\iota,c}\left(l_{n\iota c}^b, l_{n\iota c}^h, s_{n\iota c}^h, k_{n\iota c}^h\right)$.

Households of ilk ι living in n and working at a hybrid firm ($\kappa = 1$) make choices

[2] While 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).

to maximize

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

The 1 superscripts denote that the household works at a WFH firm ($\kappa = 1$). 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 that affect the desirability of working at a hybrid vs. a non-WFH firm. We include χ_ι in utility to allow the model to match employment shares at non-WFH and hybrid firms.

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 renting a home office and home equipment is costly, i.e.,

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

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 the worker lives in, and the amounts of business equipment and home office space, all of which affect worker productivity.

2.2.5 $X_{n\iota c}$ for Households in Non-Telecommuting Occupations

Households of type 3 or 4 work in an occupation that does not allow telecommuting and solve a problem similar to that of households that work in a telecommuting occupation but choose to work for a non-WFH firm. Type 3 and 4 households choose consumption, housing, and leisure to maximize

$$X_{n\iota c} \quad = \quad (1-\alpha_\iota)\ln c_{n\iota c} + \alpha_\iota \ln h_{n\iota c} + \psi \ln \ell_{n\iota c}$$

subject to budget and time constraints of

$$\begin{array}{rcl} 0 & = & (w_{\iota,c} - \tau_n)\, b_{n\iota c} - c_{n\iota c} - r_{n,c} h_{n\iota c} \\ 0 & = & 1 - (1+t_{n,c})\, b_{n\iota c} - \ell_{n\iota c}. \end{array}$$

The optimal solutions satisfy

$$
\begin{aligned}
\ell_{n\iota c} &= \frac{\psi}{1+\psi} \\
b_{n\iota c} &= \left(\frac{1}{1+\psi}\right)\left(\frac{1}{1+t_{n,c}}\right) \\
c_{n\iota c} &= (1-\alpha_\iota)\left(w_{\iota c}-\tau_n\right) b_{n\iota c} \\
r_{n,c} h_{n\iota c} &= \alpha_\iota \left(w_{\iota,c}-\tau_n\right) b_{n\iota c}.
\end{aligned}
$$

As indicated by the ι subscript, the wage for these households may differ from the wage for households of the same skill level that have a telecommuting option but choose to work for a non-WFH firm.

2.2.6 Type 5 households working remotely

Fully remote households own their own firms and produce output

$$
y_{n6c} = Z_{6,c}\left(l_{n6c}\right)^{\theta_b}\left(k_{n6c}\right)^{\theta_k}\left(s_{n6c}\right)^{\theta_s} \tag{8}
$$

where l_{n6c} is days of work, k_{n6c} is capital used , and s_{n6c} is home-office space. Households choose l_{n6c}, k_{n6c}, and s_{n6c} to maximize

$$
\max_{c_{n6c}, h_{n6c}, \ell_{n6c}, y_{n6c}, l_{n6c}, s_{n6c}, k_{n6c}} \left\{ \ (1-\alpha)\ln c_{n6c} + \alpha \ln h_{n6c} + \psi \ln \ell_{n6c} \ \right\}
$$

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

$$
0 = \mu_c\left[y_{n6c} - c_{n6c} - r_{n,c}\left(h_{n6c} + s^h_{n6c}\right) - r^k k^h_{n6c}\right] \tag{9}
$$

$$
0 = \mu_l\left[1 - l_{n6c} - \ell_{n6c}\right] \tag{10}
$$

$$
0 = \mu_h\left[Z_{6,c}\left(l_{n6c}\right)^{\theta_b}\left(k_{n6c}\right)^{\theta_k}\left(s_{n6c}\right)^{\theta_s} - y_{n6c}\right]. \tag{11}
$$

The first-order conditions are

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

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

$$\mu_c\left[c_{n6c}+r_{n,c}h_{n6c}\right] = 1. \tag{12}$$

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

$$\mu_c\left[r^k k_{n6c}+r_{n,c}s_{n6c}\right] = \mu_c y_{n6c}\left(1-\theta_b\right). \tag{13}$$

Adding equations (12) and (13) together and imposing the budget constraint implies

$$\mu_c\theta_b y_{n6c} = 1. \tag{14}$$

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

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

where the second equality uses equation (14). 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.,

$$\ell_{n6c} = \frac{\psi}{1+\psi} \text{ and } l_{n6c} = \frac{1}{1+\psi}. \tag{15}$$

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

$$k_{n6c} = \left(\frac{\theta_k}{\theta_s}\right)\left(\frac{r_{n,c}}{r_k}\right)s_{n6c}. \tag{16}$$

Insert equation (16) 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

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

rwhich we rearrange and reduce to get

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

Note that since equation (15) determines l_{n6c}, all the variables on the right-hand side are known and thus s_{n6c} is known. From equation (16), once we know s_{n6c} we know k_{n6c}, and this implies from the production function that y_{n6c} is known. 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.

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

(18) $$\begin{aligned} & y_{n\iota c} - w_{\iota,c}b_{n\iota c} - r^k k_{n\iota c} - r_c^o s_{n\iota c} \\ \text{where} \quad & y_{n\iota c} = Z_{\iota,c} b_{n\iota c}^{\theta_b} k_{n\iota c}^{\theta_k} s_{n\iota c}^{\theta_s}. \end{aligned}$$

$w_{\iota c}$ 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

The firm maximizes profits by setting

$$
\begin{aligned}
w_{\iota,c} b_{n\iota c} &= \theta_b y_{n\iota c}, && (19)\\
r^k k_{n\iota} &= \theta_k y_{n\iota c}, && (20)\\
r^o_c s_{n\iota} &= \theta_s y_{n\iota c}. && (21)
\end{aligned}
$$

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

$$
y_{n\iota c} = \left[\left(\frac{\theta_k}{r^k} \right)^{\frac{\theta_k}{\theta_b}} \left(\frac{\theta_s}{r^o_c} \right)^{\frac{\theta_s}{\theta_b}} \left(Z_{\iota,c} \right)^{\frac{1}{\theta_b}} \right] b_{n\iota c}. \tag{22}
$$

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 $\theta_s y_{n\iota c}/r^o_c$.

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

$$
y_{n\iota c} = \left[\left(y^b_{n\iota c} \right)^\rho + \left(y^h_{n\iota c} \right)^\rho \right]^{1/\rho} \tag{23}
$$

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

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

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

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

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 ilk 1, 3, and 5 days worked on-site; 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

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

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 $\bar{A}^b_{\iota,c}$.[3]

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

$$A^h_{\iota,c} \quad = \quad \bar{A}^h_{\iota,c}\left(L^{max}_h\right)^{\delta_{\iota,h}} \tag{24}$$

where L^{max}_h is the maximum amount of time that households in aggregate spent working at home in any previous year. Equation (24) 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

$$Z_{6,c} = \phi(\lambda Z_{1,c} + (1-\lambda)Z_1) \tag{25}$$

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 that are entirely on site in that particular city and a portion of the national average of the onsite 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.

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^o_c; housing and home office space in locations $1, \dots N$ for each city c, $r_{n,c}$; a wage rate for each ilk of worker $\iota = 1, \dots, 5$ working at a non-WFH firm in each city, $w^0_{\iota,c}$; a wage function $\omega_{\iota,c}\left(l^b_{n\iota c}, l^h_{n\iota}, s^h_{n\iota c}, k^h_{n\iota c}\right)$ for each ilk of worker

[3] 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.

$\iota = 1, 2, 5$ 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 and all wages and prices and subject to 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, and all prices and subject to budget and time constraints,
- type 5 households maximize utility by choosing whether or not to be fully remote. If a type 5 household chooses to be fully remote, it 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 fully remote, it then makes the same choices as a type 1 household to maximize utility.
- 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 eight 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 (forthcoming).

We select our sample of cities from the 30 most populous US cities as of 2019 that are 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 Denver despite it being a large metro area by population. 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 and that are at least 25 years old. We classify all workers that work in an IT occupation as type 5 regardless of their educational attainment. 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 where the household head has at least a four-year college degree. A household is defined as working in a telecommutable occupation when the 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 CBD county. 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 sourcefor the Phoenix and Boston 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 occured 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 (22) and (19) 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

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

We find $A_{\iota,c}$ by imposing $A^b_{1,c} = \mathcal{Z} Z_{1,c}$ and $A^b_{2,c} = \mathcal{Z} Z_{2,c}$ where $\mathcal{Z}$ is determined as described in Davis et al. (forthcoming).

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 (25).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;
- The total number of households in each city.

Table 1 shows the share of worker types in each city as 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 2 lists the city amenity values for each type. 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 while Boston, New York City, and San Diego are attractive to all types. Sunny cities typically have higher amenity values for all type while rustbelt cities such as Detroit, Cincinnati, and St. Louis have lower amenity values.

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 that 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, Types 2 and 4 have lower educational attainment than a four-year degree. 6) Cities shown correspond to CBSA definitions. 7) All data is from 2019 5-year ACS which pools data from five years up to and including 2019.

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.

Parameters common to all cities. We take several parameters that do not vary across cities from Davis et al. (forthcoming). In particular, we set

- $\psi = 1.15$
- $\nu = 3.3$
- $\frac{1}{\zeta} = 0.0634$
- $\chi_1 = 0.158$,
- $\chi_2 = 0.064$,
- $\rho = 0.719$,
- $\mathcal{Z} = 0.889$,
- $\delta_b = 0.04$,
- $\gamma = -0.15$,
- $\theta_k = 0.15$,
- $\theta_s = 0.18$,
- $\frac{A^h_{1,c}}{A^b_{1,c}} = 0.365$,
- $\frac{A^h_{2,c}}{A^b_{2,c}} = 0.348$,
- $\tau_1 =$\$5,417, and
- $\tau_2 =$\$13,542.[4]

We calculate housing expenditure shares by type by taking the median ratio of gross rent to family income for households of that type in the ACS. We find $\alpha_1 = 0.22$, $\alpha_2 = 0.27$, $\alpha_3 = 0.24$, $\alpha_4 = 0.29$, and $\alpha_5 = 0.18$.

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 $\nu_r = \frac{1}{\zeta}$.

[4] While financial commuting costs likely vary across cities in the same was as time commuting costs do, the AHS sample size is too small for us to obtain city-specific estimates of these parameters.

3.4 Counterfactuals

We consider two counterfactuals, a short-run counterfactual and a long-run counterfactual. Our short-run counterfactual is one in which we 1) impose the WFH productivity increase necessary to generate a fourfold increase in the number of days of WFH from hybrid workers, as we do in Davis et al. (forthcoming), 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, 3) allow the city-specific amenities to change to generate the cross-sectional in city population observed between 2019 and 2022.[5]

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

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

from their baseline levels of 0.365 and 0.348. We increase ϕ by 20.6% from its baseline level such that the fraction of type 5's that choose to be remote increases from 11.7% to 50.6%, which is what we observe in the 1-year ACS for 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, space adjusts in accordance with the residential elasticities in Baum-Snow and Han (forthcoming) and people choose whichever MSA gives them the highest utility. We set the elasticity of office supply to 0.1 in all cities in our long-run counterfactual.

[5]In the data, there is a large absolute decrease in US population due to the effects of COVID on mortality and the birth rate as well as 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.

4 Results

4.1 Rent Predictions

As current data on incomes and population flows do not capture the post-pandemic period we are most interested in, particularly 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 long-run implications of the improvement in WFH technology.

Office rents We compare the change in real effective office rents predicted by our model with 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

$$r_{i,t} = \beta_{post} postwfhboon_{i,t} + \beta_x X_{i,t} + \epsilon_{i,t} \tag{26}$$

where $r_{i,t}$ is the log of effective rents per square foot. In equation 26, $X_{i,t}$ 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 expense), 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, 0 otherwise. The coefficient on $postwfhboon_{i,t}$ thus measures the percent decline in office rents pre- to post-pandemic.

Table 3 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)).

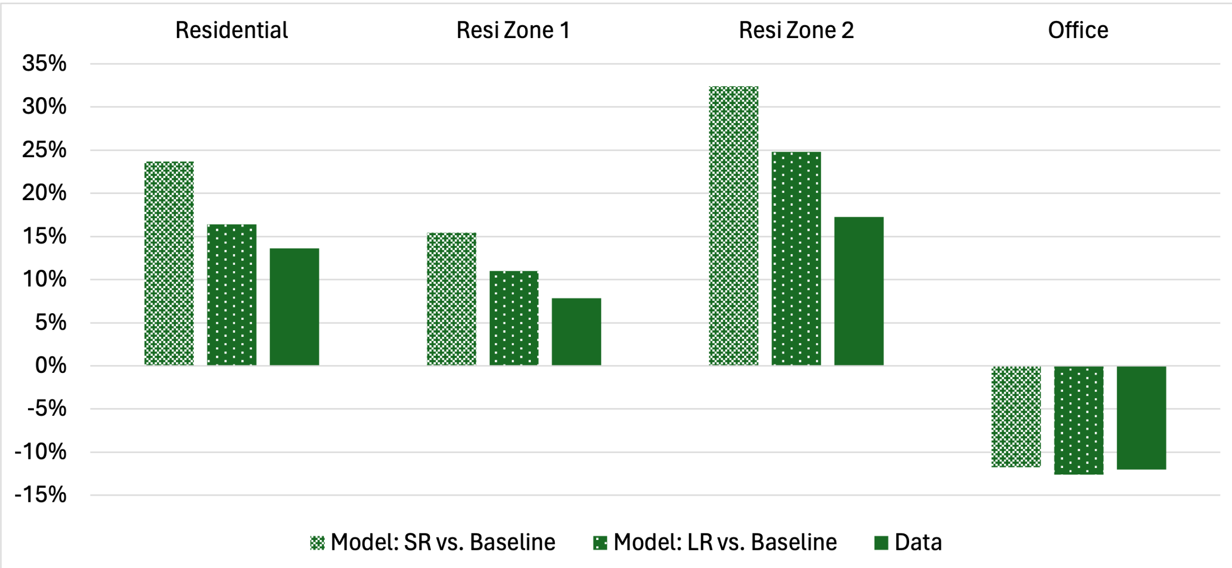
Table 3: Change in Real Office Rents 2019-2022

	(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.

Figure 1 compares the predictions of the model to those from the regression presented in Table 3. 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 an 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 (26).

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 and Ortalo-Magné, 2011). Figure 1 shows the increase in implied rents in each city between 2019 and 2023 and compares them to the model prediction for the SR and the LR. The model slightly overpredicts the aggregate rise in residential rents relative to the data. 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 locational demand for Zone 2 given less workers come into the office less frequently.

4.2 Welfare Predictions

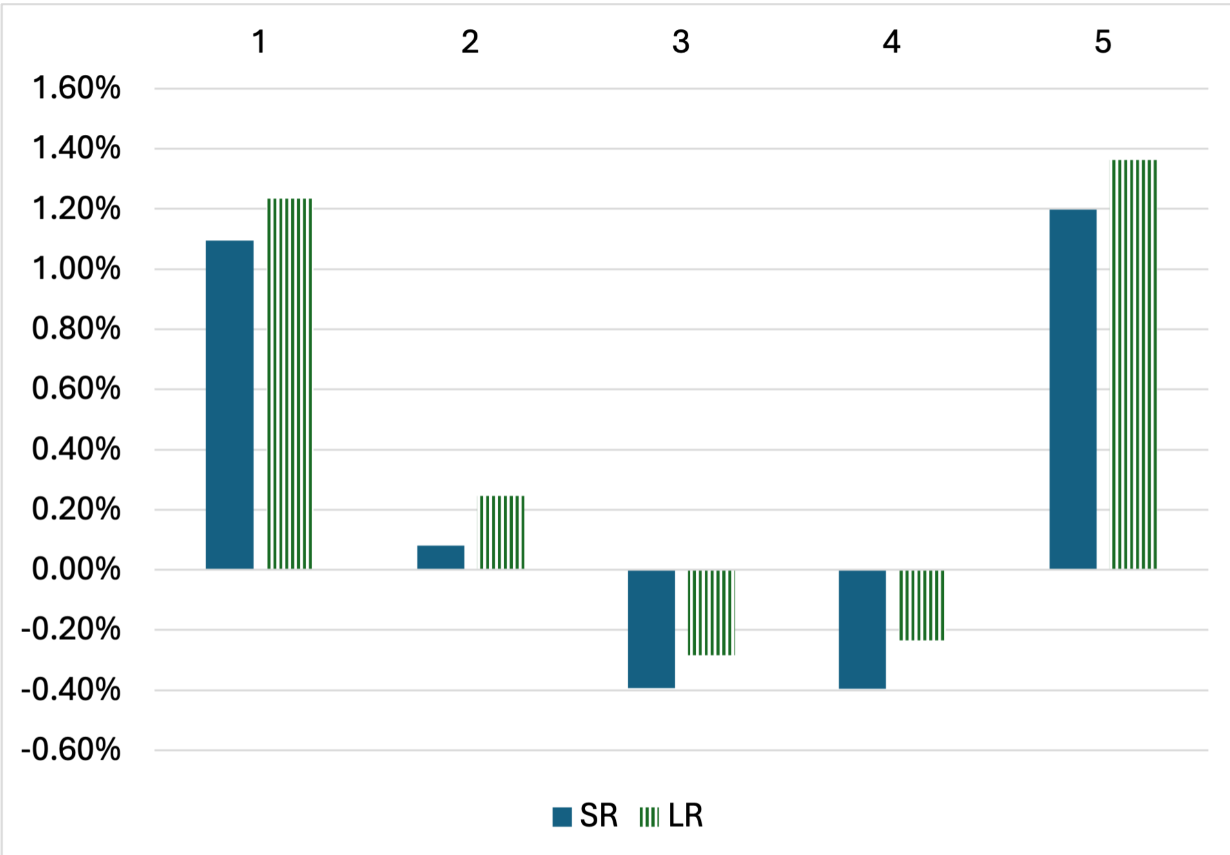
Figure 2 shows the change in welfare by worker type. The biggest gainers are the type 5 workers. These workers see substantial increases in their wages and many more of them are able to work remotely prior to the pandemic. Prior to the pandemic they earned only 65% of the wages of fully in-person workers because of their much lower TFP than them. Their relative TFP increase of 20% significantly increases their average wages in the SR relative to the baseline.

The next largest gainers are the type 1 workers. They 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 same reasons as described in Davis et al. (forthcoming). Furthermore, because they have a higher housing expenditure than type 1 workers ($\alpha_2 = 0.29$ vs. $\alpha_1 = 0.24$), the higher housing costs mitigate 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 has a chance to adjust such that they are not paying so much for housing. This 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. (forthcoming), the addition of remote workers to the model leads to modest reductions in the productivity in in-person work as Table 4 demonstrates. In-person productivity drops more for Type 3 workers than Type 1 workers because of heterogeneity in their concentration in cities and differential exposure of cities to the WFH shock. Most of the fall in productivity is because of the decline in agglomeration economies although some of it comes from workers moving to lower TFP cities between 2019 and 2022.

Both types 3 and 4 experience welfare decreases because they don't see any improvement in their productivity, since they work in occupations that cannot use WFH technology, but face higher housing costs. In the short run, the decline in welfare is the same for both worker types. Type 3 workers have lower expenditure shares than type 4 workers such that they are less exposed to the housing price increase. However, they also see their total factor productivities fall ($Z_{3,c}$) because the type 1 and type 5 workers are coming into the office less. 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 external-

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 occupations. 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 where 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 (forthcoming).

Table 4: 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 that work in a telecommutable occupation. Type 3 workers are college-educated workers that work in a non-telecommutable occupation. 3) Last two columns take city-level TFP from SR and LR but weight them according to the 2019 population distribution across cities.

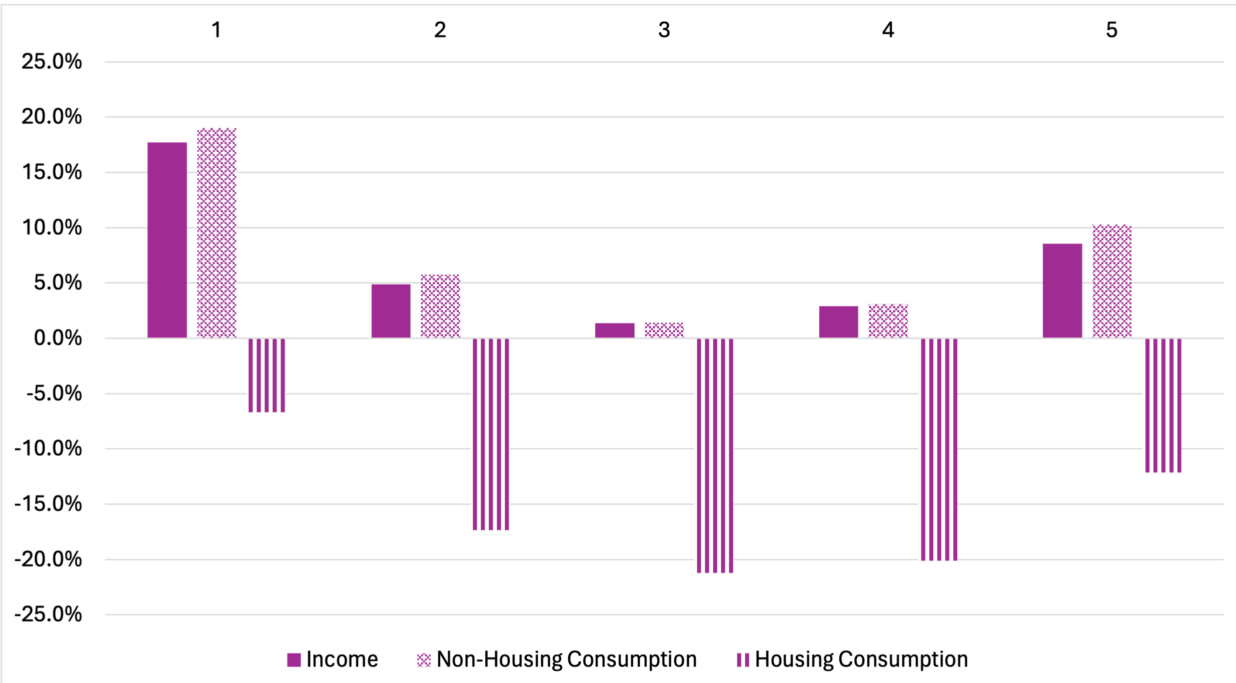
ity from in-person work. As such the biggest losers from WFH in the long run are the type 3 workers.

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 equipment to work with such that their labor productivity is higher. They also supply slightly more labor because of a decrease in commuting time since leisure is a constant given our functional form assumptions. As a result of their higher income, they consume more non-housing consumption such that it may appear that they are better off. However, their housing consumption decreases dramatically because of the higher house prices.

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. While 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 to be remote.

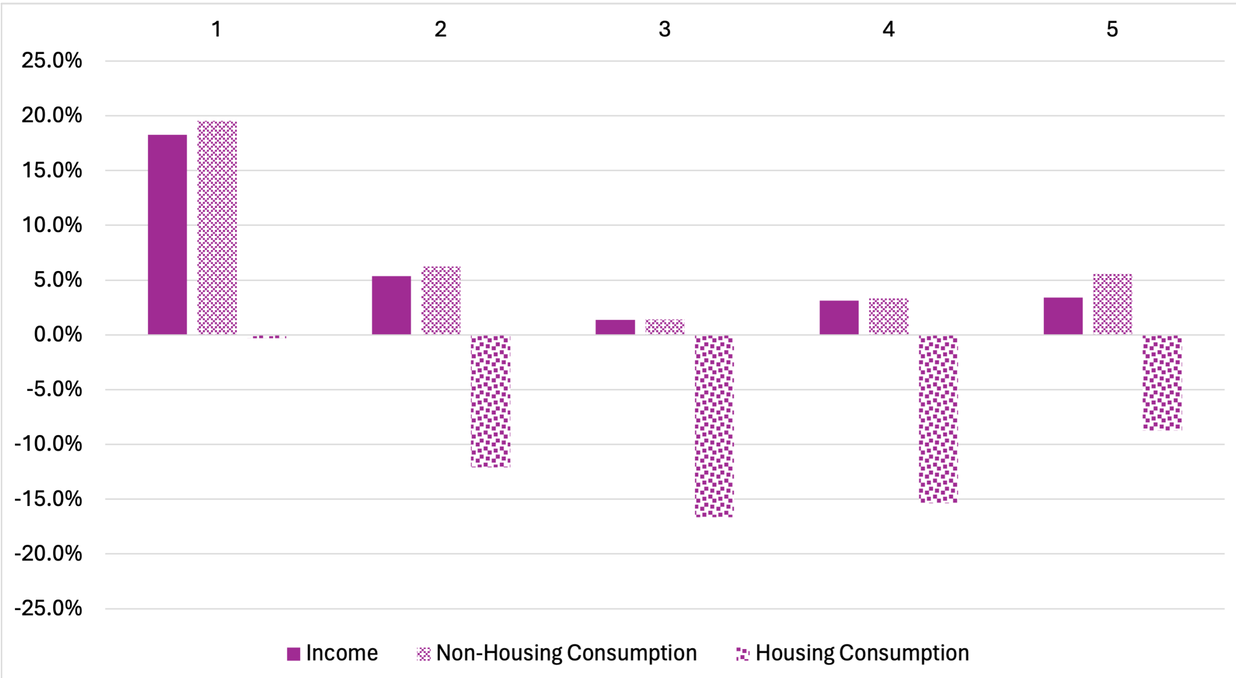
The increase in non-housing consumption considerably exceeds the increase in income for types 1, 2, and 5 in both the SR and the LR. The reason is that these households now spend less on pecuniary commuting costs given they are commuting less frequently.

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 occupations. 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 where 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 (forthcoming).

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

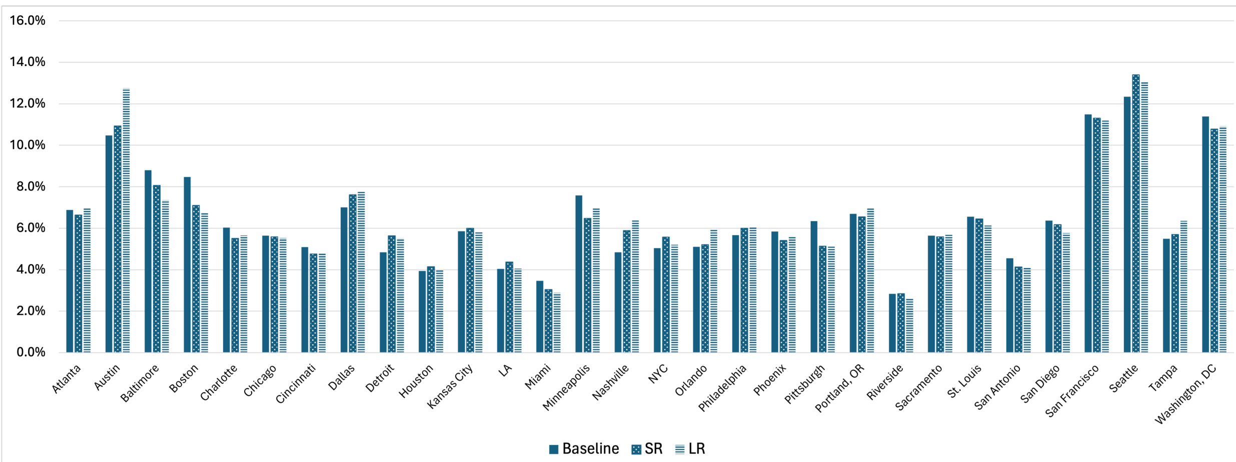


Notes: 1) A type 5 worker is a worker in an IT occupation. 2)Types 1 and 2 are in telecommutable occupations other than IT occupations. 3) Types 3 and 4 are in non-telecommutable occupations. 4) Types 1 and 3 have educational attainment of a four-year degree or greater, types 2 and 4 have lower educational attainment than a four-year degree. 5) The SR corresponds to a counterfactual where 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 (forthcoming).

4.3 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 5 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 5: 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 5 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, they tend to move to and move away from the same cities other types are moving to and moving 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 more mobile than the rest of the population, there are important population flows between 2022 and 2019 that cannot be accounted for by remote workers.

Table 5: Changes in City Population Shares

	Type 5 Share in City				Pop. Ex. Type 5 Share in City			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Baseline	SR	LR	LR Change	Baseline	SR	LR	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 a technological improvement that only increases the productivity of workers in telecommutable occupations. We find that it decreases the welfare of workers in non-telecommutable occupations despite their incomes increasing slightly.

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