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ABSTRACT

We study the impact of widespread adoption of work-from-home (WFH) technology using an equilibrium model where people choose where to live, how to allocate their time between working at home and at the office, and how much space to use in production. Motivated by cross-sectional evidence on WFH, we model WFH as a complement to work at the office. Simulations of the model and recent real estate price data indicate that the pandemic induced a large change to the relative productivity of WFH, one that will permanently affect incomes, income inequality, and city structure.

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1 Introduction

The COVID pandemic accelerated the widespread adoption of technologies that enabled households to work from home (WFH) and the amount of WFH is expected to be several times higher post pandemic than pre pandemic. We postulate that the mass adoption of remote-work technology during the pandemic permanently raised the productivity of working from home relative to working at the office. We investigate the effect of this change in relative productivity on where we work, our incomes, where we live, and the demand for and price of office space and housing. To do so, we specify a model where workers in telecommutable occupations can freely allocate their time to working from home or in the office. The model details the key tradeoffs to working from home: There is no commute, which saves time, but the productivity at home may differ from the productivity at the office. Workers that choose to work from home also choose how much physical space to rent at home and in the office. All workers choose where to live, how much to consume, and how much housing to rent.

We provide evidence on the frequency of WFH prior to the pandemic suggesting that WFH is not a perfect substitute with work at the office. Specifically, prior to the pandemic, very few workers that spent at least some full days working from home spent *all* days working from home. We thus model WFH and work at the office as potentially complementary in production. We then estimate the model using data on occupational shares, wages, household locations, and the frequency of WFH by location. Our benchmark estimates imply an elasticity of substitution (EOS) in production of full days of WFH and work at the office of 3.6, with a 95% confidence interval of 1.002 to 6.105. Since working from home and at the office are complementary, some commuting to the office will occur once the pandemic ends. This suggests that workers will not move en masse to remote, uncommutable areas with low taxes and a low cost of living but may move farther out in their current metro area, to places with long but feasible commutes and lower housing costs.

We simulate the model to understand the impact of the pandemic on WFH technology and its implications. We first study a "before" period, call it 2019, where we match the observed shares of WFH for workers in telecommutable occupations. Given the model structure, this pins down the relative level of WFH technology prior to the onset of the pandemic. We then study an "after" period, call it 2022, where we find the relative level of WFH technology that would allow the share of full days of WFH to quadruple relative to the pre-pandemic level. This increase in time spent working from home is supported by survey evidence, reported in Barrero, Bloom, and Davis (2022) and Mortensen and Wetterling (2020), on worker and firm expectations about time spent working from home once the COVID-19 pandemic ends. The assumed pre- to post-pandemic change in days of WFH allows us to size the gain in WFH productivity that occurred during the pandemic.

The change in relative total factor productivity (TFP) of WFH that is required to generate a fourfold increase in the number of days worked from home is large: 48% for low-skill workers and 88% for high-skill workers. Although WFH productivity can change over time due to slow-moving TFP growth, the model allows for a very rapid change in WFH productivity via an adoption externality. Specifically, the model includes a mechanism through which widespread adoption of WFH technology during the COVID-19 pandemic increased the productivity of WFH relative to the productivity of working in the office. This change in relative productivity causes a major, permanent shift towards WFH and away from work at the office, reducing the demand for office space and leading to an approximately 7% decline in office rents in the central business district (CBD) when the supply of office space is fixed. Residential rents rise in the short run, especially in the outer suburbs, due to increased demand for home office space. We show that after the supply of space in residential areas has a chance to increase, full days of WFH increase even more. Because high-skill workers are more likely to work in telecommutable occupations, the improvement in relative WFH productivity widens income inequality. Finally, the model forecasts a small decline in the productivity of work at the office due to a decrease in agglomeration economies.

The long-term effects of COVID on income and productivity depend on WFH technology being available but not yet fully adopted. Overall, our model suggests that the pandemic will lead to higher lifetime income for the working population because it forced many households to work at home, which in turn raised WFH productivity and thus income for those workers. While the gains we report in WFH productivity would have most likely happened eventually, the pandemic accelerated the process.

Related Literature

Our paper relates to five distinct literatures. The first is on how technological innovations get adopted and diffuse. Comin and Mestieri (2014) discuss the diffusion process in detail and several drivers of the pace of technological adoption. Katz and Shapiro (1986) and Brock and Durlauf (2010) theoretically study technology adoption in the presence of network externalities. A positive externality in technology adoption in WFH technology is consistent with the process that Foster and Rosenzweig (2010) posit for health innovations.

The second literature we speak to is the effect of technological adoption on household lifestyles. Greenwood, Seshadri, and Yorukoglu (2005) argue that the consumer durable goods revolution that arose from the invention and diffusion of electricity liberated women from the more menial tasks associated with home production. A related literature discusses how this home-production technology influences the use of time spent working at the office or working on home production in response to changes in the macroeconomic environment; see, for example, Benhabib, Rogerson, and Wright (1991), McGrattan, Rogerson, and Wright (1997), and Aruoba, Davis, and Wright (2016).

A more recent literature directly studies WFH. Bloom, Liang, Roberts, and Ying (2014) and Emanuel and Harrington (2020) find that "call center" workers are more productive when they work from home. We study a broader class of workers whose work is less routine, on average, than call-processing work, so their work from home may be less productive. Our focus, however, is on the substitutability between working at home and office work. Understanding this substitutability is important for understanding the long-term implications of changes to WFH technology. While Gaspar and Glaeser (1998) present suggestive evidence that the telephone complements rather than substitutes for face-to-face interaction, our estimates using more recent technologies suggest that WFH is an imperfect substitute for face-to-face interactions. Our findings also demonstrate how the COVID shock could permanently increase aggregate productivity. Instead of studying the productivity of WFH, Mas and Pallais (2017) study how much workers value the option to work from home. They find that prospective call center employees are willing to take an 8% pay cut to work from home. This finding suggests there may be benefits from an increase in relative WFH productivity beyond higher levels of consumption.

Our paper also relates to a more recent literature investigating the long-term effects of the COVID crisis on work and cities. Bick, Blandin, and Mertens (2021) document increased WFH during the pandemic and present a model of work in which working from home and at the office are perfect substitutes. Consistent with our findings, they argue that there was increased adoption of WFH during the pandemic.

However, they do not specify the technological processes involved nor does their model have implications for rents. Kaplan, Moll, and Violante (2020) study the effect of pandemic policies by specifying an endogenous susceptible-infected-recovered (SIR) model where people can do market work from home or at the office. Kaplan, Moll, and Violante (2020) specify disutility from WFH, home production, and work at the office and, in particular, allow for imperfect substitution between WFH and work at the office. While our concern in this paper is not with pandemic policies, the imperfect substitution in the disutility of WFH and work at the office would likely predict, as our paper does, a hybrid post-pandemic office rather than a solution where a large percentage of workers never go to the office.

We predict that the improvement in WFH productivity will lead to a further widening of income inequality because WFH technology is more widely available to high-skill workers. Our finding is consistent with evidence from Krussel, Ohanian, Rios-Rull, and Violante (2000), that rising income inequality since the 1970s is largely attributable to technological innovation that benefits high-skill workers. Violante (2008) summarizes the evidence on skill-biased technical change. Finally, our paper is related to Beaudry, Doms, and Lewis (2010), who study the implications for wages and income inequality of the endogenous adoption of a skill-biased invention (the personal computer) within a model of urban economics.

The three papers that are most closely related to ours are Delventhal, Kwon, and Parkhomenko (2022), Delventhal and Parkhomenko (2021), and Behrens, Kichko, and Thisse (2021). Delventhal, Kwon, and Parkhomenko (2022) and Delventhal and Parkhomenko (2021) model the geography of a city and firm and worker location choices in considerable detail, but assume that the changes in WFH behavior are exogenously predetermined. We consider a simpler structure of a city, in the spirit of Favilukis and Van Nieuwerburgh (2021), but we allow workers to optimally allocate their time between working at the office and at home. In addition to modeling the driving engine of the increase in WFH, our estimation of the EOS allows us to infer the relative change in WFH productivity that is required to generate an expected quadrupling of time worked from home once the pandemic subsides. Delventhal, Kwon, and Parkhomenko (2022) and Delventhal and Parkhomenko (2021) assume that working from home and working at the office are perfect substitutes in production. Behrens, Kichko, and Thisse (2021) do not consider the implications of WFH for city structure but, like us, they study the dynamics of productivity of WFH and work at the office in the presence of externalities in the number of workers at the office and in the number of workers who know how to use WFH technology.

Finally, our work relates to how cities respond to shocks in the short run and the long run. Ouazad (forthcoming) surveys this literature. Our model predicts that the trend towards suburbanization will continue, which is consistent with Ouazad (forthcoming).[1] The evidence suggests that natural disasters tend to have only transitory effects on city structure (Davis and Weinstein, 2002; Ouazad, forthcoming), while factors that influence productive capacity, such as transportation, tend to have permanent ones (Bleakley and Lin, 2012; Brooks and Lutz, 2019). Our model predicts that the COVID-induced shock to the productivity of WFH will have long-lasting effects on city structure.

In the next section, we present some key facts about the frequency of WFH along with our conception of WFH for the model. Section 3 presents our full model of household location and productivity. Section 4 describes how we estimate the elasticity of substitution of working at home and working at the office and calibrate the other parameters of the model. In Section 5 we run counterfactual experiments of the model, showing how changes to WFH technology affect the allocation of time of workers in telecommutable occupations, incomes, and rents. In Section 6, we compare our model's implications with alternative views on the increase in WFH during the pandemic. Section 7 concludes.

2 WFH Before the Pandemic

Our conception of WFH focuses on full days worked at home rather than simply a few minutes here and there doing quick tasks that could as readily be done from a cell phone as from a laptop. While these quick tasks permit additional productivity, our paper is primarily concerned with the spatial implications of WFH. Therefore, the key dimension is the tradeoff between commuting to work at the office vs. WFH.

Before providing a full spatial model where people choose where to live and how much space to rent over a given year, we provide a descriptive analysis of the frequency and duration of work activities done from home in the United States in the years just prior to the pandemic and of longer-term trends in the frequency of full

[1] Brueckner, Kahn, and Lin (2021), Gupta, Mittal, Peeters, and Van Nieuwerburgh (forthcoming), Haslag and Weagley (2021), Li and Su (2021), and Liu and Su (2021) also document an increased tendency toward suburbanization.

days spent on WFH. We use data from the Current Population Survey (CPS), the American Time Use Survey (ATUS), the Leave and Job Flexibility (LJF) module of the CPS, and the General Social Survey (GSS). The ATUS and LJF are both CPS submodules. The ATUS data allow us to examine time use within one randomly selected day per respondent. Each ATUS respondent is observed on a single day. We use the ATUS weights to estimate the share of days involving WFH so that our estimates represent the shares of all days even though the ATUS oversamples weekends. Our full sample includes all respondents who were age 15 or older and currently employed but not self-employed. The LJF survey, which was completed by a subset of ATUS respondents in 2017 and 2018, asks workers directly how frequently they work full days exclusively from home. The GSS, which was used in early WFH studies by Mas and Pallais (2017) and Mas and Pallais (2020), asks respondents, “How often do you work at home as part of your job?” Conducted in 2006, 2010, 2014, and 2018, the GSS provides a longer time series on WFH than the LJF.

The first three columns of Table 1 report the percentage of all days that include WFH using definitions ranging from broad (any observed WFH) to narrow (full workdays with only WFH), as reported from the ATUS in 2017-2019.

Column 1 of Table 1 reports the fraction of days classified as “any WFH,” defined as a day with a reported work activity of any duration performed at home. This broad notion of WFH would include, for example, days where short work activities like checking email in the evening were performed at home but the bulk of the workday was spent at the workplace. In the full sample, 23.7% of days involve any WFH. That figure varies by education group, from 13% for workers with a high school degree or less to 43% for workers with an advanced degree.

Column 2 of Table 1 reports the fraction of days classified as “only WFH,” defined as a day with a reported work activity of any duration performed at home and no work activity performed at the workplace. This notion of WFH, though narrower than “any WFH,” is still somewhat broad in that it includes days on which very little work was done, as long as all of it was done at home. In the full sample, 9.9% of days involve only WFH. The figure again varies by education group, ranging from from 3.8% for workers with a high school degree or less to 20.3% for workers with an advanced degree.

Column 3 of Table 1 reports the fraction of days classified as “only-WFH full days,” defined as a day with four hours or more of work activities performed at home and no work activity performed at the workplace. This narrow definition of WFH is close to the one in our model, in which workers must choose what fraction of full work days to spend at home and what fraction of full work days to spend at the office. In the full sample, just 4.9% of days are only-WFH full workdays. The education gradient in this classification is the steepest: 8.6% of days for workers with a bachelors degree or higher, 10.4% for workers with an advanced degree, and only 1.9% for workers with a high school degree or less.

Finally, column 4 of Table 1 reports the fraction of days that workers report working from home in the LJF module. These self-reported WFH percentages are slightly smaller than the percentages in column 3 coming from direct observation in the ATUS, but they exhibit similar patterns in terms of the relative frequencies of WFH across subgroups.

Figure 1 presents trends from 2003-2019 in the share of days classified as "only-WFH full days" from the ATUS by broad education category.[2] The data show a large increase over this period in the frequency of only-WFH full workdays, with this trend concentrated almost exclusively among workers with more than a high school degree. For workers with a bachelor's degree or higher, the share of only-WFH full workdays more than doubles, from 4.0% to 8.5%, and for workers with some college but no bachelor's degree the share more than triples, from 1.5% to 5.0%. In contrast, for workers with a high school degree or less, the share of only-WFH full workdays exhibits no strong time trend.

Figure 2 plots data from the GSS to show the frequency of WFH over time. Given the specific question in the GSS relating to WFH, these data may include partial days of WFH. This figure extends a figure shown in Mas and Pallais (2020) to include workers that ever work from home and the data for 2018. The figure shows small, gradual increases in the share of workers that report working from home at least once a week and in the share of workers that report occasionally working from home. Importantly, far more workers occasionally work from home than frequently work from home. In no year do more than 15% of workers report working from home more than once a week, but every year more than 30% of workers report ever working from home within a year.

Table 2 provides more detail on the frequency of WFH as reported in the GSS.

[2]We plot three-year moving averages, pooling years t-1, t, and t+1 for the calculation depicted at year t. We exclude observations from 2020 from the moving average calculation for year 2019.

Only about 5% of all workers report mainly working from home, while about 40% of workers work from home with some frequency. Workers that report usually working from home constitute only about 12% of all workers that ever work from home.

To summarize, when we focus on full days of WFH, the data reveals that 1) full days of WFH are much more common among college-educated workers, 2) far more workers occasionally work from home than usually work from home, and 3) WFH was slowly increasing in the years leading up to the pandemic. Our model thus allows for heterogeneity in the ability and productivity of WFH between college-educated and non-college-educated workers. Our model also allows some workers to work some of their workdays at the office and some of their workdays at home. In particular, our model allows for the possibility that WFH complements work at the office. The fact that few remote workers telecommute 100% of the time suggests this functional form.

Intuitively, complementarity between the two types of work may arise because most jobs involve a variety of tasks, some of which are better performed at home and some of which are better performed at the office. For example, some workers experience fewer interruptions from colleagues when working from home, so deep-thinking tasks might be easier to accomplish there. At the other extreme, routine tasks can easily be accomplished from home. Collaborative work, on the other hand, is likely to be easier in the office given the high costs of scheduling every single interaction with a colleague from home. While it is often easier to complete a well-defined task at home, it may be easier to start a collaborative one at the office.

Finally, our model specifies mechanisms through which the frequency of WFH can increase over time. We have in mind that, in normal times, the relative productivity of WFH changes slowly, explain the slowly moving positive trend to WFH for educated workers shown in Figure 1. The model also specifies an adoption externality that can cause a large jump in relative productivity of WFH. This jump, in turn, may rapidly alter a household's optimal mix of WFH and work at the office and induce large changes along the extensive margin. For perspective, Figure 1 shows that WFH approximately doubles in the 16 years between 2003 and 2019; available evidence suggests WFH will quadruple from pre pandemic (2019) to post pandemic (2022 and beyond). This suggests that the process determining WFH productivity was different during the pandemic than in the 16 years prior. We explain this difference with an adoption externality.

3 Model

3.1 Households

A measure 1 of worker households live in a metro area with a CBD. Households in the model vary with respect to their skill and occupation. There are two skill levels, high and low, and two types of occupations, telecommutable and not. We use the notation ι to index types of workers. $\iota = 1$ refers to high-skill workers working in a telecommutable occupation, $\iota = 2$ to low-skill workers working in a telecommutable occupation, $\iota = 3$ to high-skill workers working in a non-telecommutable occupation, and $\iota = 4$ to low-skill workers working in a non-telecommutable occupation. A worker's type is pre-determined and permanent. We denote the shares of worker types in the population by $\pi_\iota, \iota \in 1, .., 4$.

Taking their type as given, households in the model make a set of choices in a given sequence to maximize expected utility. First, they choose where to live from one of $n = 1, \ldots, N$ locations. Next, households that work in a teleworkable occupation ($\iota = 1$ or $\iota = 2$) choose whether to work for a firm that allows workers to work full days at home; households that do not work in a teleworkable occupation, $\iota = 3$ or 4, always work at firms that do not allow WFH. All 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. All households also choose non-housing consumption and housing to rent. Households choosing to work at a firm that allows WFH also choose days to work at home, 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 $\iota = 1, 2$ households also receive utility from their firm choice. Households make all choices to maximize expected utility.

The model allows the quantity of WFH to change multiple ways over time, even when the fraction of households that work in telecommutable occupations is fixed. In the model, households in a teleworkable occupation can choose to have the option of teleworking by opting to work for a firm that allows WFH — a "WFH firm" — or a firm that does not allow WFH. This is the extensive margin of WFH. Further, households that choose a WFH firm decide how much to work from home. This is the intensive margin of WFH. Thus, a change in the relative productivity of telecommuting can change both the extensive and intensive margins: households may find it more desirable to work for a WFH firm, and households that work for a WFH firm may choose to telecommute with greater frequency.

3.1.1 Location Decision

Denote the expected value of utility of non-housing consumption, housing, leisure, and firm choice (for type $\iota = 1, 2$ households) for households of type ι living in location n as $X_{n\iota}$. Household j, choosing to live in location n at the start of the period, receives utility equal to

$$V_{n\iota j} \quad = \quad \underbrace{\nu \left[a_{n\iota} + X_{n\iota} \right]}_{\equiv V_{n\iota}} \quad + \quad e_{n\iota j}. \tag{1}$$

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

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

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

3.1.2 Determining $X_{n\iota}$ 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 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 WFH firm, households can choose full days to work at the office in the CBD and full days to work at home. For reasons discussed in Section 2, we do not model the portion of WFH that involves small individual tasks done at home, such as taking a few phone calls on weekends or checking emails after dinner.

Let $\kappa = 0$ denote a non-WFH firm and $\kappa = 1$ denote a WFH firm. A household j of type ι ($\iota = 1$ or $\iota = 2$) living in location n and working for a firm of type $\kappa \in 0, 1$

receives the following utility

$$X^{\kappa}_{n\iota j} \;=\; X^{\kappa}_{n\iota} \;+\; (1/\zeta)\,\epsilon^{\kappa}_{n\iota j}\,. \tag{2}$$

As specified, the utility of households living in n and working for a firm of type κ has two components: a deterministic one, $X^{\kappa}_{n\iota}$, and a stochastic one, $(1/\zeta)\,\epsilon^{\kappa}_{n\iota j}$. 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 and household type ι. $\epsilon^{\kappa}_{n\iota j}$ is drawn IID across all locations, 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.[3]

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

$$g^{\kappa'}_{n\iota} = \frac{e^{\zeta X^{\kappa'}_{n\iota}}}{e^{\aleph_{n\iota}}} \quad \text{where} \quad \aleph_{n\iota} = \ln \sum_{\kappa=0}^{1} e^{\zeta X^{\kappa}_{n\iota}}. \tag{3}$$

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

$$X_{n\iota} \;=\; (1/\zeta)\,(\aleph_{n\iota} + \Gamma)$$

where Γ is Euler's constant.

Utility when employed by a non-WFH firm. Households of type $\iota = 1$ or 2 that choose to live in n and work for a firm operating in the CBD that does not allow WFH ($\kappa = 0$) choose consumption ($c^{0}_{n\iota}$), housing ($h^{0}_{n\iota}$), leisure ($\ell^{0}_{n\iota}$), and the fraction of

[3] Delventhal and Parkhomenko (2021) assume that idiosyncratic household preferences for the pair (residence location, firm location) are drawn iid across pairs, so a single variance parameter determines the elasticity of the household's choice of both firm and residence locations.

discretionary time to spend at the office ($b^0_{n\iota}$) to maximize

$$X^0_{n\iota} = (1-\alpha_\iota)\ln c^0_{n\iota} + \alpha_\iota \ln h^0_{n\iota} + \psi_\iota \ln \ell^0_{n\iota} \tag{4}$$

subject to the budget and time constraints of

$$\begin{aligned} 0 &= \left(w^0_\iota - \tau_n\right) b^0_{n\iota} - c^0_{n\iota} - r_n h^0_{n\iota} \\ 0 &= 1 - (1+t_n)\, b^0_{n\iota} - \ell^0_{n\iota}. \end{aligned} \tag{5}$$

In equations (4) and (5), the 0 superscripts denote that the household works at a non-WFH firm ($\kappa = 0$), and w^0_ι denotes the wage paid by non-WFH firms to type ι households 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. A household of type ι living in location n supplying $b^0_{n\iota}$ fraction of a full year of labor earns a net annual income of $(w^0_\iota - \tau_n)\, b^0_{n\iota}$. The household spends this labor income on consumption, $c^0_{n\iota}$, and housing, $h^0_{n\iota}$. The rental price per unit of housing in location n is r_n. Households also enjoy leisure. Given a total endowment of time in the year of 1, the quantity of leisure enjoyed by a household spending $b^0_{n\iota}$ percentage of the year working is $1-(1+t_n)\, b^0_{n\iota}$, where t_n is the round-trip time spent commuting from location n.

Commuting costs are multiplicative rather than fixed in the budget and time constraints. We explain in Appendix A how a daily model of whether or not to go to work each day, a fixed number of hours in the workday, and a fixed daily cost to commuting maps to an annual model with a multiplicative cost of commuting if households choose the number of days in a year in which to work at the office. While the optimal number of hours to work within a workday and the reasons why people typically lump work into five days each week rather than distributing it evenly over seven are interesting questions in their own right, we take these norms as given in order to focus on the implications of WFH for cities.

In Appendix B, we show that optimal household choices satisfy

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

Utility when employed by a WFH firm. Households of type $\iota = 1$ or $\iota = 2$ 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, $l^b_{n\iota}$, (b) the percentage of total time in the year to work at home, $l^h_{n\iota}$, (c) the size of the home office, $s^h_{n\iota}$, and (d) the amount of equipment and software to rent for use in the home office, $k^h_{n\iota}$. 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 $\omega\left(l^b_{n\iota}, l^h_{n\iota}, s^h_{n\iota}, k^h_{n\iota}\right)$.

Households of type ι living in n and working at a WFH firm ($\kappa = 1$) make choices to maximize

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

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 WFH vs. a non-WFH firm. We include χ_ι in utility to allow the model to match employment shares at non-WFH and WFH firms. In Appendix D, we show that this model is isomorphic to that of a home production model in the style of Benhabib, Rogerson, and Wright (1991) where households have four uses of time: work at the office, WFH, leisure, and work spent producing non-marketed consumption (such as home-cooked meals or clean laundry) using time and housing as inputs. We thus abstract from home production to focus on changes to WFH.

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.,

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

Note that the compensation offered by the firm to the worker, $\omega\left(l^b_{n\iota}, l^h_{n\iota}, s^h_{n\iota}, k^h_{n\iota}\right)$, depends on the household's choices for days worked at the office, days worked from home, and the amounts of business equipment and home office space, all of which affect worker productivity. There are two additional differences from the budget and time constraints of households working at a non-WFH firm. First, the budget and time constraints here only include commuting costs for time spent at the office. Second, these households have to rent a home office as well as equipment and software for it (at a cost per unit of r^k), all of which raises productivity and therefore income. As for households working at non-WFH firms, time and financial commuting costs for households at WFH firms are multiplicative. See Appendix A for details.

As shown in Appendix C.1, the solutions for consumption, housing, and leisure look similar to those of households working at a non-WFH firm. Leisure is a constant fraction of total discretionary time, and consumption and housing are $(1-\alpha_\iota)$ and α_ι fractions of income net of financial commuting costs, expenditures on home offices, and expenditures on equipment and software, which implies

$$\begin{aligned} c^1_{n\iota} &= (1-\alpha_\iota)\left[\omega\left(l^b_{n\iota}, l^h_{n\iota}, s^h_{n\iota}, k^h_{n\iota}\right) - \tau_n l^b_{n\iota} - r_n s^h_{n\iota} - r^k k^h_{n\iota}\right] \\ r_n h^1_{n\iota} &= \alpha_\iota\left[\omega\left(l^b_{n\iota}, l^h_{n\iota}, s^h_{n\iota}, k^h_{n\iota}\right) - \tau_n l^b_{n\iota} - r_n s^h_{n\iota} - r^k k^h_{n\iota}\right] \\ \ell^1_{n\iota} &= \frac{\psi_\iota}{1+\psi_\iota} \end{aligned}$$

Additionally, the marginal impact on income of an extra unit of home office space must be equal to the rent on that space, $\partial\omega/\partial s^h_{n\iota} = r_n$. Finally, the impact on income, less commuting costs of an extra day at the office and adjusted for time spent commuting that extra day, must be equal to the impact on income of an extra day working from home, i.e.,

$$\left(\frac{1}{1+t_n}\right)\left[\frac{\partial\omega}{\partial l^b_{n\iota}} - \tau_n\right] = \frac{\partial\omega}{\partial l^h_{n\iota}}. \tag{6}$$

3.1.3 $X_{n\iota}$ for Households in Non-Telecommuting Occupations

Households of type $\iota = 3$ 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 $\iota = 3$ or 4 households choose consumption, housing, and leisure to maximize

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

subject to budget and time constraints of

$$\begin{aligned} 0 &= (w_\iota - \tau_n)\, b_{n\iota} - c_{n\iota} - r_n h_{n\iota} \\ 0 &= 1 - (1+t_n)\, b_{n\iota} - \ell_{n\iota}. \end{aligned}$$

The optimal solutions satisfy

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

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.

3.2 Firms and Production

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

$$\begin{aligned} & y_{n\iota} - w_\iota b_{n\iota} - r^k k_{n\iota} - r^s s_{n\iota} \\ \text{where} \quad & y_{n\iota} = Z_\iota b_{n\iota}^{\theta_b} k_{n\iota}^{\theta_k} s_{n\iota}^{\theta_s}. \end{aligned} \tag{7}$$

w_ι is the prevailing wage rate for a worker of type ι working at a non-WFH firm, r^k is the cost per unit of equipment and software, and r^s is the cost per unit of office space in the CBD. While the worker's location does not affect their TFP, workers in different locations may choose different amounts of labor supply. A different labor supply will in turn affect the amount of office space and business equipment the firm rents for the worker, such that the subscript n on the variables in equation (7) is necessary.[4]

Under competitive labor and factor markets, the firm maximizes profits by setting

$$
\begin{aligned}
w_\iota b_{n\iota} &= \theta_b y_{n\iota}, && (8)\\
r^k k_{n\iota} &= \theta_k y_{n\iota}, && (9)\\
r^s s_{n\iota} &= \theta_s y_{n\iota}. && (10)
\end{aligned}
$$

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 type ι living in location n is equal to

$$
y_{n\iota} = \left[\left(\frac{\theta_k}{r^k}\right)^{\frac{\theta_k}{\theta_b}}\left(\frac{\theta_s}{r^s}\right)^{\frac{\theta_s}{\theta_b}}(Z_\iota)^{\frac{1}{\theta_b}}\right] b_{n\iota}. \tag{11}
$$

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

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

$$
y_{n\iota} = \left[\left(y^b_{n\iota}\right)^\rho + \left(y^h_{n\iota}\right)^\rho\right]^{1/\rho} \tag{12}
$$

[4] We assume Cobb-Douglas production functions for both non-WFH firms and for the output from WFH and work at the office for WFH firms. Jones (2005) discusses the microfoundations for the use of Cobb-Douglas production functions in macroeconomics. In addition to being consistent with the balanced growth path and the microfoundations, a key advantage of using a conventional functional form for a production function is that we can use well-established, existing estimates to parameterize the model.

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

$$\begin{aligned} y_{n\iota}^b &= A_\iota^b \left(l_{n\iota}^b\right)^{\theta_b} \left(k_{n\iota}^b\right)^{\theta_k} \left(s_{n\iota}^b\right)^{\theta_s} \\ y_{n\iota}^h &= A_\iota^h \left(l_{n\iota}^h\right)^{\theta_b} \left(k_{n\iota}^h\right)^{\theta_k} \left(s_{n\iota}^h\right)^{\theta_s}. \end{aligned}$$

$k_{n\iota}^b$ and $s_{n\iota}^b$ are equipment and software and office space rented at the CBD by this firm for household of type ι living in location n.[5]

Given $y_{n\iota}^h$ and $l_{n\iota}^b$, the firm chooses $k_{n\iota}^b$ and $s_{n\iota}^b$ to maximize $y_{n\iota} - r^k k_{n\iota}^b - r^s s_{\iota i}^b$. The choices satisfy

$$\begin{aligned} y_{n\iota}^{1-\rho}\left(y_{n\iota}^b\right)^{\rho-1}\theta_k\left(y_{n\iota}^b/k_{n\iota}^b\right) &= r^k \\ y_{n\iota}^{1-\rho}\left(y_{n\iota}^b\right)^{\rho-1}\theta_s\left(y_{n\iota}^b/s_{n\iota}^b\right) &= r^s \end{aligned}$$

Assuming labor markets are competitive such that firms make zero profits, the firm pays any household supplying $l_{n\iota}^b$, $l_{n\iota}^h$, $k_{n\iota}^h$, and $s_{n\iota}^h$ the output that remains. Households know this and choose $l_{n\iota}^b$, $l_{n\iota}^h$, $k_{n\iota}^h$, and $s_{n\iota}^h$ accordingly. We characterize the solutions for the optimal quantities of these variables in Appendix C.2.[6]

3.3 Technology

Commuting Speed. Denote $\mathcal{L}_n$ as the aggregate quantity of work at the office in the CBD by households living in zone n during the year and define d_n as the distance from location n to the CBD. We define aggregate distance commuting, $\mathcal{V}$, as

$$\sum_{n=1}^{N} d_n \mathcal{L}_n.$$

[5]Note that if firms cannot observe $l_{n\iota}^h$, $k_{n\iota}^h$, or $s_{n\iota}^h$ directly, we assume they can observe home output $y_{n\iota}^h$ and hours of work at the office $l_{n\iota}^b$, which is sufficient to determine $k_{n\iota}^b$ and $s_{n\iota}^b$ given the production function.

[6]To be specific, in Appendix C.2, we derive quantities assuming that the household owns the firm or (equivalently) that the firm chooses quantities of office space and business equipment jointly with household decisions on labor supply, home equipment, and home office space to maximize household utility.

Following Couture, Duranton, and Turner (2018), we assume that the travel speed of any commuter, $\mathcal{S}$, is subject to a negative congestion externality in aggregate distance spent commuting, determined as

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

such that time spent commuting from location n is $d_n/\mathcal{S}$. Couture, Duranton, and Turner (2018) estimate a specification where log commuting speed per vehicle is a linear function of (MSA total) log vehicle time traveled. Equation (2) on page 729 of Couture, Duranton, and Turner (2018) can be rewritten as

$$\begin{aligned}
\log \mathcal{S} &= \text{const.} + \theta \log (\text{Total Time Traveled}) \\
\log \mathcal{S} &= \text{const.} + \theta \log (\text{Total Distance Traveled}) - \theta \log(\mathcal{S}) \\
\log \mathcal{S} &= \text{new const.} + \gamma \log (\text{Total Distance Traveled}) .
\end{aligned}$$

where $\gamma = \theta / (1+\theta)$. For example, if $\theta = -0.13$, then $\gamma = -0.15$.

TFP of Working at the Office. Denote $\mathcal{H}$ as the aggregate quantity of high-skill labor worked at the office during the period. For high-skill households (type $\iota = 1$ or $\iota = 3$), TFP at the office is positively affected by $\mathcal{H}$ via a high-skill agglomeration externality

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

In this formulation, TFP at the office can change over time due to changes to the human capital externality, or due to exogenous changes in $\bar{Z}_{\iota}$ and $\bar{A}^b_{\iota}$.[7]

TFP of WFH. For type $\iota = 1$ and 2, we specify

$$A^h_{\iota} = \bar{A}^h_{\iota} \left(L^{max}_h\right)^{\delta_{\iota h}} \tag{13}$$

where L^{max}_h is the maximum amount of time that households in aggregate spent working at home in any previous year. Equation (13) specifies that A^h_{ι} can change over time

[7] 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.

due to exogenously increasing TFP, i.e., changes to $\bar{A}_{\iota}^{h}$, or changes to the adoption externality if the total amount of time that households spent working at home in any previous year increases.

Equation (13) is a reduced form for a more complex human capital acquisition process — one capturing the idea that if suddenly many more people have had experience working at home, then all workers will be more productive in the future at working at home. In this sense, WFH productivity is subject to agglomeration economies in the number of people that know how to use WFH technology. Consistent with the earlier literature on technology adoption (e.g., Greenwood, Seshadri, and Yorukoglu (2005) and Brock and Durlauf (2010)), this specification implies that people do not forget how to use a technology once they have adopted it.

3.4 Solution

In Appendices B and C we derive optimal quantities and choices for all types of households and firms. We assume that firms observe individual worker output from WFH and labor supply at the office. Additionally, when we derive the optimal quantities of business capital and office space rented for WFH firms, we assume that each household working for a WFH firm owns that firm and that these inputs are therefore jointly chosen along with all other variables to maximize household utility. Intuitively, we have in mind that labor markets are frictionless and competitive, with firms competing for workers by offering the highest level of utility. The allocation we derive maximizes household utility given the environment.

For households working at WFH firms, we show that the optimal ratio of days worked at the office to days of WFH satisfies

$$\text{(14)}\qquad \left(\frac{l_{n\iota}^{b}}{l_{n\iota}^{h}}\right) = \left(\frac{r^{s}}{r_{n}}\right)^{\frac{-\rho\theta_{s}}{1-\rho}} \left(\frac{A_{\iota}^{b}}{A_{\iota}^{h}}\right)^{\frac{\rho}{1-\rho}} \left[(1+t_{n}) + \frac{\tau_{n}}{(1+\psi)\left(c_{n\iota}+r_{n}h_{n\iota}\right)}\right]^{\frac{-(1-\rho\theta_{k}-\rho\theta_{s})}{1-\rho}} .$$

Households spend a larger fraction of their days working at home as $\frac{A_{\iota}^{h}}{A_{\iota}^{b}}$ rises, as rents rise in the CBD relative to the residential zones, and as both types of commuting costs rise. In each zone we compute the model solution by finding the value of this ratio that is consistent with annual income and the optimal choice of $c_{n\iota}$ and $h_{n\iota}$.

Having solved for all optimal choices of all household types in each location and all firms, we then use the implications of equations (1) and (2) to identify the fraction of households of each type that live in each zone and the fraction of type 1 and 2 households that choose WFH firms. Given all prices and wages, we compute aggregate demand for housing in each zone as the sum of demand for housing of types 3 and 4 and the sum of demand for housing and home offices of types 1 and 2. We compute aggregate demand for office space as the sum of demand for office space for all non-WFH firms and WFH firms.

4 Estimation

4.1 Data

To estimate model parameters, we use data from four sources: the 2018 GSS, the 2017-2018 LJF, the 2019 5-year American Community Survey (ACS), which pools data collected in 2015-2019, and the 2017 and 2019 waves of the American Housing Survey (AHS).

4.2 Matching Model Concepts to Data

Before describing specific moments we use to estimate the model, we provide a description of empirical counterparts to the concepts in the model.

Workers. We conceive of agents in our model as full-time workers and restrict our sample to these workers. We restrict our sample in the ACS to household heads ($relate == 1$) who are working full-time ($uhrswork >= 30 \& uhrswrk < 99$), not living in group quarters, who worked at least 40 weeks ($wkswork >= 4$) last year, and who are 25 years of age or older. We also exclude households working in the armed forces. 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.[8]

[8]While we observe a small amount of WFH for workers whose occupations Dingel and Neiman (2020) classify as not allowing remote work, we attribute this to occupational missclassification for these workers given the careful work that Dingel and Neiman (2020) undertake in classifying occupa-

Cities. We choose the cities with which to estimate the model as follows. We start with the 30 largest US cities by population. We then keep all cities that are approximately monocentric and whose CBSA definition spans more than one county. We exclude the Los Angeles, Minneapolis-St. Paul, Riverside, and San Francisco CBSAs because they are not monocentric and the Las Vegas, Phoenix, and San Diego CBSAs because each is located in only one county. Finally, there is no FIPS code in the 2015-2019 ACS data for the CBD county for Miami (Miami-Dade) or Denver (Denver).[9] Our final sample thus includes 21 cities.

Zones. We allow for two residential zones. To match the zones to the data, we interpret Zone 1 as the same county as the CBD and Zone 2 as all other counties in the CBD. We focus on the county as the unit of geography because it is the smallest unit of geography that we can consistently observe in the ACS data.

4.3 Fixed Parameters

Table 3 summarizes our parameterization of the model. Existing studies inform us of the values of several parameters of the model that are not the model's focus. We use evidence from Valentinyi and Herrendorf (2008) on the share of labor, real estate, business equipment and software, and labor in production to set $\theta_b = 0.67$, $\theta_s = 0.18$, and $\theta_k = 0.15$.

ν measures how sensitive location choice is to variation in utility. In many models of urban economics, utility has to be the same everywhere. This is what emerges as $\nu \to \infty$. When ν is finite, people are willing to live in a place that provides lower utility on average because they get a good random draw of household-specific preferences e_{nj} from living there. We set $\nu = 3.3$ based on the estimates in Monte, Redding, and Rossi-Hansberg (2018). In Sections 4.7 and 5.6, we examine the sensitivity of our results to this parameter value.

We set $\alpha_2 = \alpha_4 = 0.33$ and $\alpha_1 = \alpha_3 = 0.20$ to roughly match the relative size of housing of college- and non-college-educated workers in the 2019 AHS.[10] These

tions.

[9]We identify the CBSA, county FIPS code, and state FIPS code using the variables $met2013$, $countyfip$, and $statefip$ in the IPUMS data.

[10]The average home sizes for non-college-educated and college-educated households are 1,582 and 2,025 square feet.

values of α bracket the Davis and Ortalo-Magné (2011) estimate of 0.24 for the median expenditure share on rents for all renting households in the United States.[11]

Given our specification of preferences, leisure is a constant and is independent of wage, location choice, and firm choice. We set the parameter ψ equal to 1.15 to generate a leisure share of total discretionary time in the year of 53.5%. This calculation assumes 15 discretionary hours in the day, a nine-hour work day, and households working five days per week and 50 weeks per year. Appendix A details how daily time use translates into annual time use.

We measure the population shares, π_ι, directly from the ACS.

In our benchmark parameterization, we compute the quantity of space demanded in each zone and in the CBD at specific rental prices that we calibrate from data. In our counterfactual simulations, we either solve for new rental prices holding quantities of space in each zone and the CBD as fixed, or we solve for new quantities holding rental prices fixed. We compute average annual office rents per square foot (psf) in the CBD using data from Real Capital Analytics Trends by multiplying the average transaction price psf for office space in that city by the cap rate specific to that city.[12] Consistent with the long-term value of the rent-price ratio documented by Davis, Lehnert, and Martin (2008), we apply a 5% cap rate to the median price per square foot for the residential prices by county reported by Realtor.com (available via FRED at the Federal Reserve Bank of St. Louis). We normalize the rental price of office space in the CBD $r^s = 1.0$, giving us rental prices for housing in Zones 1 and 2 of $r_1 = 0.81$ and $r_2 = 0.47$.

4.4 Parameters Estimated Outside the Model

While the existing literature informs us of the values of some parameters, we can estimate other parameters unique to our model directly from the data. Below, we describe the moments we target. Appendix E describes how we calculate the standard errors.

[11]Many studies find that a 1% increase in income results in an increase of much less than 1% in housing expenditure. See, for example, Rosen (1979), Glaeser, Kahn, and Rappaport (2008), and Rosenthal (2014).

[12]The cap rate is pre-tax net operating income divided by price. In leases where most of the expenses are paid by tenants, the cap rate is close to gross rents divided by price.

Commuting Costs. We estimate the time costs of commuting, t_1 and t_2, using data from the ACS on the average one-way commute time by workers commuting into Zone 1. Workers living in Zones 1 and 2 commuted an average of 25.7 and 47.7 minutes each way.

We estimate the financial commuting cost parameters, τ_1 and τ_2, using information from a special survey in the 2017 AHS. Our target financial commuting costs for Zones 1 and 2 are \$2,226 and \$5,565 per year for households working all days at the office.[13]

Productivity Parameters. To estimate Z_ι, we first estimate hourly wages for people working full time by household type 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 ι.[14]

Given values of θ_k, θ_s, θ_b, r^k, and r^s and estimates of hourly wages by ι, we use equations (11) and (8) to solve for Z_ι. Denote $\widetilde{w}_\iota$ as our estimate of hourly wages of type ι households. Given an assumed 15 hours of discretionary time each day, we can use the derivations in Appendix A to show $w_\iota = \widetilde{w}_\iota \cdot 15 \cdot 365$. Then the model implies

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

where the constant is equal to

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

[13]We assume that the distribution of financial commuting costs mimics the distribution of time commuting costs and use the financial commuting costs associated with the same percentile of time commuting costs that we observe for Zones 1 and 2 in the ACS, i.e., the percentiles of financial commuting costs corresponding to percentiles of commute times of 26 and 48 minutes.

[14]See Gutiérrez-i-Puigarnau and van Ommeren (2010), Black, Kolesnikova, and Taylor (2014), and Pabilonia and Vernon (2021) for discussions of the demographic differences in the relationship between commuting time and work.

Importance of Idiosyncratic Preferences for WFH Firm Choice. To estimate $1/\zeta$, note that equation (3) implies the following relationship of the difference in the log probability of choosing a WFH firm and a non-WFH firm

$$\log g^1_{n\iota} - \log g^0_{n\iota} = \zeta \left[X^1_{n\iota} - X^0_{n\iota}\right]. \tag{15}$$

Now define net annual wage for non-WFH and WFH employees as

$$\begin{aligned}
\mathcal{W}^0_{n\iota} &= \left(w^0_\iota - \tau_n\right) b^0_{n\iota} \\
\mathcal{W}^1_{n\iota} &= \left(\omega\left(l^b_{n\iota}, l^h_{n\iota}, s^h_{n\iota}, k^h_{n\iota}\right) - \tau_n l^b_{n\iota} - r_n s^h_{n\iota} - r^k k^h_{n\iota}\right).
\end{aligned}$$

The optimal choices for housing and consumption imply that equation (15) can be written as

$$\log g^1_{n\iota} - \log g^0_{n\iota} = \zeta \left[\chi_\iota + \log \mathcal{W}^1_{n\iota} - \log \mathcal{W}^0_{n\iota}\right. \tag{16}$$

Holding location fixed, the above expression implies that ζ determines the elasticity of firm choice with respect to annual net wage. We can use data from Table 5 of Mas and Pallais (2017) to estimate this elasticity. In that table, the wage discount at the 75th percentile is \$0.20 and the wage discount at the 25th percentile is \$2.45, both off of a base of \$17.50. If we compute equation (16) for each of these data points and then evaluate the difference, we get

$$\log(0.75/0.25) - \log(0.25/0.75) = \zeta\left[\log\left(1 - \frac{\$0.20}{\$17.50}\right) - \log\left(1 - \frac{\$2.45}{\$17.50}\right)\right] \tag{17}$$

This gives $\zeta = 15.77$ and $1/\zeta = 0.0634$, implying that people are willing to switch to a non-WFH firm in response to a small increase in wages. Intuitively, we can see this directly from Table 5 of Mas and Pallais (2017): 50% of the sample is willing to change jobs when the WFH discount changes by only 13 percentage points.[15]

4.5 Jointly Estimated Parameters

Moments Table 4 summarizes 10 additional moments we use to estimate the remaining 10 parameters of the model using method of moments. Based on our under-

[15]Mas and Pallais (2017) hold fixed the non-pecuniary aspects of the WFH and non-WFH jobs such that we can ignore possible changes to the parameter χ_ι when computing the difference.

standing of the model, we select moments of the data to be informative of the model's key parameters. These moments are:

1-4. The shares of each type of worker living in Zone 2,

5-6. The shares of type 1 and type 2 households working at WFH firms,

7-8. The shares of feasible days of WFH of all type 1 households in each of Zone 1 and Zone 2,

9. The share of days of WFH of all type 2 workers in all zones, and

10. The relative wage such that 60% of type 1 and type 2 workers choose a WFH firm.

For moments 5 and 6, we set the share of households working at WFH firms equal to (a) the share of workers in the ACS that mainly work from home, by type, multiplied by (b) the ratio (total WFH workers / usually WFH workers) in the GSS, also by type. This ratio is stable over time (see Section 2). For moments 7-9, we use data from the LJF to determine the total share of days worked at home by zone. We assign workers with a commute time of at least 15 minutes and less than or equal to 30 minutes to Zone 1 and all other workers to Zone 2.[16] After this sorting, we compute the total share of days worked at home by type of worker and by zone.

Finally, to compute the value of moment 10, we use experimental evidence from Mas and Pallais (2017) on workers' willingness to pay (WTP) to work at a firm that allows WFH. Mas and Pallais (2017) present the 25th percentile, mean, and 75th percentile of the WTP to work at a WFH firm. We linearly interpolate the WTP between the 25th and 75th percentiles to match the observed shares of all type 1 and 2 households working at WFH firms of 60%. This yields a relative wage of 95%.

Identification The 10 moments jointly identify the 10 parameters. We briefly describe the intuition for the identification below. Starting with the most straightforward parameters, we normalize $a_{1\iota} = 0$. Then, moments 1-4 identify the relative amenities that Zone 2 ($a_{2\iota}$) provides to each type of worker. $a_{2\iota}$ governs the model's

[16]We sort respondents in the LJF into zones based on commute time because we cannot directly identify the county of residence for most observations. We also exclude the small number of workers in the LJF who report working from home five days per week since we do not have a reliable commute time for these workers.

predictions for population of type ι in Zone 2 all else equal; therefore, population shares identify $a_{2\iota}$.

Next, patterns related to the intensive margins of WFH identify A^h_ι/A^b_ι and ρ. From equation (14), we can see that when there are no commuting costs, i.e., when $t_n = \tau_n = 0$, the ratio of time spent at the office to time working from home is a function of A^h_ι/A^b_ι and ρ, given estimates of r^s, r_n, and θ_s. Since A^h_ι/A^b_ι is fixed for each type, as commuting costs and rental prices change, equation (14) shows that ρ determines how the optimal allocation of time changes. The response of $l^b_{n\iota}/l^h_{n\iota}$ to variation in A^h_ι/A^b_ι, t_n, τ_n, and r_n identifies ρ. Given ρ, the level of $l^b_{n\iota}/l^h_{n\iota}$ is determined by A^h_ι/A^b_ι, conditional on all other variables and parameters.

To identify the remaining parameters, we impose $A^b_1 = \mathcal{Z}Z_1$ and $A^b_2 = \mathcal{Z}Z_2$. Patterns related to wages and the extensive margin then identify $\mathcal{Z}$ and χ_ι. Given estimates of Z_ι (from Section 4.4) and A^h_ι/A^b_ι , $\mathcal{Z}$ pins down the levels of A^b_ι and therefore A^h_ι. An increase in $\mathcal{Z}$ boosts the level of productivity and wages of WFH, which in turn increases the percentage of workers that optimally choose to work for a WFH firm. An increase in χ_ι also increases the percentage of workers that optimally choose to work for a WFH firm but does not change worker productivity or wages. Thus, the relative wage of households that work from home determines $\mathcal{Z}$. Given $\mathcal{Z}$, the percentage of workers optimally choosing to work for a WFH firm pins down χ_ι.

Mapping this intuition to the data, moments 5, 6, and 10 are informative about parameters related to the extensive margin: χ_1, χ_2, and $\mathcal{Z}$. Moments 7-9 are a mix of data from the intensive and extensive margins since they measure time worked from home as a percentage of total available time for all households, not just WFH households. Conditional on estimates of χ_1, χ_2, $\mathcal{Z}$, and ζ, moments 7-9 are informative about A^h_1/A^b_1 and A^h_2/A^b_2, which govern the model's predictions for the average value of the intensive margin, and about ρ, which governs the model's predictions for how the intensive margin varies with rents and commuting costs.

4.6 Results

Our point estimates for A^h_1/A^b_1 and A^h_2/A^b_2 are 0.365 and 0.348 with standard errors of 0.14 and 0.13. Our estimate of ρ is 0.72 with a standard error of 0.1. The point estimate of ρ implies an EOS between WFH and work at the office of 3.56. Using the delta method, we calculate a 95% confidence interval on the EOS of 1.002 (essentially Cobb-Douglas) to 6.105 confirming that WFH and work at the office are highly complementary in production, consistent with the descriptive evidence in Section 2. Conditional on being at a WFH firm, workers are most productive when they work occasionally at home given the complementarity between the two types of work.

4.7 Sensitivity of Parameter Estimates to Value of ν

When we map the model to data, Zone 2 corresponds to a group of several counties. However, we take our baseline value of ν from Monte, Redding, and Rossi-Hansberg (2018) where the geographic unit is a single county. We therefore consider how our estimates would be affected by using a lower value of ν that corresponds to a larger geographic unit. Table 5 presents our parameter estimates when we use $\nu = 2$, which is in the range of estimates from Appendix Table A.17 of Fajgelbaum, Morales, Suárez Serrato, and Zidar (2019). The estimates of the productivity parameters are extremely similar to our benchmark estimation. The estimates of the amenity parameters, $a_{2\iota}$, change more, but their change in values has little impact on our counterfactual scenarios.

4.8 Parameters for Counterfactuals

The last panel of Table 3 presents the values for the parameters that we use only in our counterfactuals. We do not use these parameters to estimate the model but set them in order to compute moments in our counterfactual scenarios of the next section. γ measures the elasticity of driving speed with respect to aggregate commuting miles. We set $\gamma = -0.15$ based on the preferred estimates in Couture, Duranton, and Turner (2018).[17] δ_b governs the extent of agglomeration returns in production for high-skill workers working in the CBD. We set this to 0.04 based on Davis, Fisher, and Whited (2014). Section 5.4 below uses our counterfactuals to calculate δ_{1h} and δ_{2h}.

[17] The estimates in Couture, Duranton, and Turner (2018) assume that driving is the mode of transportation. A different γ may prevail in more transit-dependent cities such as New York City.

5 Counterfactuals

Our model is designed to explain how the economy will change in response to the improvement in WFH productivity during COVID. We thus size the technological change such that the model-predicted number of WFH days quadruples immediately after the pandemic relative to its pre-pandemic level. The mechanism that generates the productivity change need not be specified to study its consequences. However, because the pandemic lasted only two years, we can size the adoption externality by treating the baseline levels of technology, $\bar{A}^h_\iota$, as fixed. We do so after discussing our post-pandemic counterfactuals.

Our target of a fourfold increase in total WFH days for both type 1 and type 2 workers immediately post COVID is slightly below the fivefold increase predicted by Barrero, Bloom, and Davis (2022). Barrero, Bloom, and Davis (2022) survey the subset of households that report having some experience with WFH during the pandemic so their survey corresponds with those in telecommutable occupations — our type 1 and type 2 households. Noting that Barrero, Bloom, and Davis (2020) report a divergence between household and firm preferences for WFH, we conservatively target a fourfold rather than fivefold increase since households may be optimistic about their employers' WFH plans and since the Barrero, Bloom, and Davis (2022) survey is a household survey.

We consider three counterfactual experiments that bracket the possible changes to city form and the use of space after the pandemic's health-related impacts subside and people can freely interact again. In all three counterfactuals, people can adjust where they live, how much they spend on housing, their labor supply, and their non-housing consumption. Households that are in a telecommutable occupation also choose their business equipment at home, their home-office space, and how much to work in the CBD and at home. What varies across counterfactuals is the extent to which aggregate quantities or prices of space, by zone, are allowed to vary from the pre-pandemic baseline.

5.1 Immediately After the Pandemic

To begin our counterfactuals, we size the technological improvement required to achieve the fourfold increase in WFH days for both type 1 and type 2 workers. In this first post-COVID counterfactual, called SR in Tables 6 and 7, we hold fixed the supply of office space in the CBD and the aggregate amount of available structures for use in housing and WFH in Zones 1 and 2 (separately) at the baseline levels. We then search for three market-clearing prices, r^b, r_1, and r_2, such that the demand for space is equal to the supply of space in each zone. We think of this as a short-run response in the sense that populations can move and the demand for space can immediately change, but the supply of space has not yet responded.

In the SR counterfactuals, A^h_ι / A^b_ι increases from 0.365 to 0.665 (88%) for high-skill workers and from 0.348 to 0.515 (48%) for low-skill workers. This enormous and sudden change in TFP for both worker types is inconsistent with the slow-moving trend in the amount of WFH in Section 2, motivating our inclusion of an adoption externality in the model. The percentage change in relative TFP is greater for high-skill workers because most of the increase in their WFH has to come along the intensive margin given that 70% of them did some WFH prior to the pandemic. In contrast, the model predicts a much greater change along the extensive margin for low-skill workers: the share of type 2 workers choosing a WFH firm rises from 32% pre pandemic to 65% post pandemic (Table 7).

Comparing columns 1 and 2 of Table 6 shows that, while incomes for both low- and high-skill workers rise (rows 8 and 9), the increase is more pronounced for high-skill workers. The difference is large enough to raise the ratio of high-skill to low-skill income by 16%, from 1.61 to 1.87 (row 10). Not surprisingly, the majority of the wage increases for both high-skill and low-skill households are in the occupations that allow WFH. Because a much larger share of high-skill than low-skill workers work in a telecommutable occupation, the average increase in wages is highest for high-skill workers. There is a small increase in wages for types 3 and 4 in the short run because the decline in office rents causes firms to rent more office space per worker, which raises worker productivity at the office. This wage increase more than offsets the slight decrease in agglomeration benefits for Type 3 households arising from the type 1 households working more from home.

Although high-skill workers work in the office less, the share of high-skill workers living in Zone 2 in this counterfactual increases modestly (row 20) as the quantity of space has not yet had a chance to adjust. Relative to the pre-pandemic benchmark, rent for office space in the CBD falls by a modest 7% (row 41). Residential rents rise in both zones, with the increase larger in Zone 2 (28%, row 43) than in Zone 1 (17%, row 42). The change in residential rents is driven by a large increase in demand for home offices (rows 37 and 40); the quantity of housing that is not used for home offices declines in both zones (rows (36) and (39)) as a result of the increased demand for home office space and the fixed supply of housing.

5.2 Long-Run Counterfactuals

In the second post-COVID counterfactual experiment, shown as LR in column 3 of Tables 6 and 7, we keep the level of technology fixed at the level that is required to generate the SR increase in total days of WFH (rows (1) and (2)). Rather than hold the supply of space in each zone fixed (as we did in the SR), our LR counterfactual holds rents in the CBD and in both zones fixed at their baseline levels and allows the supply of space in each zone to flexibly accommodate any change in demand.

Once the quantity of space has adjusted, the share of days worked from home rises even further, to 42% for type 1 and 22% for type 2, from 38% and 18% immediately after the pandemic (rows (28) and (29)). This occurs because once the supply of home-office space in the residential zones has increased, labor productivity from WFH rises, holding fixed the TFP of WFH. The increase in WFH slightly reduces the TFP from working at the office because of a reduction in agglomeration benefits, reinforcing the incentive for more WFH.

The demand for office space in the CBD declines by about 11% relative to its pre-pandemic level (row (34)). The demand for space for all uses increases by 16% in Zone 1 (row 35) and 30% in Zone 2. Housing for both types of workers increases from the benchmark, as both types earn more income. However, workers in telecommutable occupations occupy larger home offices in this environment, and this makes them even more productive at home. With this in mind, it is useful to compare the SR results, where the quantity of space in each zone is fixed and the price is flexible, to the LR results, where the price is fixed and the quantity is flexible. In the SR, home office space approximately quadruples from the pre-pandemic level, shown in rows (37) and (40). In the LR, space for home offices increases by about a factor of five relative to the pre-pandemic level.

The predicted changes to the size of home offices in the SR and LR experiments are large. The model forecasts these changes because the quantity of hours worked from home quadruples and because labor at home and home office space are complements in production with constant factor shares. Evidence in Stanton and Tiwari

(2021) supports our model's predictions for expenditures on home office. Stanton and Tiwari (2021) estimate that the expenditure share on housing for renting households where at least one member is working remotely is significantly higher than the expenditure share of otherwise similar households where no one works remotely. While our predictions for the size of home offices may seem large, keep in mind that much of the space in most office buildings is non-desk space such as conference rooms, lunch rooms, auditoriums, and even gyms, all of which is included in office space. Analogously, when households work from home, they use the home's bathroom, eat lunch in the kitchen, and watch Netflix while working out in the den during breaks. For workers that work from home, an accounting of costs would allocate some portion of the rent on those spaces to the home office and not housing.

In our final post-COVID counterfactual, we hold the quantity of office space in the CBD fixed and find the rent r^b such that demand is equal to supply, but fix rents in Zones 1 and 2 at their baseline levels assuming that additional development in these zones is feasible at current prices. Column 4 shows the results of this experiment, LR Putty-Clay. This experiment recognizes that depreciation rates on structures are sufficiently low that areas with a large decline in the rental price of office space may not see a reduction in the total amount of rented space for some time. In this experiment, rents on office space in the CBD fall to 92% of their pre-pandemic level (row (41)); and, relative to the LR experiment, a smaller share of days are worked at home (rows (28) and (29)), because office space is cheap in the CBD.

In all the experiments we have reported so far, consumption inequality (row 17) increases by less than income inequality. In the post-COVID counterfactuals, average wages rise for high-skill workers because these workers have become relatively more productive. The increase in productivity arises from the increase in A_1^h/A_1^b and expansions in the amount of home equipment and the size of home offices. Workers are compensated for the increase in their productivity, but some of the gains in income directly offset the additional expenses of the equipment and home offices. To match the model with data, we do not subtract expenditures on home equipment and offices from labor income as typical survey questions measuring wage and salary income do not ask respondents to net out expenditures on these items. Measured consumption inequality does not increase as much as income inequality because rent for home equipment and home office space reduces the income available for consumption for type 1 and type 2 workers that choose WFH firms.

5.3 The COVID-19 Pandemic

Our simulation for the COVID-19 pandemic consists of forcing the possible days that can be worked in the CBD for all households to only 40% of total days of WFH prior to the pandemic, consistent with the share of work done at home during the pandemic reported by Barrero, Bloom, and Davis (2020). Households continue to optimize over all other choice variables subject to this constraint. Appendix F characterizes the model solution during pandemic counterfactuals. We hold the model parameters fixed at their pre-pandemic levels during the COVID-19 counterfactual.

Column 2 of Table 8 shows how the pandemic affected the model economy at the start of the COVID-19 pandemic. Consumption for workers who can work remotely falls to about two-thirds of the pre-pandemic level. Type 3 and 4 workers are hurt much more since they cannot work remotely — their consumption falls to less than half of the pre-pandemic level. Because a larger fraction of high-skill workers can work remotely and because remote work is more productive for them, income inequality rises.

5.4 Identifying the Adoption Externality

In Equation (13), we specify the level of A_ι^h as equal to $\bar{A}_\iota^h \left(L_h^{max}\right)^{\delta_{\iota h}}$. Denote the pre-pandemic level of A_ι^h as $A_{\iota,pre}^h$ and the (immediate) post-pandemic level of A_ι^h as $A_{\iota,post}^h$. Total WFH labor supply prior to the pandemic was 0.059. In our COVID counterfactual, total WFH labor supply rises to 0.341. Assuming that $\bar{A}_\iota^h$ is fixed during the COVID pandemic, which is reasonable given that the pandemic lasted about 24 months, we can use the simulated aggregate days worked from home before and during the pandemic to solve for δ_{1h} as

$$\frac{A_{1,post}^h}{A_{1,pre}^h} = \frac{6153}{3404} = \left(\frac{0.341}{0.059}\right)^{\delta_{1h}}$$

where we have substituted $A_{1,post}^h = 6153$ and $A_{1,pre}^h = 3404$ using the results in rows (1) and (3) from columns (2) and (1) of Table 6. This yields $\delta_{1h} = 0.338$, implying that a 10% increase in aggregate hours (ever) worked at home boosts the productivity of working at home for high-skill workers by 3.4%. We similarly compute the adoption externality for low-skill workers as $\delta_{2h} = 0.224$.

5.5 A Hypothetical 2009 Pandemic

In Columns (4)-(6) of Table 8, we consider a counterfactual that corresponds to the effect of the COVID pandemic at a time when WFH was less viable than in 2020. In particular, we consider what would have happened had the pandemic hit in 2009, the earliest year for which we have the ACS five-year sample. In this counterfactual, we first reestimate the parameters of the model by changing the moments in Table 4 to their 2009 counterparts. Because we do not observe the LJF for any years other than the 2017-2018 wave, we scale the ratios of WFH in Zone 1 and Zone 2 by the ratio of total days of WFH in the ATUS in 2008-2010 relative to 2017-2019. For type 1 workers, we use the ratio specific to college-educated workers, and for type 2 workers we use the ratio specific to non-college educated workers. We then simulate the model at these parameters assuming a pandemic occurs. As in the COVID-19 simulations, during the pandemic we assume that each type of worker in each zone works in the CBD at an amount equal to 40% of their pre-pandemic work-time there.

Comparing column (6) to column (3) of Table 8, we see that the decline in income and consumption would have been worse for high-skill workers in telecommutable occupations had the pandemic happened in 2009 instead of 2019. This occurs because the relative TFP of WFH for these workers is lower in 2009 than in 2019, consistent with Figure 1 data showing that the quantity of WFH for high-skill workers was much lower in 2009 than in 2019. The change is much smaller for type 2 workers because they had such a small share of WFH both in 2019 and in 2009.

5.6 Robustness

5.6.1 Sensitivity to Agglomeration Economies in the CBD

Our benchmark parameterization sets $\delta_b = 0.04$ based on the estimates in Davis, Fisher, and Whited (2014). However, these estimates are based on data from entire metropolitan areas. To the extent that agglomeration economies may be stronger in a smaller location like a CBD, we compute counterfactuals after reestimating all model parameters with δ_b set to a much higher value (0.10). Table 9 presents these results. Overall, the change in δ_b does not materially affect any of our main results. The higher value of δ_b slightly reduces the skilled workers' gains from the increase in A^h_ι / A^b_ι, so their incomes rise less after the pandemic ends which moderates the increase in income inequality. The lower productivity from being at the office also reduces the demand for office space slightly, such that office rents fall by an additional percentage point relative to our benchmark scenario.

5.6.2 Sensitivity to Low-Skill Households Being Immobile

Our benchmark parameterization sets $\nu = 3.3$ for all workers, consistent with the existing literature (e.g., Monte, Redding, and Rossi-Hansberg (2018)). Coven, Gupta, and Yao (2020), however, document that low-skill workers did not move nearly as much as high-skill workers during the pandemic. In Table 10, we therefore consider a set of counterfactuals where we reestimate the parameters of the model after assuming that low-skill workers do not move in response to changes to economic fundamentals; we do this by setting $V_{n\iota j} = a_{n\iota} + e_{n\iota j}$ for type 2 and type 4 workers (see Equation (1)). Not surprisingly, the composition of residents in each zone changes less in the counterfactual experiments with low-skill workers being immobile than in the experiments with all workers being mobile. Prior to the pandemic, most low-skill workers did not work from home and, in our baseline parameterization, some of these workers moved to Zone 1 in the SR experiment. Thus, making low-skill workers immobile slightly reduces the demand for space in Zone 1 in the SR experiment which moderates the predicted increase in rents in that zone.

5.7 Dynamics

We can also examine how rents evolve after the pandemic if we combine our model with an assumption on the length of the adjustment period between the short run and the long run. Given the very high cost of converting many office buildings to residential uses, we view our Putty-Clay counterfactual as the most likely scenario for the long run. Figure 3 presents our estimates of rents for office space in the CBD and for housing in Zones 1 and 2 assuming the supply of residential space takes 10 years to fully adjust. We assume the quantity of space in each zone increases by a constant amount in each year of the adjustment period. Appendix Tables A.1 and A.2 show the full results over the adjustment period.

The sequence of rents shown in Figure 3 allows us to compute the post-COVID price of office buildings and residential space and compare them to pre-COVID levels. Assuming a 7% annual discount rate and that rent is paid in arrears, our simulation in Figure 3 implies that the price of office space post COVID should be 92.2% of its pre-COVID level. The price impacts for office space is insensitive to the discount rate: assuming a discount rate of anywhere from 2% to 10% implies that, immediately post COVID, prices are 91.99% to 92.24% of their pre-pandemic level. Assuming a 7% discount rate, the prices of residential space in Zones 1 and 2 should be 5% and 8% higher than pre-pandemic levels. Note that our dynamic counterfactual predicts that residential rents fall after COVID ends as the supply of space expands, particularly in Zone 2. This result is consistent with the findings of Gupta, Mittal, Peeters, and Van Nieuwerburgh (forthcoming).

Our model predicts a smaller increase in residential prices during the pandemic than actually occurred between the start of 2020 and the end of 2021 (see Figure 4). There are several possible reasons why home prices rose more in the data than in our model. First, our model does not contain a government such that there is no role for the influence of fiscal stimulus on house prices. Second, our counterfactual assumes that the supply of space is perfectly elastic in both residential zones such that rents return completely to their pre-pandemic values after 10 years. To the extent that land use restrictions or imperfect substitutability between vertical and horizontal residential space create less than perfectly elastic supply even in the long run, our counterfactual will understate the long-run increase in residential prices. Our dynamic counterfactuals may actually be used to infer the changes to the economy if housing supply is not perfectly elastic as it is unlikely to be in some cities. Finally, our model does not capture pandemic-period changes to the US labor force which have raised construction costs and may persist.

6 Distinguishing Between Misallocation and Productivity Change

The pandemic forced a large number of workers to work from home. According to our model, this caused a large increase in the relative productivity of WFH due to the presence of an adoption externality. After the pandemic ends, we expect the quantity of WFH to fall but still be four times greater than its pre-pandemic value. Our assumption that WFH will decline once the pandemic ends is consistent with (a) firm surveys of the expected amount of WFH once the pandemic ends and (b) our estimates that the TFP of WFH is lower than that of working at the office, i.e., $A_\iota^h/A_\iota^b < 1$. Of course, given that households optimally allocate their time, the *marginal* day worked at home is as productive as work at the office net of commuting costs (see Equation (6)).

An alternative view is that employees would have been able to work productively from home pre pandemic with the existing level of technology adoption, but employers did not know this and thus prevented them from doing so. Under this "misallocation" view, the increase in WFH that occurred during the pandemic could be much more permanent than surveys such as Barrero, Bloom, and Davis (2022) report. One articulation of the misallocation view, which is consistent with our technology adoption narrative, is that employers were unaware of the productivity of working from home until the pandemic forced a large number of workers to attempt it, enabling the full potential of existing WFH technology to be realized. We consider three ways to distinguish between other articulations of the misallocation view and the shift in productivity that we propose.

6.1 Misallocation in the Model

In our first exercise, we conceptualize the misallocation view as the view that there was no change in the productivity of WFH over the course of the pandemic but employers for some reason constrained the frequency of WFH to the levels we observed pre pandemic. Appendix H solves the model under these assumptions. Operationally, this implies that all of the productivity parameters in our model are unchanged between the pre-pandemic baseline and post-pandemic levels. In particular, in this counterfactual we assume that the relative TFPs of WFH and work at the office are $A_1^h/A_1^b = 0.66$ and $A_2^h/A_2^b = 0.515$ as in column (2) of Table 6. We also set $\mathcal{Z}$, ρ, and Z_ι for $\iota = 1, \ldots, 4$ equal to their baseline values. We then estimate the six remaining parameters of the model, $a_{2\iota}$ for $\iota = 1, \ldots, 4$ and χ_ι for $\iota = 1, 2$, using pre-pandemic moments on the fraction of each type living in Zone 1 for $\iota = 1, \ldots, 4$ and the percentage of each type $\iota = 1, 2$ choosing to work at a WFH firm.

Table 11 presents estimates of the preference parameters in this scenario and compares them to our benchmark estimates. The main change is that the workers' preferences for WFH firms significantly decline relative to the baseline estimates. In particular, to match the pre-pandemic shares of households choosing WFH firms, χ_2 becomes negative, implying that low-skill workers dislike being at a firm that allows

WFH. These preferences are inconsistent with the experimental findings of Mas and Pallais (2017) and He, Neumark, and Weng (2019) that workers value the option to work from home. Further, the surveys by Barrero, Bloom, and Davis (2020) indicate that employees would prefer to work more from home than employers want them to, suggesting that households have a high, positive preference for being able to do some WFH. On balance, the evidence is not consistent with employees disliking the option to work at a firm that allows some WFH.

6.2 Implications of Misallocation and Productivity Change for Office Prices

Another prediction of the misallocation view is that the low demand for office space during the pandemic will persist into the future due to a much greater share of post-pandemic WFH than we assume in our baseline counterfactual simulations. That is, in this interpretation of the misallocation view, the demand for office space in the long run is roughly the same as during the COVID-19 pandemic.

In our COVID-19 counterfactual, office rents fall to just $0.486 — less than half their pre-pandemic level. If this is a permanent change, then the decline in the price of office buildings should be large, roughly 50%. Even assuming that some office space can be profitably converted to residential space despite the high costs of conversion, the fall in the price of office space should be substantial. For comparison, our dynamic exercise in Section 5.7 finds that the price of office space will fall by about 8%.[18]

We use data on changes in the price of office space from real estate investment trusts (REITs) to distinguish between the productivity and misallocation views. Figure 4 presents changes in the price of REIT equity by property type (lined bars) and the implied change in underlying asset values (solid bars) after adjusting for leverage between January 1, 2020 and December 31, 2021 for office, apartments, and single-family rental housing. The REIT data show that the implied decline in the value of office buildings is less than 5%, which is closer to our counterfactual than the misallocation view.[19]

[18]We also considered an alternative COVID-19 counterfactual where there is no change in the amount of work that can be done in the CBD for types 3 and 4, such that the office rent decline is less dramatic. In this counterfactual, office rents fall to 75% of their pre-pandemic level.

[19]The data in Figure 4 are from the FTSE-NAREIT US price indices for office, apartments, and single-family rental property. To compute the implied property price changes, we use Compustat data on the leverage of REITs by property type in 2019.

While our model simplifies the office market by assuming that leases are just one year, rather than long-term, evidence from newly signed commercial leases is consistent with the magnitude of the rent declines it predicts. Table 1 of Rosenthal, Strange, and Urrego (2022) reports that, for car-dependent cities, the change in median rent per square foot on newly executed office leases is about 10%. For transit-dependent cities, the decline at the median is 8%.

6.3 Microeconomic Evidence

There is also important microeconomic evidence indicating that WFH was less productive on average than work at the office prior to the pandemic. For work that requires more coordination across workers and especially work that it is likely to produce substantial knowledge spillovers, the literature has generally found that WFH is less productive than work at the office if either type of work is considered separately. For example Gibbs, Mengel, and Siemroth (2021) look at skilled professionals at an Asian IT firm and find that forcing them to work from home led to a 10%-25% decline in productivity. In their comprehensive survey of employers, Bartik, Cullen, Glaeser, Luca, and Stanton (2020) report a 20% average decrease in productivity during the pandemic as a result of working from home. In their survey of NABE economists, Bartik, Cullen, Glaeser, Luca, and Stanton (2020) report a nearly 30% decrease in productivity from working at home. Morikawa (2020) presents survey evidence from an economic research institute showing that most employees consider themselves less productive at home but that productivity increases as employees become more familiar with WFH technology. Although Kruger, Maturana, and Nickerson (2020) report greater output of finance academics during COVID-19, this is likely because of greater input of hours and the particular task of completing papers early in the pandemic. In their study of finance academics, Barber, Jiang, Morse, Puri, Tookes, and Werner (2021) find that feelings of isolation and the inability to obtain feedback as a result of WFH decrease research productivity.

Additional micro evidence is consistent with the idea that WFH and work at the office are complements in production. In particular, it may be easier to complete certain tasks at the office and other tasks at home. Bloom, Liang, Roberts, and Ying (2014) find that call processing tasks can be done more productively from home. Dutcher (2012) provides experimental evidence that more creative tasks are more productively done at home, while telecommuting has negative impacts on the productivity of workers assigned dull tasks.

7 Conclusions

Expectations about how much time will be spent working from home as compared to the office have permanently changed as a result of the improvement in the relative productivity of WFH. Surveys suggest that once the pandemic subsides, workers will approximately quadruple their time spent working from home relative to pre-pandemic levels. Both descriptive evidence and our estimates of the elasticity of substitution imply that WFH is a complement to work at the office. Simulations of our model suggest that these changes will markedly reduce office rents, significantly increase the quantity of housing in the suburbs, and widen income inequality.

While our model has a rich production structure, we abstract from certain details. For example, although we capture heterogeneity in WFH productivity by occupation and by skill level, there is surely additional heterogeneity at the household and firm level. Additionally, all work at the office occurs in the CBD in our model. It seems plausible that both the technological changes we document and the change in urban form implied by our model increase the frequency of commutes to work locations outside of the CBD. We hope future research explores how improvements in the technology of remote work affect firms' location choice. Finally, our estimation approach aggregates data from across the entire United States, ignoring heterogeneity across cities in the composition of the labor force (Althoff, Eckert, Ganapati, and Walsh, 2022) and in rent gradients. We expect future research will explore how differences across cities in the skill and occupational composition of the labor force, and the rent gradient, will influence the impact of changes in WFH technology on urban form, the price of space, and income inequality.

References

ALTHOFF, L., F. ECKERT, S. GANAPATI, AND C. WALSH (2022): "The Geography of Remote Work," Regional Science and Urban Economics, 93, 1–21.

ARUOBA, S. B., M. A. DAVIS, AND R. WRIGHT (2016): "Homework in Monetary

Economics: Inflation, Home Production, and the Production of Homes," Review of Economic Dynamics, 21, 105–124.

BACOLOD, M., B. S. BLUM, AND W. C. STRANGE (2009): "Skills in the City," Journal of Urban Economics, 65, 136 – 153.

BARBER, B. M., W. JIANG, A. MORSE, M. PURI, H. TOOKES, AND I. M. WERNER (2021): "What Explains Differences in Finance Research Productivity during the Pandemic?" The Journal of Finance, 76, 1655–1697.

BARRERO, J. M., N. BLOOM, AND S. J. DAVIS (2020): "Why Working From Home Will Stick," Tech. rep., Stanford University.

——— (2022): "SWAA February 2022 updates," Tech. rep., ITAM.

BARTIK, A. W., Z. CULLEN, E. L. GLAESER, M. LUCA, AND C. STANTON (2020): "What Jobs are Being Done at Home During the COVID-19 Crisis? Evidence from Firm-Level Surveys," Tech. rep., Harvard University.

BEAUDRY, P., M. DOMS, AND E. LEWIS (2010): "Should the Personal Computer Be Considered a Technological Revolution? Evidence from U.S. Metropolitan Areas," Journal of Political Economy, 118, 988–1036.

BEHRENS, K., S. KICHKO, AND J.-F. THISSE (2021): "Working from home: Too much of a good thing?" Tech. rep., Université du Québec à Montréal.

BENHABIB, J., R. ROGERSON, AND R. WRIGHT (1991): "Homework in Macroeconomics: Household Production and Aggregate Fluctuations," Journal of Political Economy, 99, 1166–1187.

BICK, A., A. BLANDIN, AND K. MERTENS (2021): "Work from Home Before and After the COVID-19 Outbreak," Tech. rep., Arizona State University.

BLACK, D. A., N. KOLESNIKOVA, AND L. J. TAYLOR (2014): "Why do so few women work in New York (and so many in Minneapolis)? Labor supply of married women across US cities," Journal of Urban Economics, 79, 59–71, spatial Dimensions of Labor Markets.

BLEAKLEY, H. AND J. LIN (2012): "Portage and Path Dependence," The Quarterly Journal of Economics, 127, 587–644.

BLOOM, N., J. LIANG, J. ROBERTS, AND Z. J. YING (2014): "Does Working from Home Work? Evidence from a Chinese Experiment," The Quarterly Journal of Economics, 130, 165–218.

BROCK, W. A. AND S. N. DURLAUF (2010): "Adoption Curves and Social Interactions," Journal of the European Economic Association, 8, 232–251.

BROOKS, L. AND B. LUTZ (2019): "Vestiges of Transit: Urban Persistence at a Microscale," The Review of Economics and Statistics, 101, 385–399.

BRUECKNER, J. K., M. E. KAHN, AND G. C. LIN (2021): "A New Spatial Hedonic Equilibrium in the Emerging Work-from-Home Economy?" Tech. rep., University of California, Irvine.

COMIN, D. AND M. MESTIERI (2014): "Chapter 2 - Technology Diffusion: Measurement, Causes, and Consequences," in Handbook of Economic Growth, ed. by P. Aghion and S. N. Durlauf, Elsevier, vol. 2, 565 – 622.

COUTURE, V., G. DURANTON, AND M. A. TURNER (2018): "Speed," The Review of Economics and Statistics, 100, 725–739.

COVEN, J., A. GUPTA, AND I. YAO (2020): "Urban Flight Seeded the COVID-19 Pandemic Across the United States," Tech. rep., New York University.

DAVIS, D. R. AND D. E. WEINSTEIN (2002): "Bones, Bombs, and Break Points: The Geography of Economic Activity," American Economic Review, 92, 1269–1289.

DAVIS, M. A., J. D. M. FISHER, AND T. M. WHITED (2014): "Macroeconomic Implications of Agglomeration," Econometrica, 82, 731–764.

DAVIS, M. A., A. LEHNERT, AND R. F. MARTIN (2008): "The Rent-Price Ratio for the Aggregate Stock of Owner-Occupied Housing," Review of Income and Wealth, 54, 279–284.

DAVIS, M. A. AND F. ORTALO-MAGNÉ (2011): "Household Expenditures, Wages, Rents," Review of Economic Dynamics, 14, 248–261.

DELVENTHAL, M. J., E. KWON, AND A. PARKHOMENKO (2022): "JUE Insight: How do cities change when we work from home?" Journal of Urban Economics, 127.

DELVENTHAL, M. J. AND A. PARKHOMENKO (2021): "Spatial Implications of Telecommuting," Tech. rep., Clarement McKenna College.

DINGEL, J. I. AND B. NEIMAN (2020): "How Many Jobs can be Done at Home?" Journal of Public Economics, 189, 104235.

DUTCHER, E. G. (2012): "The effects of telecommuting on productivity: An experimental examination. The role of dull and creative tasks," Journal of Economic Behavior & Organization, 84, 355–363.

EMANUEL, N. AND E. HARRINGTON (2020): ""Working" Remotely?" Tech. rep., Harvard University.

FAJGELBAUM, P. D., E. MORALES, J. C. SUÁREZ SERRATO, AND O. ZIDAR (2019): "State Taxes and Spatial Misallocation," The Review of Economic Studies, 86, 333–376.

FAVILUKIS, J. Y. AND S. VAN NIEUWERBURGH (2021): "Out-of-Town Home Buyers and City Welfare," Journal of Finance, forthcoming.

FOSTER, A. D. AND M. R. ROSENZWEIG (2010): "Microeconomics of Technology Adoption," Annual Review of Economics, 2, 395–424.

GASPAR, J. AND E. L. GLAESER (1998): "Information Technology and the Future of Cities," Journal of Urban Economics, 43, 136–156.

GIBBS, M., F. MENGEL, AND C. SIEMROTH (2021): "Work from Home and Productivity: Evidence from Personnel and Analytics Data on IT Professionals," Tech. rep., University of Chicago.

GLAESER, E. L., M. E. KAHN, AND J. RAPPAPORT (2008): "Why do the Poor Live in Cities? The Role of Public Transportation," Journal of Urban Economics, 63, 1 – 24.

GOULD, E. D. (2007): "Cities, Workers, and Wages: A Structural Analysis of the Urban Wage Premium," The Review of Economic Studies, 74, 477–506.

GREENWOOD, J., A. SESHADRI, AND M. YORUKOGLU (2005): "Engines of Liberation," The Review of Economic Studies, 72, 109–133.

GUPTA, A., V. MITTAL, J. PEETERS, AND S. VAN NIEUWERBURGH (forthcoming): "Flattening the Curve: Pandemic-Induced Revaluation of Urban Real Estate," Journal of Financial Economics.

GUTIÉRREZ-I-PUIGARNAU, E. AND J. N. VAN OMMEREN (2010): "Labour supply and commuting," Journal of Urban Economics, 68, 82–89.

HASLAG, P. AND D. WEAGLEY (2021): "From L.A. to Boise: How Migration Has Changed During the COVID-19 Pandemic," Tech. rep., Vanderbilt University.

HE, H., D. NEUMARK, AND Q. WENG (2019): "Do Workers Value Flexible Jobs? A Field Experiment," Tech. rep., National Bureau of Economic Research Working Paper 25423.

JONES, C. I. (2005): "The Shape of Production Functions and the Direction of Technical Change," The Quarterly Journal of Economics, 120, 517–549.

KAPLAN, G., B. MOLL, AND G. L. VIOLANTE (2020): "The Great Lockdown and the Big Stimulus: Tracing the Pandemic Possibility Frontier for the U.S." Tech. rep., University of Chicago.

KATZ, M. L. AND C. SHAPIRO (1986): "Technology Adoption in the Presence of Network Externalities," Journal of Political Economy, 94, 822–841.

KRUGER, S., G. MATURANA, AND J. NICKERSON (2020): "How has COVID-19 Impacted Research Productivity in Economics and Finance?" Tech. rep., University of Texas-Austin.

KRUSSEL, P., L. E. OHANIAN, J.-V. RIOS-RULL, AND G. L. VIOLANTE (2000): "Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis," Econometrica, 68, 1029–1053.

LI, W. AND Y. SU (2021): "The Great Reshuffle: Residential Sorting During the COVID-19 Pandemic and Its Welfare Implications," Tech. rep., Federal Reserve Bank of Philadelphia.

LIU, S. AND Y. SU (2021): "The impact of the COVID-19 pandemic on the demand for density: Evidence from the U.S. housing market," Economics Letters, 207, 110010.

MAS, A. AND A. PALLAIS (2017): "Valuing Alternative Work Arrangements," American Economic Review, 107, 3722–59.

——— (2020): "Alternative Work Arrangements," Annual Review of Economics, 12, 631–658.

MCGRATTAN, E. R., R. ROGERSON, AND R. WRIGHT (1997): "An Equilibrium Model of the Business Cycle with Household Production and Fiscal Policy," International Economic Review, 38, 267–290.

MONTE, F., S. J. REDDING, AND E. ROSSI-HANSBERG (2018): “Commuting, Migration, and Local Employment Elasticities,” American Economic Review, 108, 3855–90.

MORIKAWA, M. (2020): “COVID-19, teleworking, and productivity,” VOX EU, 10 April.

MORTENSEN, S. AND N. WETTERLING (2020): “Nordic Real Estate: Remote Work to Permanently Double,” Tech. rep., DNB Markets.

OUAZAD, A. (forthcoming): “Resilient Urban Housing Markets: Shocks vs. Fundamentals,” in Covid and Resilience, ed. by I. Linkov, B. Trump, and J. Keenan, Springer Verlag.

PABILONIA, S. W. AND V. VERNON (2021): “Telework, Wages, and Time Use in the United States,” Tech. rep., U.S. Bureau of Labor Statistics.

ROCA, J. D. L. AND D. PUGA (2016): “Learning by Working in Big Cities,” The Review of Economic Studies, 84, 106–142.

ROSEN, H. S. (1979): “Housing Decisions and the U.S. Income Tax: An Econometric Analysis,” Journal of Public Economics, 11, 1 – 23.

ROSENTHAL, S. S. (2014): “Are Private Markets and Filtering a Viable Source of Low-Income Housing? Estimates from a “Repeat Income” Model,” American Economic Review, 104, 687–706.

ROSENTHAL, S. S. AND W. C. STRANGE (2008): “The Attenuation of Human Capital Spillovers,” Journal of Urban Economics, 64, 373 – 389.

ROSENTHAL, S. S., W. C. STRANGE, AND J. A. URREGO (2022): “JUE Insight: Are city centers losing their appeal? Commercial real estate, urban spatial structure, and COVID-19,” Journal of Urban Economics, 127, 103381, jUE Insights: COVID-19 and Cities.

ROSSI-HANSBERG, E., P.-D. SARTE, AND F. SCHWARTZMAN (2019): “Cognitive Hubs and Spatial Redistribution,” Tech. rep., Princeton University.

STANTON, C. AND P. TIWARI (2021): “Housing Consumption and the Cost of Remote Work,” Tech. rep., Harvard Business School.

VALENTINYI, A. AND B. HERRENDORF (2008): "Measuring factor income shares at the sectoral level," Review of Economic Dynamics, 11, 820 – 835.

VIOLANTE, G. L. (2008): "Skill-Biased Technical Change," in The New Palgrave Dictionary of Economics, 2nd Edition, ed. by L. Blume and S. Durlauf, MacMillan.

Table 1: Frequency of WFH by Demographics and Definition

Group	(1) Any WFH	(2) ATUS Only WFH	(3) Only WFH Full Days	(4) LJF Only WFH Full Days
All	23.7	9.9	4.9	3.4
Full time	23.3	9.7	5.1	3.5
Part time	24.8	9.6	3.7	3.0
Male	22.3	8.7	4.2	3.2
Male, full time	22.4	8.6	4.3	3.3
Male, part time	20.7	7.2	3.0	2.5
Female	25.4	11.3	5.8	3.7
Female, full time	24.7	11.2	6.2	3.8
Female, part time	27.4	11.1	4.1	3.3
Holds one job	22.4	9.4	4.7	3.3
Multiple jobs	33.6	12.2	6.6	4.4
Education groups (age 25+ only):				
No bachelor's degree	15.9	5.6	3.0	1.8
High school dregree or less	13.0	3.8	1.9	1.2
High school dregree	11.8	2.9	0.8	0.9
High school dropout	13.3	4.0	2.2	1.3
Some college	19.9	8.0	4.5	2.6
Bachelor's degree or higher	37.3	16.8	8.6	6.4
Bachelor's degree only	33.3	14.4	7.3	5.8
Advanced degree	43.0	20.3	10.4	7.3

Notes: 1) Columns (1)-(3) report data from the 2017-2019 American Time Use Survey (ATUS). 2) Column (4) reports data from the 2017-2018 Leave and Job Flexibility Module (LJF) of the ATUS.

Table 2: Intensity of WFH in the GSS

Frequency of WFH	2010	2014	2018
Never	57%	59%	60%
A few times a year	10%	8%	8%
About once a month	8%	5%	7%
About once a week	8%	8%	9%
More than once a week	13%	14%	12%
Worker works mainly at home	5%	5%	5%
Share of workers that WFH that work mainly at home	11%	13%	12%

Notes: GSS asks respondents "[H]ow often do you work at home as part of your job?"

Table 3: Model Parameterization

Parameter	Description	Determined	Value	Std. Error
θ_b	Labor share in production	Fixed	0.67	
θ_s	Structures share in production	Fixed	0.18	
θ_k	Business equipment share in production	Fixed	0.15	
ν	Importance of deterministic utility for n	Fixed	3.3	
α_1	Housing exp. share for type 1	Fixed	0.20	
α_2	Housing exp. share for type 2	Fixed	0.33	
α_3	Housing exp. share for type 3	Fixed	0.20	
α_4	Housing exp.share for type 4	Fixed	0.33	
ψ	Pref. for leisure	Fixed	1.15	
$\mathcal{T}$	Daily discretionary hours available for work	Fixed	15	
$\hat{b}$	Hours worked per working day	Fixed	9	
π_1	Share of workers of type 1	Fixed	0.34	
π_2	Share of workers of type 2	Fixed	0.12	
π_3	Share of workers of type 3	Fixed	0.17	
π_4	Share of workers of type 4	Fixed	0.37	
r^s	Office rent psf in CBD	Normalized	1.00	
r_1	Residential rent psf in Zone 1	Fixed	0.81	
r_2	Residential rent psf in Zone 2	Fixed	0.47	
t_1	Time cost of commuting from Zone 1 to CBD	Estimated	0.0953	0.0001
t_2	Time cost of commuting from Zone 2 to CBD	Estimated	0.1766	0.0003
τ_1	Financial commuting cost from Zone 1 to CBD	Estimated	5,417	270
τ_2	Financial commuting cost from Zone 2 to CBD	Estimated	13,542	518
Z_1	TFP of non-WFH firm hiring type 1 workers	Estimated	10,493	4
Z_2	TFP of non-WFH firm hiring type 2 workers	Estimated	8,305	5
Z_3	TFP of firm hiring type 3 workers	Estimated	9,249	6
Z_4	TFP of firm hiring type 4 workers	Estimated	6,900	5
$\frac{1}{\zeta}$	Importance of deterministic utility for κ	Estimated	0.0634	0.0198
$\mathcal{Z}$	TFP of work at office for WFH firm ($A_\iota^b = \mathcal{Z} Z_\iota$ for $\iota = 1, 2$)	Jointly Est.	0.889	0.029
a_{21}	Amenities in Zone 2 for type 1 worker	Jointly Est.	0.149	0.003
a_{22}	Amenities in Zone 2 for type 2 worker	Jointly Est.	0.146	0.004
a_{23}	Amenities in Zone 2 for type 3 worker	Jointly Est.	0.191	0.004
a_{24}	Amenities in Zone 2 for type 4 worker	Jointly Est.	0.132	0.004
χ_1	Pref. for WFH firm for type 1	Jointly Est.	0.158	0.035
χ_2	Pref. for WFH firm for type 2	Jointly Est.	0.064	0.038
ρ	EOS between WFH and work at the office $= \frac{1}{1-\rho}$	Jointly Est.	0.719	0.103
A_1^h/A_1^b	Relative productivity of WFH for type 1 at a WFH firm	Jointly Est.	0.365	0.141
A_2^h/A_2^b	Relative productivity of WFH for type 2 at a WFH firm	Jointly Est.	0.348	0.130
Parameters only used in or determined by counterfactuals:				
δ_b	Agglomeration externality	Fixed	0.04	
$\bar{Z}_1$	Base level of TFP for type 1 at non-WFH firm	Fixed	11202	
$\bar{Z}_3$	Base level of TFP for type 3 at non-WFH firm	Fixed	9875	
$\bar{A}_1^b$	Base level of TFP for type 1 at WFH firm	Fixed	9961	
γ	Congestion externality	Fixed	-0.15	
d_1	Distance from Zone 1 to CBD	Fixed	12.9	
d_2	Distance from Zone 2 to CBD	Fixed	23.8	
$\bar{\mathcal{S}}$	Commuting speed parameter	Fixed	41.2	
δ_{1h}	Adoption externality for type 1 worker	Fixed	0.338	
δ_{2h}	Adoption externality for type 2 worker	Fixed	0.224	

Notes: A type worker is a high-skill household in a telecommutable occupation. A type 2 worker is a low-skill household in a telecommutable occupation. A type 3 worker is a high-skill household in a non-telecommutable occupation. A type 4 worker is a low-skill household in a non-telecommutable occupation.

Table 4: Moments Used in Method of Moments Estimation

Moment	Value	Std. Error	Source
Share of type 1 workers living in Zone 2	0.639	0.001	ACS
Share of type 2 workers living in Zone 2	0.672	0.001	ACS
Share of type 3 workers living in Zone 2	0.653	0.002	ACS
Share of type 4 workers living in Zone 2	0.645	0.001	ACS
Share of type 1 working at WFH firms, i.e., $P(WFH = 1 \mid \iota = 1)$	0.697	0.001	ACS & GSS (for scaling ACS WFH)
Share of type 2 working at WFH firms, i.e., $P(WFH = 1 \mid \iota = 2)$	0.322	0.001	ACS & GSS (for scaling ACS WFH)
Type 1 living in Zone 1 share of days WFH	0.066	0.007	LJF
Type 1 living in Zone 2 share of days WFH	0.119	0.011	LJF
Type 2 living in all zones share of days WFH	0.045	0.007	LJF
Relative wage such that 60% of type 1 and 2 population chooses WFH firm	0.949	0.029	Interpolation of Mas and Pallais (2017)

Notes: A type worker is a high-skill household in a telecommutable occupation. A type 2 worker is a low-skill household in a telecommutable occupation. A type 3 worker is a high-skill household in a non-telecommutable occupation. A type 4 worker is a low-skill household in a non-telecommutable occupation.

Table 5: Sensitivity of Parameter Estimates to $\nu = 2$

	Benchmark		$\nu = 2$	
	Point Estimate	Std. Error	Point Estimate	Std. Error
$\mathcal{Z}$	0.889	0.029	0.889	0.029
a_{21}	0.149	0.003	0.262	0.004
a_{22}	0.146	0.004	0.287	0.005
a_{23}	0.191	0.004	0.315	0.005
a_{24}	0.132	0.004	0.249	0.005
χ_1	0.158	0.035	0.158	0.035
χ_2	0.064	0.038	0.064	0.038
ρ	0.719	0.103	0.719	0.103
A_1^h/A_1^b	0.365	0.141	0.365	0.141
A_2^h/A_2^b	0.348	0.130	0.348	0.130

Notes: 1) Our benchmark estimation in Table 3 sets $\nu = 3.3$. 2) ν controls the strength of households' idiosyncratic preferences for a particular zone.

Table 6: Model Prediction for Distribution of Incomes and Population

Row		Pre-COVID Baseline (1)	Post-COVID Scenarios SR (2)	LR (3)	LR Putty-Clay (4)
	Technology:				
(1)	A_1^h/A_1^b	0.365	0.665	0.666	0.665
(2)	A_2^h/A_2^b	0.348	0.515	0.515	0.515
(3)	A_1^b	9330	9254	9241	9245
	Incomes:				
(4)	Type 1 avg. ann. income per worker	$ 108,862	$ 141,424	$ 144,440	$ 146,114
(5)	Type 2 avg. ann. income per worker	$ 77,776	$ 84,921	$ 85,302	$ 86,685
(6)	Type 3 avg. ann. income per worker	$ 93,135	$ 94,170	$ 91,804	$ 94,184
(7)	Type 4 avg. ann. income per worker	$ 60,176	$ 61,630	$ 60,176	$ 61,688
(8)	High-skill avg. ann. income per worker	$ 103,620	$ 125,673	$ 126,894	$ 128,804
(9)	Low-skill avg. ann. income per worker	$ 64,486	$ 67,334	$ 66,329	$ 67,810
(10)	Ratio of high-skill to low-skill Income	1.61	1.87	1.91	1.90
	Consumption:				
(11)	Type 1 avg. non-housing consumption	$ 80,664	$ 94,557	$ 95,170	$ 96,721
(12)	Type 2 avg. non-housing consumption	$ 48,463	$ 50,634	$ 50,038	$ 51,125
(13)	Type 3 avg. non-housing consumption	$ 71,074	$ 71,925	$ 70,010	$ 71,902
(14)	Type 4 avg. non-housing consumption	$ 37,457	$ 38,468	$ 37,457	$ 38,459
(15)	High-skill avg. non-housing consumption	$ 77,467	$ 87,013	$ 86,784	$ 88,448
(16)	Low-skill avg. non-housing consumption	$ 40,152	$ 41,447	$ 40,538	$ 41,561
(17)	Ratio of high-skill to low-skill avg. consumption	1.93	2.10	2.14	2.13
	Population Location:				
(18)	Total high-skill	51.0%	51.0%	51.0%	51.0%
(19)	Living in Zone 1	35.6%	34.0%	32.0%	32.0%
(20)	Living in Zone 2	64.4%	66.0%	68.0%	68.0%
(21)	Total low-skill	49.0%	49.0%	49.0%	49.0%
(22)	Living in Zone 1	34.8%	36.5%	34.2%	34.1%
(23)	Living in Zone 2	65.2%	63.5%	65.8%	65.9%

Notes: 1) We parameterize the model to the pre-COVID world. 2) In columns (2)-(4), we increase A_1^h/A_1^b and A_2^h/A_2^b to the level required to increase the number of days in the year worked from home fourfold. 3) We hold the supply of space fixed at the pre-COVID baseline in counterfactual (2). In counterfactual (3), we adjust the supply of space such that rents are equal to their pre-COVID benchmark in column (1) but keep the technology parameters fixed at the SR level. In column (4), we keep the stock of office space at the level in column (1) but adjust the stocks of residential space such that residential rents return to the level in column (1).

Table 7: Model Predictions for Work Location, Space, and Rents

		Pre-COVID	Post-COVID Scenarios		
		Baseline	SR	LR	LR Putty-Clay
Row		(1)	(2)	(3)	(4)
	Labor Supply:				
(24)	Type 1	0.411	0.427	0.429	0.429
(25)	Type 2	0.407	0.416	0.417	0.417
	Labor Supply of WFH:				
(26)	Type 1	0.041	0.164	0.181	0.176
(27)	Type 2	0.018	0.073	0.091	0.086
	Days WFH to Total Days Worked:				
(28)	Type 1	0.099	0.383	0.423	0.410
(29)	Type 2	0.045	0.176	0.218	0.205
	Extensive Margin of WFH:				
(30)	Share of type 1 choosing WFH firm	0.697	0.974	0.983	0.981
(31)	Share ot type 2 choosing WFH firm	0.322	0.646	0.718	0.697
	Intensive Margin of WFH:				
(32)	Days worked WFH to total days for type 1 at WFH firm	0.140	0.390	0.430	0.420
(33)	Days worked WFH to total days for type 2 at WFH firm	0.140	0.270	0.300	0.290
	Demand for Space:				
(34)	Office space per worker in CBD	21,403	21,403	19,097	21,403
(35)	Total space per household in Zone 1	26,680	26,681	30,982	31,535
(36)	Housing per household in Zone 1	25,904	23,331	26,752	27,366
(37)	Home office per household in Zone 1	775	3,350	4,229	4,169
(38)	Total space per household in Zone 2	42,092	42,091	54,849	55,584
(39)	Housing per household in Zone 2	39,995	34,240	43,496	44,435
(40)	Home office per household in Zone 2	2,097	7,852	11,353	11,149
	Rent per Unit of Space:				
(41)	CBD	1.000	0.928	1.000	0.919
(42)	Zone 1	0.810	0.945	0.810	0.810
(43)	Zone 2	0.470	0.601	0.470	0.470

Notes: 1) Labor supply is the fraction of total discretionary time spent working. 2) See notes to Table 6.

Table 8: Pandemic Counterfactuals

	COVID-19 Pandemic			Hypothetical 2009 Pandemic		
	Pre-COVID	COVID Start	Ratio	Pre-COVID	COVID Start	Ratio
	(1)	(2)	(3)	(4)	(5)	(6)
Technology:						
A_1^h/A_1^b	0.365	0.365		0.290	0.290	
A_2^h/A_2^b	0.348	0.348		0.331	0.331	
Incomes:						
Type 1 avg. ann. income per worker	$ 108,862	$ 81,109	74.5%	$109,198	$ 73,437	67.3%
Type 2 avg. ann. income per worker	$ 77,776	$ 56,393	72.5%	$ 78,854	$ 57,715	73.2%
Type 3 avg. ann. income per worker	$ 93,135	$ 42,801	46.0%	$ 93,065	$ 42,906	46.1%
Type 4 avg. ann. income per worker	$ 60,176	$ 29,263	48.6%	$ 60,168	$ 29,365	48.8%
High-skill avg. ann. income per worker	$ 103,620	$ 68,340	66.0%	$103,820	$ 63,260	60.9%
Low-skill avg. ann. income per worker	$ 64,486	$ 35,907	55.7%	$ 64,744	$ 36,308	56.1%
Consumption:						
Type 1 avg. non-housing consumption	$ 80,664	$ 54,903	68.1%	$ 82,065	$ 50,930	62.1%
Type 2 avg. non-housing consumption	$ 48,463	$ 32,182	66.4%	$ 49,222	$ 32,974	67.0%
Type 3 avg. non-housing consumption	$ 71,074	$ 32,876	46.3%	$ 70,992	$ 32,950	46.4%
Type 4 avg. non-housing consumption	$ 37,457	$ 18,474	49.3%	$ 37,448	$ 18,540	49.5%
High-skill avg. non-housing consumption	$ 77,467	$ 47,561	61.4%	$ 78,374	$ 44,937	57.3%
Low-skill avg. non-housing consumption	$ 40,152	$ 21,831	54.4%	$ 40,331	$ 22,075	54.7%

Table 9: Sensitivity to Greater Agglomeration Economies

	(1)	(2)	(3)	(4)
	Pre-COVID	Post-COVID Scenarios		
	Baseline	SR	LR	LR Putty-Clay
A. Rents				
		$\delta_b = 0.04$		
CBD	1.00	0.93	1.00	0.92
Zone 1	0.81	0.95	0.81	0.81
Zone 2	0.47	0.60	0.47	0.47
		$\delta_b = 0.10$		
CBD	1.00	0.92	1.00	0.91
Zone 1	0.81	0.94	0.81	0.81
Zone 2	0.47	0.60	0.47	0.47
B. Incomes				
		$\delta_b = 0.04$		
High-skill avg. income	$ 103,620	$ 125,673	$ 126,894	$ 128,804
Low-skill avg. income	$ 64,486	$ 67,334	$ 66,329	$ 67,810
High-skill/low-skill avg. income	1.61	1.87	1.91	1.90
		$\delta_b = 0.10$		
High-skill avg. income	$ 103,620	$ 123,636	$ 124,294	$ 126,445
Low-skill avg. income	$ 64,486	$ 67,485	$ 66,329	$ 67,959
High-skill/low-skill avg. income	1.61	1.83	1.87	1.86
C. Population Location				
		$\delta_b = 0.04$		
Share of high-skill living in Zone 1	35.6%	34.0%	32.0%	32.0%
Share of low-skill living in Zone 1	34.8%	36.5%	34.2%	34.1%
		$\delta_b = 0.10$		
Share of high-skill living in Zone 1	35.6%	34.0%	32.0%	32.0%
Share of low-skill living in Zone 1	34.8%	36.5%	34.2%	34.1%

Table 10: Sensitivity to Immobility for Low-Skill Workers

	(1)	(2)	(3)	(4)
	Pre-COVID	Post-COVID Scenarios		
	Baseline	SR	LR	LR Putty-Clay
A. Rents				
		$\nu = 3.3$		
CBD	1.00	0.93	1.00	0.92
Zone 1	0.81	0.95	0.81	0.81
Zone 2	0.47	0.60	0.47	0.47
		$\nu_2 = \nu_4 = 0$		
CBD	1.00	0.93	1.00	0.92
Zone 1	0.81	0.93	0.81	0.81
Zone 2	0.47	0.60	0.47	0.47
B. Incomes				
		$\nu = 3.3$		
High-skill avg. income	$ 103,620	$ 125,673	$ 126,894	$ 128,804
Low-skill avg. income	$ 64,486	$ 67,334	$ 66,329	$ 67,810
High-skill/low-skill avg. income	1.61	1.87	1.91	1.90
		$\nu_2 = \nu_4 = 0$		
High-skill avg. income	$ 103,620	$ 125,708	$ 126,941	$ 128,845
Low-skill avg. income	$ 64,486	$ 67,259	$ 66,326	$ 67,812
High-skill/low-skill avg. income	1.61	1.87	1.91	1.90
C. Population Location				
		$\nu = 3.3$		
Share of high-skill living in Zone 1	35.6%	34.0%	32.0%	32.0%
Share of low-skill living in Zone 1	34.8%	36.5%	34.2%	34.1%
		$\nu_2 = \nu_4 = 0$		
Share of high-skill living in Zone 1	35.6%	34.3%	32.0%	32.0%
Share of low-skill living in Zone 1	34.8%	34.8%	34.8%	34.8%

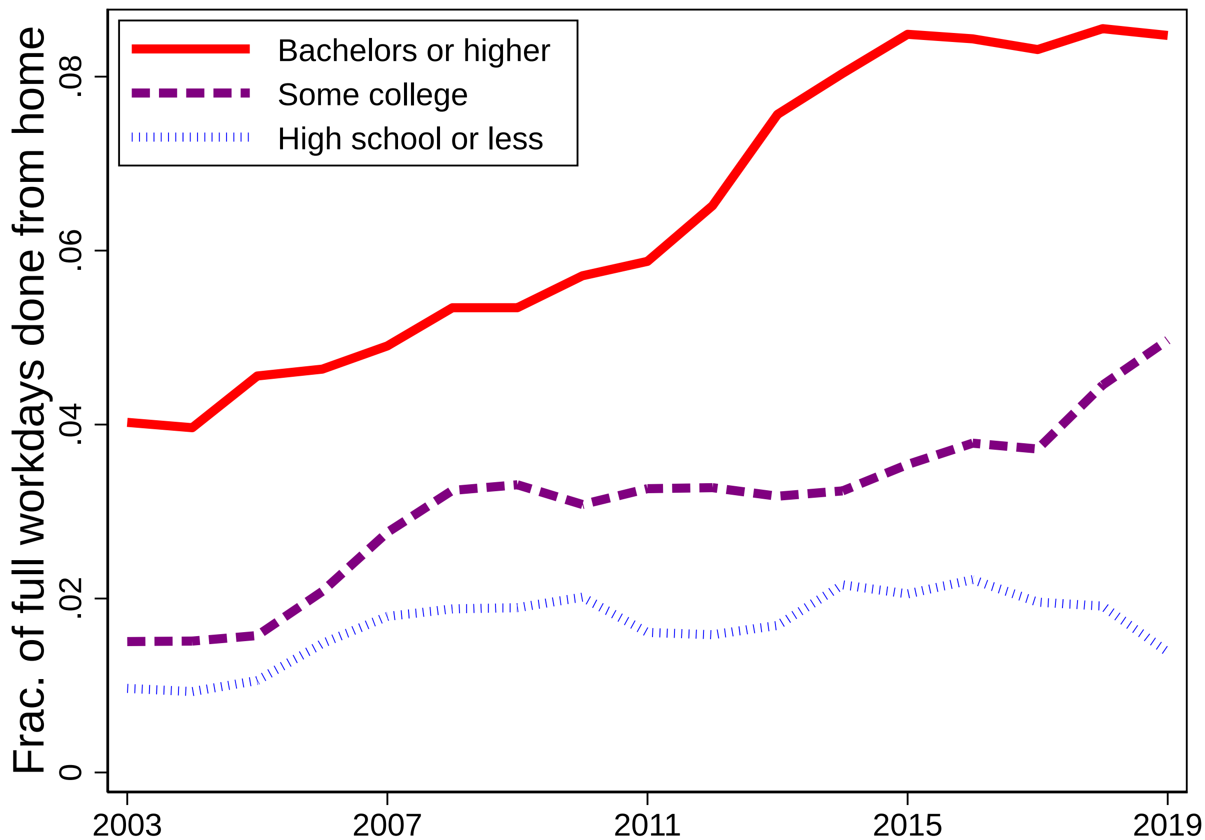
Notes: 1) In our benchmark specification, we set $\nu = 3.3$ for all worker types. 2) $\nu_2 = \nu_4 =$ counterfactuals correspond to setting $\nu = 0$ for type 2 and type 4 workers and keeping $\nu = 3.3$ for type 1 and type 3 workers.

Table 11: Misallocation Parameter Estimates

Parameter Value	Benchmark	Misallocation
$\mathcal{Z}$	0.889	0.889
a_{21}	0.149	0.114
a_{22}	0.146	0.137
a_{23}	0.191	0.191
a_{24}	0.132	0.132
χ_1	0.158	0.018
χ_2	0.064	-0.020
ρ	0.719	0.719
A_1^h/A_1^b	0.365	0.665
A_2^h/A_2^b	0.348	0.515

Notes: 1) Productivity parameters in this exercise are held fixed at their post-pandemic values shown in Table 6. 2) Moments used to estimate the model are the same as shown in Table 4.

Figure 1: Fraction of All Days with More than Four Hours of Work Performed Only at Home, 2003-2019

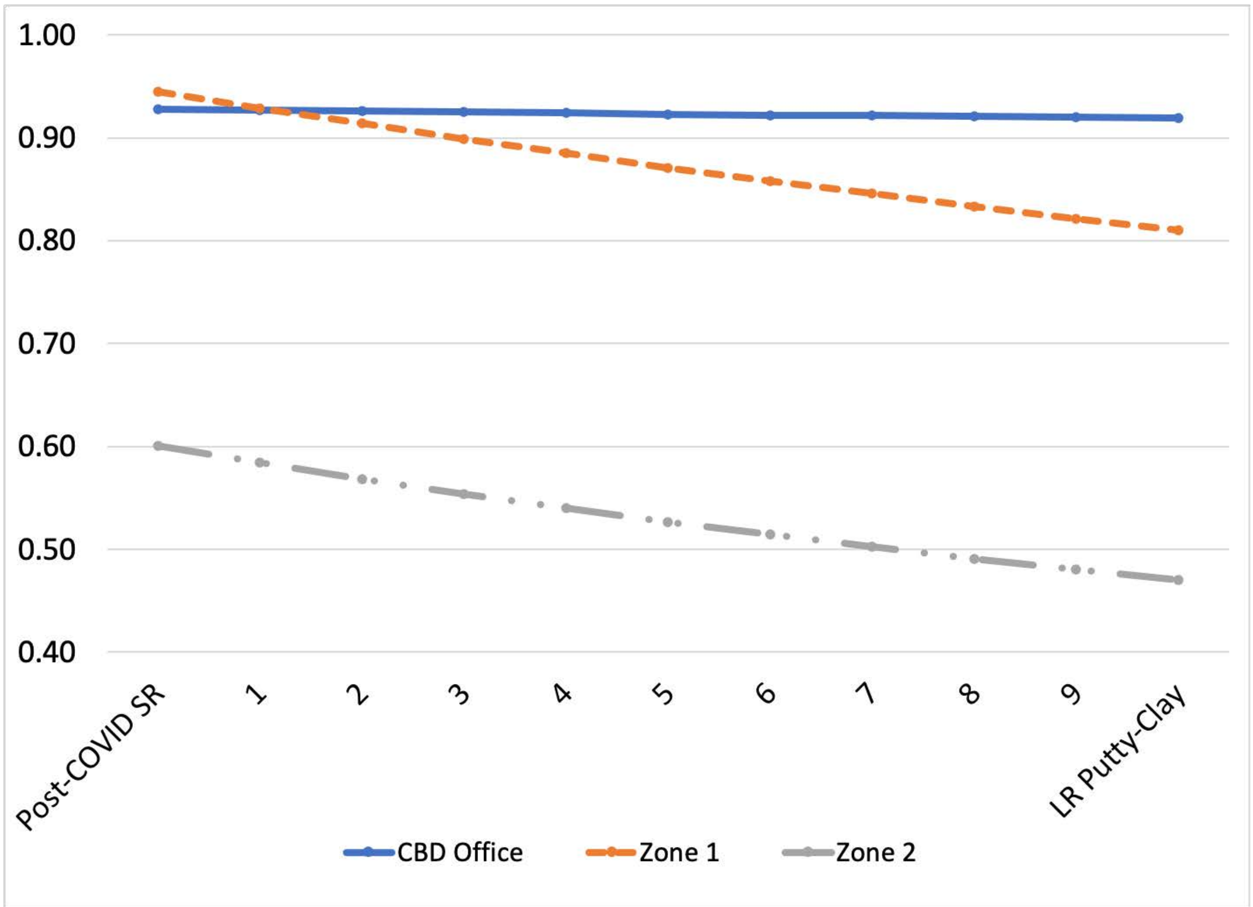


Notes: All data from American Time Use Survey (ATUS).

Figure 2: Intensity of WFH Over Time

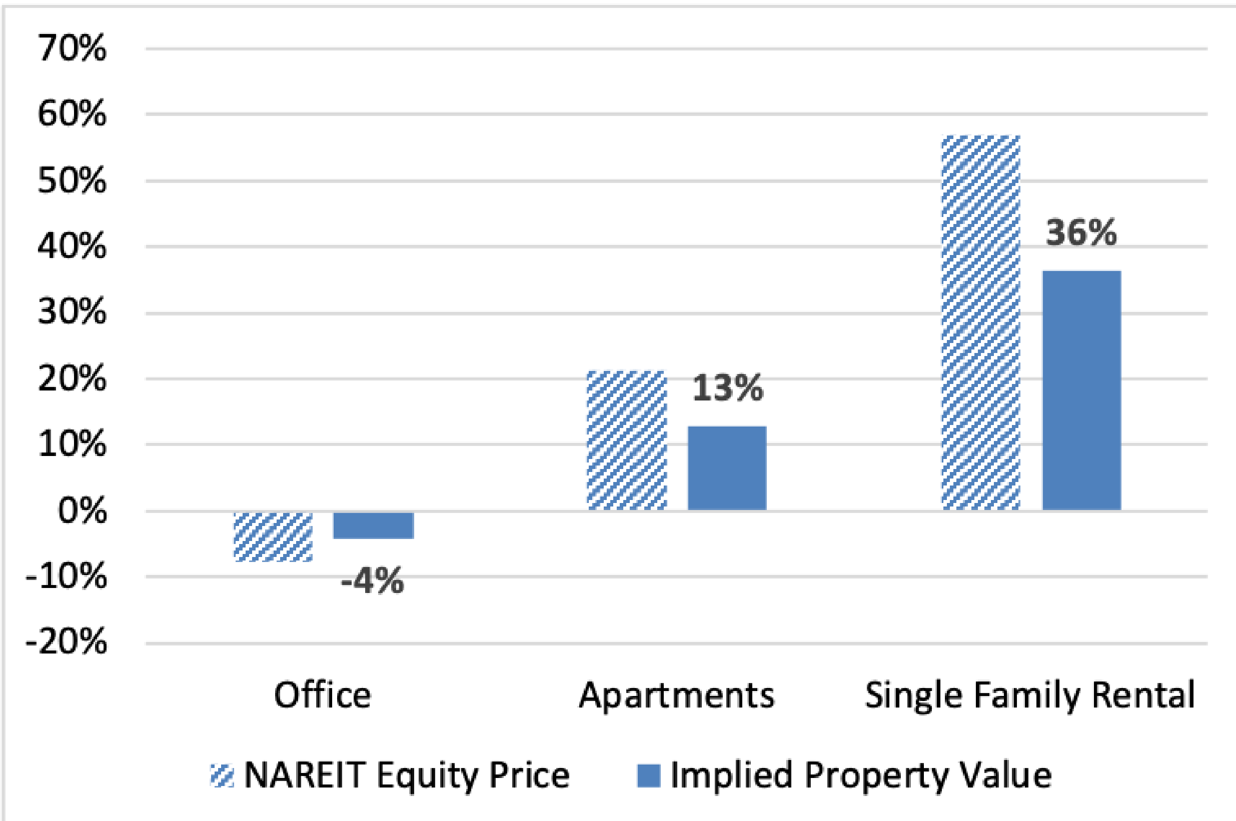
Notes: 1) GSS data. 2) Survey asks respondents "How often do you work at home as part of your job?" 3) Error bands are 95% confidence intervals. 4) Figure extends Figure 1 of Mas and Pallais (2020).

Figure 3: Model-Implied Rental Prices



Notes: This figure shows the rental price per unit of office space and residential housing in each year starting with the SR experiment and ending with the LR Putty-Clay experiment assuming the supply of office space does not adjust and the stock of residential space expands to its LR value linearly over a 10-year adjustment period.

Figure 4: Change in REIT Prices from January 1, 2020 to December 31, 2021



Notes: FTSE-NAREIT price index series. Property price changes are calculated assuming 2019 REIT leverage levels by property type.

A Explaining the Budget and Time Constraints

A.1 Time constraint, no WFH

Suppose a worker can choose the number of days she goes to work but not the number of hours she spends at work on a given day. On a day the person goes to work, hours of work are fixed at $\hat{b}$ and the amount of leisure is determined by hours commuting $\hat{t}$

$$\hat{\ell}\,(\text{work=1}) \quad = \quad \mathcal{T} - \hat{b} - \hat{t}.$$

On a day the worker does not work, hours of leisure is the time endowment,

$$\hat{\ell}\,(\text{work=0}) \quad = \quad \mathcal{T}.$$

Denote η as the number of days the worker chooses to go to work in the year. Hours of leisure in the year is

$$\eta\left(\mathcal{T} - \hat{b} - \hat{t}\right) + (365 - \eta)\,\mathcal{T} \quad = \quad 365 * \mathcal{T} - \left(\hat{b} + \hat{t}\right)\eta.$$

Define $t = \hat{t}/\hat{b}$. Then hours of leisure in the year is

$$365 * \mathcal{T} - (1 + t)\,\eta\hat{b}.$$

Leisure as a percentage of the total time endowment (of hours) in a year is

$$1 - (1 + t)\left[\frac{\eta}{365}\frac{\hat{b}}{\mathcal{T}}\right].$$

Now replace the term in brackets with b defined as

$$b \quad = \quad \frac{\eta * \hat{b}}{365 * \mathcal{T}} \tag{A.1}$$

such that leisure can be written as

$$1 - (1 + t)\,b.$$

As an example, set $\hat{b} = 9$ and $\mathcal{T} = 15$. Then $\hat{b}/(365 * \mathcal{T}) = 0.001644$ such that b is a discrete choice with 365 evenly spaced values with range of $0.001644, 0.003288, \ldots, 0.6$. We abstract from the discreteness of b and allow it to be a continuous choice ranging from 0 to 0.6. Whatever the value of b, it can be mapped to days worked using equation (A.1) such that if $b = 0.411$ then $\eta = 250$ days, implying people do not work for 115 days during the year (=52 weekends and 11 other vacation days). Suppose a one-way commute is 30 minutes, such that (in hours) $\hat{t} = 1$ and $\hat{t}/\hat{b} = 1/9 = 0.1111$. Then leisure as a percentage of total time in the year is $1 - 1.1111 * 0.411 = 0.543$.

A.2 Budget constraint, no WFH

Denote $\hat{w}$ as the daily wage paid for $\hat{b}$ hours of work and let $\hat{\tau}$ denote the financial cost of commuting both ways, such that daily net pay is $\hat{w} - \hat{\tau}$, and a person that works η days per year takes home $\eta\,[\hat{w} - \hat{\tau}]$. Now use equation (A.1) to replace η with b, so annual net wage can be re-expressed as a fraction of total available time, the daily gross wage, and the daily gross commute cost

$$\left(\frac{b * 365 * \mathcal{T}}{\hat{b}}\right)[\hat{w} - \hat{\tau}]\,. \tag{A.2}$$

If we define $w = \hat{w}\,(365 * \mathcal{T})\,/\hat{b}$ and $\tau = \hat{\tau}\,(365 * \mathcal{T})\,/\hat{b}$, then this can be written as $b\,[w - \tau]$.

Continuing with the previous example, suppose $\hat{w} = 315$ ($315 per day wage and salary), $\hat{\tau} = 9$ ($9 per day in financial commute costs), $\mathcal{T} = 15$, and $\hat{b} = 9$ as before. Then we would set $w = \$191,625$ and $\tau = \$5,475$. At a value of $b = 0.411$, gross take-home pay would be $78,758 and total financial commuting costs would be $2,250 such that take-home pay net of commuting costs would be $76,508 per year.

A.3 Time and budget constraints, WFH option

Time Constraint: Denote η^b as the number of days a worker goes to the office and η^h as the number of days a worker works from home. On a day the worker goes to the office, hours spent commuting are $\hat{t}$ that day. There is no commute to work at home. At either the office or at home, hours of work in a day are fixed at $\hat{b}$. This gives hours of leisure in the year of

$$\eta^b\left(\mathcal{T}-\hat{b}-\hat{t}\right)+\eta^h\left(\mathcal{T}-\hat{b}\right)+\left(365-\eta^b-\eta^h\right)\mathcal{T} \quad = \quad 365*\mathcal{T}-\left(\hat{b}+\hat{t}\right)\eta^b-\hat{b}\eta^h.$$

Define $t=\hat{t}/\hat{b}$ and divide by the total time endowment of hours in a year to express leisure as a percentage of the total yearly time endowment, i.e.,

$$1-(1+t)\left[\frac{\eta^b}{365}\frac{\hat{b}}{\mathcal{T}}\right]-\left[\frac{\eta^h}{365}\frac{\hat{b}}{\mathcal{T}}\right].$$

Now define l^b and l^h as

$$l^b=\frac{\eta^b}{365}\frac{\hat{b}}{\mathcal{T}} \qquad l^h=\frac{\eta^h}{365}\frac{\hat{b}}{\mathcal{T}} \tag{A.3}$$

such that leisure as a percent of total discretionary hours in a year can be written as

$$1-(1+t)\,l^b-l^h.$$

Budget Constraint: Define $\hat{w}$ as the average daily wage paid for $\hat{b}$ hours of work at the office on η^b days and $\hat{b}$ hours of work done at home on η^h days, assuming a home office size of s^h and business equipment at home of k^h. Keep in mind that $\hat{w}$ is a function of these inputs; we temporarily suppress the function notation. Assume one unit of home office space costs r to rent each year and one unit of home equipment costs r^k to rent each year. The cost of commuting each day to work is $\hat{\tau}$. The total pay for the year net of commuting, home equipment, and office expenses is $\eta^b\left[\hat{w}-\hat{\tau}\right]+\eta^h\hat{w}-r^kk^h-rs^h$. Now use equation (A.3) to replace η^b and η^h to yield

$$\left(\frac{l^b*365*\mathcal{T}}{\hat{b}}\right)\left[\hat{w}-\hat{\tau}\right]+\left(\frac{l^h*365*\mathcal{T}}{\hat{b}}\right)\hat{w}-r^kk^h-rs^h.$$

If we define

$$w=\left(365*\mathcal{T}/\hat{b}\right)\hat{w} \quad \text{and} \quad \tau=\left(365*\mathcal{T}/\hat{b}\right)\hat{\tau}$$

then total pay net of expenditures on home offices and commuting can be written as

$$w\left(l^b+l^h\right)-\tau l^b-r^kk^h-rs^h.$$

Now revisiting the fact that w is a function of l^b, l^h, s^h, and k^h, in the body of the text we write

$$\omega\left(l^b, l^h, s^h, k^h\right) - \tau l^b - r^k k^h - r s^h.$$

B Solution: Households at Non-WFH Firms

In this section we derive optimal choices for consumption, housing, leisure, and the fraction of time spent working at the office for type ι households working for a non-WFH firm and residing in location n. To keep notation as clean as possible, we will drop location and type subscripts in the derivation that follows. Denote the Lagrange multiplier on the budget constraint as μ_c and the Lagrange multiplier on the time constraint as μ_l. In what follows, we have removed the χ term from utility as χ does not affect any household decision once the location and type of firm have been chosen. After eliminating location subscripts, we can write the household problem as

$$\max_{c,h,\ell,b}\left\{ \quad (1-\alpha)\ln c + \alpha \ln h + \psi \ln \ell \quad \right\}$$

subject to

$$\begin{aligned} 0 &= \mu_c\left[(w-\tau)\, b - c - rh\right] \\ 0 &= \mu_l\left[1 - (1+t)\, b - \ell\right]. \end{aligned}$$

The first-order conditions are

$$\begin{aligned} c: \qquad (1-\alpha)/c &= \mu_c \\ h: \qquad \alpha/h &= \mu_c r \\ \ell: \qquad \psi/\ell &= \mu_l \\ b: \qquad \mu_c\,(w-\tau) &= \mu_l\,(1+t)\,. \end{aligned}$$

We can rewrite the FOC for h as $\alpha = \mu_c r h$, substitute into the FOC for c, and use the budget constraint to get

$$1 = \mu_c\,(w-\tau)\, b. \tag{A.4}$$

We can substitute μ_c into the FOC for b using equation (A.4), multiply by b, and then use the FOC for ℓ to get

$$1 \quad = \quad \psi\,(1+t)\,b/\ell.$$

Since $1-\ell=(1+t)\,b$, this implies

$$\ell=\psi/\,(1+\psi) \quad \text{and} \quad (1+t)\,b=1/\,(1+\psi)\,.$$

Finally, given b and therefore $(w-\tau)\,b$, the first two FOCs imply

$$c=(1-\alpha)\,(w-\tau)\,b \quad \text{and} \quad rh=\alpha\,(w-\tau)\,b.$$

C Solution: Households at WFH Firms

C.1 Solving taking wage function as given

In this section we derive optimal choices for consumption, housing, leisure, fraction of time spent working at the office, fraction of time spent working at home, equipment and software for the home office, and home office space rented for type 1 and 2 households residing in location n and working for WFH firms. As before, to reduce clutter we remove location and type subscripts and the χ term from utility.

Denote the Lagrange multiplier on the budget constraint as μ_c and the Lagrange multiplier on the time constraint as μ_l. Then the household problem can be written as

$$\max_{c,h,\ell,l^b,l^h,k^h,s^h} \left\{ \quad (1-\alpha)\ln c+\alpha\ln h+\psi\ln\ell \quad \right\}$$

subject to

$$\begin{aligned} 0 &= \mu_c\left[\omega\left(l^b,l^h,k^h,s^h\right)-\tau l^b-c-r\left(h+s^h\right)-r^k k^h\right] \\ 0 &= \mu_l\left[1-(1+t)\,l^b-l^h-\ell\right] \end{aligned}$$

The first-order conditions are

$$\begin{array}{lrcl} c: & (1-\alpha)/c & = & \mu_c \\ h: & \alpha/h & = & \mu_c r \\ \ell: & \psi/\ell & = & \mu_l \\ l^b: & \mu_c\left[\left(\partial\omega/\partial l^b\right)-\tau\right] & = & \mu_l\,(1+t) \\ l^h: & \mu_c\left(\partial\omega/\partial l^h\right) & = & \mu_l \\ k^h: & \left(\partial\omega/\partial k^h\right) & = & r^k \\ s^h: & \left(\partial\omega/\partial s^h\right) & = & r. \end{array}$$

We can rewrite the FOC for h as $\alpha = \mu_c r h$, substitute into the FOC for c, and use the budget constraint to get

$$1 = \mu_c\left[\omega\left(l^b, l^h, k^h, s^h\right) - \tau l^b - r s^h - r^k k^h\right] \tag{A.5}$$

which implies

$$\begin{aligned} c &= (1-\alpha)\;\left[\omega\left(l^b, l^h, k^h, s^h\right) - \tau l^b - r s^h - r^k k^h\right] \\ rh &= \alpha\;\left[\omega\left(l^b, l^h, k^h, s^h\right) - \tau l^b - r s^h - r^k k^h\right]. \end{aligned}$$

We can combine the FOCs for l^b and l^h to get

$$\frac{\left(\partial\omega/\partial l^b\right)-\tau}{1+t} = \frac{\partial\omega}{\partial l^h}.$$

Multiply the FOC for l^b by l^b, multiply the FOC for l^h by l^h, and add those two FOCs together to get

$$\mu_c\left[\left(\frac{\partial\omega}{\partial l^b}\right) l^b - \tau l^b + \left(\frac{\partial\omega}{\partial l^h}\right) l^h\right] = \mu_l\left[(1+t)\, l^b + l^h\right].$$

Insert the FOC for ℓ and use the time constraint to get

$$\mu_c\left[\left(\frac{\partial\omega}{\partial l^b}\right) l^b - \tau l^b + \left(\frac{\partial\omega}{\partial l^h}\right) l^h\right] = \psi\left(\frac{1-\ell}{\ell}\right).$$

Add and subtract $\left(\partial\omega/\partial k^h\right) k^h$ and $\left(\partial\omega/\partial s^h\right) s^h$ from the left-hand side (using the FOCs for k^h and s^h) to get

$$\mu_c\left[\left(\frac{\partial\omega}{\partial l^b}\right) l^b + \left(\frac{\partial\omega}{\partial l^h}\right) l^h + \left(\frac{\partial\omega}{\partial k^h}\right) k^h + \left(\frac{\partial\omega}{\partial s^h}\right) s^h - \tau l^b - r s^h - r^k k^h\right] = \psi\left(\frac{1-\ell}{\ell}\right).$$

Now use the results from equation (A.21):

$$\frac{\left(\frac{\partial\omega}{\partial l^b}\right)l^b+\left(\frac{\partial\omega}{\partial l^h}\right)l^h+\left(\frac{\partial\omega}{\partial k^h}\right)k^h+\left(\frac{\partial\omega}{\partial s^h}\right)s^h-\tau l^b-rs^h-r^k k^h}{\omega\left(l^b,l^h,k^h,s^h\right)-\tau l^b-rs^h-r^k k^h} \quad = \quad \psi\left(\frac{1-\ell}{\ell}\right).$$

Provided the wage function is homogeneous of degree 1, as in the case of a production function with constant returns to scale, Euler's homogeneous function theorem implies

$$\omega\left(l^b,l^h,k^h s^h\right) \quad = \quad \left(\frac{\partial\omega}{\partial l^b}\right)l^b+\left(\frac{\partial\omega}{\partial l^h}\right)l^h+\left(\frac{\partial\omega}{\partial k^h}\right)k^h+\left(\frac{\partial\omega}{\partial s^h}\right)s^h$$

such that

$$\ell \quad = \quad \frac{\psi}{1+\psi}.$$

C.2 Full solution

We will write the problem as if the household chooses k^b and s^b, i.e., as if the household owns the firm and claims all profits. For households choosing to work at a WFH firm, we write the revised problem, inclusive of all production functions, as

$$\max_{c,h,\ell,y,y^b,y^h,l^b,l^h,s^b,s^h,k^b,k^h}\left\{\ (1-\alpha)\ln c+\alpha\ln h+\psi\ln\ell\ \right\}$$

subject to

$$\begin{aligned}
&\text{(A.6)} && 0 = \mu_c\left[y-r^k k^b-r^s s^b-\tau l^b-c-r\left(h+s^h\right)-r^k k^h\right]\\
&\text{(A.7)} && 0 = \mu_l\left[1-(1+t)\,l^b-l^h-\ell\right]\\
&\text{(A.8)} && 0 = \mu_y\left[\left[\left(y^b\right)^\rho+\left(y^h\right)^\rho\right]^{1/\rho}-y\right]\\
&\text{(A.9)} && 0 = \mu_b\left[A^b\left(l^b\right)^{\theta_b}\left(k^b\right)^{\theta_k}\left(s^b\right)^{\theta_s}-y^b\right]\\
&\text{(A.10)} && 0 = \mu_h\left[A^h\left(l^h\right)^{\theta_b}\left(k^h\right)^{\theta_k}\left(s^h\right)^{\theta_s}-y^h\right].
\end{aligned}$$

The first-order conditions are

$$\begin{array}{llrcl}
1 & y: & \mu_y & = & \mu_c \\
2 & y^b: & \mu_b & = & y^{1-\rho}\left(y^b\right)^{\rho-1}\mu_y \\
3 & y^h: & \mu_h & = & y^{1-\rho}\left(y^h\right)^{\rho-1}\mu_y \\
4 & l^b: & \mu_\ell\left(1+t\right)+\mu_c\tau & = & \mu_b\theta_b\left(y^b/l^b\right) \\
5 & l^h: & \mu_\ell & = & \mu_h\theta_b\left(y^h/l^h\right) \\
6 & k^b: & \mu_c r^k & = & \mu_b\theta_k\left(y^b/k^b\right) \\
7 & k^h: & \mu_c r^k & = & \mu_h\theta_k\left(y^h/k^h\right) \\
8 & s^b: & \mu_c r^s & = & \mu_b\theta_s\left(y^b/s^b\right) \\
9 & s^h: & \mu_c r & = & \mu_h\theta_s\left(y^h/s^h\right) \\
10 & c: & \mu_c & = & \left(1-\alpha\right)/c \\
11 & h: & \mu_c r & = & \alpha/h \\
12 & \ell: & \mu_\ell & = & \psi/\ell.
\end{array}$$

We start by showing leisure is a constant. Note that FOCs 6+8, 7+9, and 10+11 imply the following (after imposing $\theta_b+\theta_k+\theta_s=1$)

$$\begin{aligned}
\mu_c\left[r^k k^b+r^s s^b\right] &= \mu_b y^b\left(1-\theta_b\right) \\
\mu_c\left[r^k k^h+r s^h\right] &= \mu_h y^h\left(1-\theta_b\right) \\
\mu_c\left[c+rh\right] &= 1.
\end{aligned}$$

Adding these three equations together and imposing (A.6) implies

$$\mu_c\left(y-\tau l^b\right) = 1+\left(1-\theta_b\right)\left(\mu_b y^b+\mu_h y^h\right) \tag{A.11}$$

$$= 1+\left(1-\theta_b\right)\mu_c y \tag{A.12}$$

$$\rightarrow \theta_b\mu_c y = 1+\mu_c\tau l^b \tag{A.13}$$

where the second line of the above comes from FOCs 1, 2, and 3.

Now add the FOCs for l^b, l^h, and ℓ (after multiplying each by l^b, l^h, and ℓ) and use the time constraint to get

$$\begin{aligned}
\mu_\ell+\mu_c\tau l^b &= \psi+\theta_b\left[\mu^b y^b+\mu^h y^h\right] \\
&= \psi\ +\ \theta_b\mu_c y \\
\rightarrow \mu_\ell &= 1+\psi
\end{aligned}$$

where the third line uses (A.13). Finally, insert the result of FOC 12 to get the result that leisure is constant

$$\ell = \frac{\psi}{1+\psi}.$$

Next, divide FOC 6 by FOC 8 and FOC 7 by FOC 9 and rearrange terms to get

$$\frac{k^b}{k^h} = \frac{r^s s^b}{r s^h}.$$

Divide FOC 8 by FOC 9 and use the results of FOCs 2 and 3 to get

$$\frac{y^b}{y^h} = \left(\frac{r^s s^b}{r s^h}\right)^{\frac{1}{\rho}}.$$

Now work with the office and home production functions to get an expression for s_b/s_h as a function of l_b/l_h.

$$\begin{aligned}
\left(\frac{y^b}{y^h}\right) &= \frac{A^b}{A^h}\left(\frac{l^b}{l^h}\right)^{\theta_b}\left(\frac{k^b}{k^h}\right)^{\theta_k}\left(\frac{s^b}{s^h}\right)^{\theta_s} \\
\left(\frac{r^s s^b}{r s^h}\right)^{\frac{1}{\rho}} &= \left(\frac{A^b}{A^h}\right)\left(\frac{l^b}{l^h}\right)^{\theta_b}\left(\frac{r^s s^b}{r s^h}\right)^{\theta_k}\left(\frac{s^b}{s^h}\right)^{\theta_s} \\
\left(\frac{s^b}{s^h}\right)^{\frac{1-\rho\theta_k-\rho\theta_s}{\rho}} &= \left(\frac{r^s}{r}\right)^{\frac{\rho\theta_k-1}{\rho}}\left(\frac{A^b}{A^h}\right)\left(\frac{l^b}{l^h}\right)^{\theta_b} \\
\left(\frac{s^b}{s^h}\right) &= \left[\left(\frac{r^s}{r}\right)^{\frac{\rho\theta_k-1}{\rho}}\left(\frac{A^b}{A^h}\right)\left(\frac{l^b}{l^h}\right)^{\theta_b}\right]^{\frac{\rho}{1-\rho\theta_k-\rho\theta_s}}.
\end{aligned}$$

Given l^b/l^h, this determines s^b/s^h, k^b/k^h, and y^b/y^h.

Now we wish to solve for levels given these ratios. We start by substituting for k^b and k^h by using FOCs 6, 2 and 1 as well as 7, 3 and 1:

$$\begin{aligned}
k^b &= y^{1-\rho}\left(y^b\right)^{\rho}\theta_k/r^k \\
k^h &= y^{1-\rho}\left(y^h\right)^{\rho}\theta_k/r^k.
\end{aligned} \tag{A.14}$$

We now insert these into the production function for y^b and y^h.

(A.15)

$$
\begin{array}{rclcrcl}
y^b & = & A^b \left(l^b\right)^{\theta_b} \left[y^{1-\rho} \left(y^b\right)^{\rho} \theta_k / r^k\right]^{\theta_k} \left(s^b\right)^{\theta_s} & \rightarrow & y^b & = & \widetilde{A}^b \left(l^b\right)^{\frac{\theta_b}{1-\rho\theta_k}} (y)^{\frac{(1-\rho)\theta_k}{1-\rho\theta_k}} \left(s^b\right)^{\frac{\theta_s}{1-\rho\theta_k}} \\
y^h & = & A^h \left(l^h\right)^{\theta_b} \left[y^{1-\rho} \left(y^h\right)^{\rho} \theta_k / r^k\right]^{\theta_k} \left(s^h\right)^{\theta_s} & \rightarrow & y^h & = & \widetilde{A}^h \left(l^h\right)^{\frac{\theta_b}{1-\rho\theta_k}} (y)^{\frac{(1-\rho)\theta_k}{1-\rho\theta_k}} \left(s^h\right)^{\frac{\theta_s}{1-\rho\theta_k}}
\end{array}
$$

where we have defined

$$
\widetilde{A}^b \;=\; \left(A^b\right)^{\frac{1}{1-\rho\theta_k}} \left(\theta_k / r^k\right)^{\frac{\theta_k}{1-\rho\theta_k}} \quad \text{and} \quad \widetilde{A}^h \;=\; \left(A^h\right)^{\frac{1}{1-\rho\theta_k}} \left(\theta_k / r^k\right)^{\frac{\theta_k}{1-\rho\theta_k}} .
$$

We can rewrite the production function using equation (A.15) as follows

$$
\begin{array}{rcl}
y^{\rho} & = & \left(y^b\right)^{\rho} \qquad\qquad\qquad\qquad\qquad + \; \left(y^h\right)^{\rho} \\
& = & \left(\widetilde{A}^b\right)^{\rho} \left(l^b\right)^{\frac{\rho\theta_b}{1-\rho\theta_k}} (y)^{\frac{(1-\rho)\rho\theta_k}{1-\rho\theta_k}} \left(s^b\right)^{\frac{\rho\theta_s}{1-\rho\theta_k}} + \left(\widetilde{A}^h\right)^{\rho} \left(l^h\right)^{\frac{\rho\theta_b}{1-\rho\theta_k}} (y)^{\frac{(1-\rho)\rho\theta_k}{1-\rho\theta_k}} \left(s^h\right)^{\frac{\rho\theta_s}{1-\rho\theta_k}} .
\end{array}
$$

Combining terms gives

$$
y^{\frac{\rho(1-\theta_k)}{1-\rho\theta_k}} \;=\; \left(\widetilde{A}^b\right)^{\rho} \left(l^b\right)^{\frac{\rho\theta_b}{1-\rho\theta_k}} \left(s^b\right)^{\frac{\rho\theta_s}{1-\rho\theta_k}} + \left(\widetilde{A}^h\right)^{\rho} \left(l^h\right)^{\frac{\rho\theta_b}{1-\rho\theta_k}} \left(s^h\right)^{\frac{\rho\theta_s}{1-\rho\theta_k}}
$$

and thus

(A.16)
$$
y \;=\; \left[\left(\widetilde{A}^b\right)^{\rho} \left(l^b\right)^{\frac{\rho\theta_b}{1-\rho\theta_k}} \left(s^b\right)^{\frac{\rho\theta_s}{1-\rho\theta_k}} + \left(\widetilde{A}^h\right)^{\rho} \left(l^h\right)^{\frac{\rho\theta_b}{1-\rho\theta_k}} \left(s^h\right)^{\frac{\rho\theta_s}{1-\rho\theta_k}}\right]^{\frac{1-\rho\theta_k}{\rho(1-\theta_k)}} .
$$

To conclude, add FOCs 8 and 9 after multiplying by s^b and s^h respectively to get

$$
\begin{array}{rcl}
\mu_c \left(r^s s^b + r s^h\right) & = & \theta_s \left[\mu_b y^b + \mu_h y^h\right] \\
& = & \mu_c \theta_s y
\end{array}
$$

which yields the expression

(A.17)
$$
\begin{array}{rcl}
r^s s^b + r s^h & = & \theta_s y \\
\rightarrow \; s^h \left[r^s \left(\frac{s^b}{s^h}\right) + r\right] & = & \theta_s y.
\end{array}
$$

Now insert the expression for y from equation (A.16) to get

$$
\begin{aligned}
s^h\left[r^s\left(\frac{s^b}{s^h}\right)+r\right] &= \theta_s\left[\left(\widetilde{A}^b\right)^\rho\left(l^b\right)^{\frac{\rho\theta_b}{1-\rho\theta_k}}\left(s^b\right)^{\frac{\rho\theta_s}{1-\rho\theta_k}} + \left(\widetilde{A}^h\right)^\rho\left(l^h\right)^{\frac{\rho\theta_b}{1-\rho\theta_k}}\left(s^h\right)^{\frac{\rho\theta_s}{1-\rho\theta_k}}\right]^{\frac{1-\rho\theta_k}{\rho(1-\theta_k)}} \\
&= \theta_s\left(s^h\right)^{\frac{\theta_s}{1-\theta_k}}\left[\left(\widetilde{A}^b\right)^\rho\left(l^b\right)^{\frac{\rho\theta_b}{1-\rho\theta_k}}\left(\frac{s^b}{s^h}\right)^{\frac{\rho\theta_s}{1-\rho\theta_k}} + \left(\widetilde{A}^h\right)^\rho\left(l^h\right)^{\frac{\rho\theta_b}{1-\rho\theta_k}}\right]^{\frac{1-\rho\theta_k}{\rho(1-\theta_k)}}
\end{aligned}
$$

which gives

$$
\text{(A.18)}\quad s^h = \left[\frac{\theta_s\left[\left(\widetilde{A}^b\right)^\rho\left(l^b\right)^{\frac{\rho\theta_b}{1-\rho\theta_k}}\left(\frac{s^b}{s^h}\right)^{\frac{\rho\theta_s}{1-\rho\theta_k}} + \left(\widetilde{A}^h\right)^\rho\left(l^h\right)^{\frac{\rho\theta_b}{1-\rho\theta_k}}\right]^{\frac{1-\rho\theta_k}{\rho(1-\theta_k)}}}{r^s\left(\frac{s^b}{s^h}\right)+r}\right]^{\frac{1-\theta_k}{1-\theta_k-\theta_s}}.
$$

If we know l^b/l^h, we know (a) s^b/s^h (from A.38) and (b) l^b and l^h separately given that leisure is a constant. Equation (A.18) implies we then know s^h. This gives s^b and then y from equation (A.16), which then gives y^b and y^h from equation (A.15) and therefore k^b and k^h from equation (A.14).

Once we know l^b/l^h, we can analytically solve for the optimal solution to the household problem. Computation involves searching for the correct value of l^b/l^h. To verify we have selected the correct value of l^b/l^h, we work with FOCs 10 and 11 to derive

$$
\mu_c\left(c+rh\right) = 1.
$$

We can then use FOCs 4 and 5 to derive

$$
\begin{aligned}
\left(\frac{l^b}{l^h}\right) &= \left(\frac{\mu_b}{\mu_h}\right)\left(\frac{y^b}{y^h}\right)\left[(1+t)+\frac{\tau\mu_c}{\mu_\ell}\right]^{-1} \\
&= \left(\frac{y^b}{y^h}\right)^\rho\left[(1+t)+\frac{\tau}{(1+\psi)\left(c+rh\right)}\right]^{-1}.
\end{aligned}
$$

From earlier, we know

$$\left(\frac{y^b}{y^h}\right)^{\rho} = \left(\frac{r^s}{r}\right)\left(\frac{s^b}{s^h}\right)$$
$$= \left(\frac{r^s}{r}\right)\left[\left(\frac{r^s}{r}\right)^{\frac{\rho\theta_k-1}{\rho}}\left(\frac{A^b}{A^h}\right)\left(\frac{l^b}{l^h}\right)^{\theta_b}\right]^{\frac{\rho}{1-\rho\theta_k-\rho\theta_s}}$$
$$= \left(\frac{r^s}{r}\right)^{\frac{-\rho\theta_s}{1-\rho\theta_k-\rho\theta_s}}\left[\left(\frac{A^b}{A^h}\right)\left(\frac{l^b}{l^h}\right)^{\theta_b}\right]^{\frac{\rho}{1-\rho\theta_k-\rho\theta_s}}. \tag{A.19}$$

Inserting equation (A.19) gives

$$\left(\frac{l^b}{l^h}\right) = \left(\frac{r^s}{r}\right)^{\frac{-\rho\theta_s}{1-\rho\theta_k-\rho\theta_s}}\left[\left(\frac{A^b}{A^h}\right)\left(\frac{l^b}{l^h}\right)^{\theta_b}\right]^{\frac{\rho}{1-\rho\theta_k-\rho\theta_s}}\left[(1+t)+\frac{\tau}{(1+\psi)(c+rh)}\right]^{-1}$$
$$\rightarrow \left(\frac{l^b}{l^h}\right)^{\frac{1-\rho}{1-\rho\theta_k-\rho\theta_s}} = \left(\frac{r^s}{r}\right)^{\frac{-\rho\theta_s}{1-\rho\theta_k-\rho\theta_s}}\left(\frac{A^b}{A^h}\right)^{\frac{\rho}{1-\rho\theta_k-\rho\theta_s}}\left[(1+t)+\frac{\tau}{(1+\psi)(c+rh)}\right]^{-1}$$

where the second equation uses $\theta_b+\theta_k+\theta_s=1$. This implies

$$\left(\frac{l^b}{l^h}\right) = \left(\frac{r^s}{r}\right)^{\frac{-\rho\theta_s}{1-\rho}}\left(\frac{A^b}{A^h}\right)^{\frac{\rho}{1-\rho}}\left[(1+t)+\frac{\tau}{(1+\psi)(c+rh)}\right]^{\frac{-(1-\rho\theta_k-\rho\theta_s)}{1-\rho}}.$$

D Households with Home Production

Consider a slightly different framework where households have utility over market consumption c^m, non-market consumption produced at home (e.g., meals, laundry) c^n, and leisure ℓ of the form

$$\mathbf{a}_0 \ln c^m + \mathbf{a}_1 \ln c^n + \mathbf{a}_2 \ln \ell$$

where we have omitted type and location subscripts to save on notation. Non-market consumption is produced as a Cobb-Douglas aggregate of housing h and time spent working at non-market consumption l^n according to

$$c^n = A^n h^{\theta_n}\left(l^n\right)^{1-\theta_n}$$

where θ_n is the share of home-produced consumption attributable to the housing input. Utility can be rewritten as

$$\mathrm{a}_0 \ln c^m + \left[\mathrm{a}_1 \ln A^n + \mathrm{a}_1 \theta_n \ln h + \mathrm{a}_1 (1-\theta_n) \ln l^n\right] + \mathrm{a}_2 \ln \ell. \tag{A.20}$$

Notice that this utility function is nearly identical to what we had before, with some terms and coefficients relabeled

$$\underbrace{\mathrm{a}_1 \ln A^n}_{A} + \underbrace{\mathrm{a}_0 \ln c^m}_{B} + \underbrace{\mathrm{a}_1 \theta_n \ln h}_{C} + \underbrace{\mathrm{a}_2 \ln \ell}_{D} + \underbrace{\mathrm{a}_1 (1-\theta_n) \ln l^n}_{E}.$$

Terms A-D have a direct mapping to the model without production of non-market consumption: A is equivalent to a (amenities), suggesting amenities has the interpretation of scaled TFP of production of non-market consumption, the coefficient a_0 in term B is equal to $1-\alpha$ and the coefficient $\mathrm{a}_1\theta_n$ is equal to α. The coefficient a_2 may not be the same as ψ because in this model there are more uses of time than in the model without production of non-market consumption. The only term in utility that is new to this model is E. The goal of the rest of this section is to show that this term is constant, such that its inclusion does not affect any other trade-offs in the model.

D.1 Households at non-WFH firms

Consider households that do not have a WFH option. These households choose b, l^n, ℓ, c^m, and h to maximize the utility written in (A.20) subject to the following two constraints

$$\begin{array}{ll} \text{budget:} & \mu_c \left[(w-\tau) b - c^m - rh\right] \\ \text{time:} & \mu_l \left[1 - (1+t) b - l^n - \ell\right] \end{array}$$

where μ_c and μ_l are Lagrange multipliers. The first-order conditions are

$$\begin{array}{lrcl} c^m: & \mathrm{a}_0 & = & \mu_c c^m \\ h: & \mathrm{a}_1 \theta_n & = & \mu_c r h \\ b: & \mu_c (w-\tau) b & = & \mu_l (1+t) b \\ \ell: & \mathrm{a}_2 & = & \mu_l \ell \\ l^n: & \mathrm{a}_1 (1-\theta_n) & = & \mu_l l^n. \end{array}$$

Add the FOCs for b, ℓ, and l^n and impose the time constraint to get

$$\mu_l = \mu_c (w - \tau) b + \mathrm{a}_2 + \mathrm{a}_1 (1 - \theta_n).$$

Add the FOCs for c^m and h and impose the budget constraint to get

$$\mu_c (w - \tau) b = \mathrm{a}_0 + \mathrm{a}_1 \theta_n.$$

Inserting this second equation into the first gives

$$\mu_l = \mathrm{a}_0 + \mathrm{a}_1 + \mathrm{a}_2.$$

This gives us a solution for ℓ and l^n of

$$\ell = \frac{\mathrm{a}_2}{\mathrm{a}_0 + \mathrm{a}_1 + \mathrm{a}_2} \text{ and } l^n = \frac{\mathrm{a}_1 (1 - \theta_n)}{\mathrm{a}_0 + \mathrm{a}_1 + \mathrm{a}_2}$$

In other words, both leisure and time spent in home production are constant. This means we can parameterize the model to deliver an allocation of consumption and housing that is identical to our baseline model that does not have home production. This parameterization will have the properties

$$\begin{aligned} \mathrm{a}_0 &= (1 - \alpha) \\ \mathrm{a}_1 \theta_n &= \alpha \\ \frac{\mathrm{a}_1 (1 - \theta_n) + \mathrm{a}_2}{\mathrm{a}_0 + \mathrm{a}_1 + \mathrm{a}_2} &= \frac{\psi}{1 + \psi} \end{aligned}$$

where $1-\alpha$, α, and ψ are the coefficients on market consumption, housing, and leisure in the model without home production. For example, if we set $\alpha = 0.25$, $\psi = 1$, and $\theta_n = 0.33$ in the model without home production, then the model with home production will produce an identical allocation of consumption and housing at any wage w or rental price r when $\mathrm{a}_0 = 0.75$, $\mathrm{a}_1 = 0.758$, and $\mathrm{a}_2 = 0.492$.

D.2 Households at WFH firms

Now we repeat the above exercise but consider households that work at WFH firms. These households have budget and time constraints as follows

$$
\begin{array}{ll}
\text{budget:} & \mu_c \left[\omega\left(l^b, l^h, k^h, s^h\right) - \tau l^b - c - r\left(h + s^h\right) - r^k k^h\right] \\
\text{time:} & \mu_l \left[1 - (1+t)\, l^b - l^h - l^n - \ell\right] \, .
\end{array}
$$

As before, μ_c and μ_l are the Lagrange multipliers on the constraints.

The first-order conditions are

$$
\begin{array}{lrcl}
c^m : & \mathrm{a}_0 & = & \mu_c c^m \\
h : & \mathrm{a}_1 \theta_n & = & \mu_c r h \\
l^b : & \mu_c \left[\left(\partial\omega/\partial l^b\right) - \tau\right] l^b & = & \mu_l (1+t)\, l^b \\
l^h : & \mu_c \left(\partial\omega/\partial l^h\right) l^h & = & \mu_l l^h \\
k^h : & \left(\partial\omega/\partial k^h\right) k^h & = & r^k k^h \\
s^h : & \left(\partial\omega/\partial s^h\right) s^h & = & r s^h \\
\ell : & \mathrm{a}_2 & = & \mu_l \ell \\
l^n : & \mathrm{a}_1 (1 - \theta_n) & = & \mu_l l^n.
\end{array}
$$

Add the first two FOCs and impose the budget constraint to get

$$
\text{(A.21)} \qquad \mu_c = \frac{\mathrm{a}_0 + \mathrm{a}_1 \theta_n}{\omega\left(l^b, l^h, k^h, s^h\right) - \tau l^b - r s^h - r^k k^h}.
$$

Add the FOCs for l^b and l^h to get

$$
\mu_c \left[\left(\frac{\partial\omega}{\partial l^b}\right) l^b - \tau l^b + \left(\frac{\partial\omega}{\partial l^h}\right) l^h\right] = \mu_l \left[(1+t)\, l^b + l^h\right].
$$

Insert the FOC for ℓ and use the time constraint to get

$$
\begin{aligned}
\mu_c \left[\left(\frac{\partial\omega}{\partial l^b}\right) l^b - \tau l^b + \left(\frac{\partial\omega}{\partial l^h}\right) l^h\right] &= \mu_l (1 - l^n - \ell) \\
&= \frac{\mathrm{a}_2}{\ell} - \mathrm{a}_1 (1 - \theta_n) - \mathrm{a}_2.
\end{aligned}
$$

The second line in the above is from the FOCs for ℓ and l^n. For convenience define $\hat{\mathrm{a}} = \mathrm{a}_1 (1 - \theta_n) + \mathrm{a}_2$. Add and subtract $\left(\partial\omega/\partial s^h\right) s^h$ and $\left(\partial\omega/\partial k^h\right) k^h$ from the left-hand side and use the FOCs for s^h and k^h to get

$$\mu_c\left[\left(\frac{\partial\omega}{\partial l^b}\right)l^b+\left(\frac{\partial\omega}{\partial l^h}\right)l^h+\left(\frac{\partial\omega}{\partial k^h}\right)k^h+\left(\frac{\partial\omega}{\partial s^h}\right)s^h-\tau l^b-rs^h-r^kk^h\right] = \frac{\mathrm{a}_2}{\ell}-\hat{\mathrm{a}}.$$

Now use the results from equation (A.21) to get

$$\frac{\left(\frac{\partial\omega}{\partial l^b}\right)l^b+\left(\frac{\partial\omega}{\partial l^h}\right)l^h+\left(\frac{\partial\omega}{\partial k^h}\right)k^h+\left(\frac{\partial\omega}{\partial s^h}\right)s^h-\tau l^b-rs^h-r^kk^h}{\omega\left(l^b,l^h,k^h,s^h\right)-\tau l^b-rs^h-r^kk^h} = \frac{\mathrm{a}_2/\ell-\hat{\mathrm{a}}}{\mathrm{a}_0+\mathrm{a}_1\theta_n}. \tag{A.22}$$

As long as the output function is homogeneous of degree 1, such that

$$\omega\left(l^b,l^h,k^h,s^h\right) = \left(\frac{\partial\omega}{\partial l^b}\right)l^b+\left(\frac{\partial\omega}{\partial l^h}\right)l^h+\left(\frac{\partial\omega}{\partial k^h}\right)k^h+\left(\frac{\partial\omega}{\partial s^h}\right)s^h$$

then equation (A.22) implies leisure is a constant since the left-hand side of that equation is equal to 1. To solve for leisure, insert the definition of $\hat{\mathrm{a}}$ into equation (A.22) to get

$$\ell = \frac{\mathrm{a}_2}{\mathrm{a}_0+\mathrm{a}_1+\mathrm{a}_2},$$

and thus leisure is constant. From the FOCs for ℓ and l^n we can derive that time spent in home production l^n is also a constant and equal to

$$l^n = \frac{\mathrm{a}_1\left(1-\theta_n\right)}{\mathrm{a}_0+\mathrm{a}_1+\mathrm{a}_2}.$$

These are the same results as for households that work for firms that do not allow WFH. Therefore, we know we can calibrate the model such that it delivers the exact same allocations as the baseline model without home production for any values of r^k and r and any homeogenous-of-degree-one wage function $\omega\left(l^b,l^h,k^h,s^h\right)$.

E Estimation Details

E.1 Standard errors of parameters estimated outside the model

We directly calculate the standard errors of the commuting cost parameters, as these parameters are sample means. For parameters that are transformations of moments in the data, we calculate standard errors using the delta method.

Importance of idiosyncratic preferences for WFH firms. For $1/\zeta$, the delta method requires as an input the variance-covariance matrix for the estimates of the wage discounts at the 25th and 75th percentiles. Mas and Pallais (2017) report standard errors for the estimate at the 75th percentile, \$0.50, and the 25th percentile, \$0.68, but not the covariance of these estimates. We expect a nonzero correlation because, by definition, the 25th percentile will have a greater wage discount than the 75th percentile. We use a simulation procedure that we describe next to assign a correlation of these two estimates of 0.375, which then implies a standard error for the estimate of $1/\zeta$ equal to 0.0198.

To estimate the correlation, we simulate 100,000 data sets of WTP from the Normal distribution with mean μ_{sim}, standard deviation σ_{sim}, and sample size N_{sim}. In each data set, we keep the 25th and 75th percentiles of WTP. We set $\mu_{sim} = 1.325$, $\sigma_{sim} = 1.668$ and $N_{sim} = 16$ to match three facts:

1. The average value of the WTP at the 75th percentile is 2.45 (off of a base of 17.50). Our simulated estimate is 2.44.
2. The average value of the WTP at the 25th percentile is 0.20 (off of a base of 17.50). Our simulated estimate is 0.21.
3. The standard deviation of the WTP at each of the 25th and 75th percentiles is about 0.60. Our simulated estimate is 0.54.

There are two reasons we write "about 0.60" when Mas and Pallais report a standard error around the estimate of the 25th percentile of 0.50 and a standard error around the estimate of the 75th percentile of 0.68. First, the simulated standard errors around the 25th and 75th percentiles are approximately equal. This is why we attempt to hit the midpoint in simulations of about 0.59, although our simulated estimate is a little low at 0.54. Second, to generate such a large standard error, we need a very small number of directly observable draws: 16 per data set delivers the approximately correct standard error around each of the 25th and 75th percentiles. This may seem low, given that the data set in Mas and Pallais (2017) consists of 608 observations. In the data of Mas and Pallais (2017), respondents are not directly asked their WTP. Instead, they are randomly assigned a wage gap between non-WFH and WFH and asked if they would take the WFH job at that wage gap.

For each of the simulated WTP data sets, we compute $1/\zeta$. The standard deviation across data sets of $1/\zeta$ is 0.0172 and the 5th and 95th percentile estimates of $1/\zeta$ are 0.0365 and 0.0928 with a median of 0.0616, not too far from our baseline estimate that uses the reported data of 0.0634. Across the 100,000 simulated data sets, the correlation of the estimates of the 25th and 75th percentiles is 0.375.

E.2 Standard errors of jointly estimated parameters

We calculate the standard errors of our jointly estimated parameters as follows. Denote $m(\theta)$ as an $Mx1$ vector of moments to match and let θ be a $Kx1$ vector of parameters. Denote $\widehat{\theta}$ as the estimator of θ, where $\widehat{\theta}$ satisfies

$$\widehat{\theta} = \arg\min\left[m(\theta) - m(\theta^*)\right]'\left[m(\theta) - m(\theta^*)\right]. \tag{A.23}$$

In our application, $K = M = 19$. The first 10 moments correspond to moments 1-10 as we describe in Section 4.5. The remaining 9 moments are the average hourly wage by type (4), financial commuting costs by zone (2), time commuting costs by zone (2), and the elasticity of choosing to WFH with respect to the wage (1). Our estimation strategy is to start with the last 9 moments, as for these moments there is a 1-1 mapping of parameters to moments, and find the values of the 9 parameters to exactly match the last 9 moments. Then, we search for the remaining parameters of the model to minimize the objective function in equation (A.23). This objective function depends on 19 parameters, 9 of which are fixed; we search for the remaining parameters. The value of the minimized objective function is very nearly zero, which is expected as the model is exactly identified.[20]

Now take the Taylor expansion of the moments at $\widehat{\theta}$, around the true but unobserved values of θ, denoted as θ^*:

$$m\left(\widehat{\theta}\right) - m(\theta^*) = \left[\frac{\partial m(\theta)}{\partial \theta}\right]\left[\widehat{\theta} - \theta^*\right] \tag{A.24}$$

where $\left[\frac{\partial m(\theta)}{\partial \theta}\right]$ is the MxK matrix produced by taking the derivative of each of the M moments with respect to each of the K parameters.

[20] The value of the minimized objective function at our reported estimates is 2.12E-11.

Multiply both sides of equation A.24 by $\left[\frac{\partial m(\theta)}{\partial \theta}\right]'$ and take the inverse to get

$$\left[\widehat{\theta}-\theta^{*}\right] = \left[\left[\frac{\partial m(\theta)}{\partial \theta}\right]'\left[\frac{\partial m(\theta)}{\partial \theta}\right]\right]^{-1}\left[\frac{\partial m(\theta)}{\partial \theta}\right]'\left[m\left(\widehat{\theta}\right)-m\left(\theta^{*}\right)\right].$$

Take the expected value of $\left[\widehat{\theta}-\theta^{*}\right]\left[\widehat{\theta}-\theta^{*}\right]'$ and consider the case of $K=M$ to get

$$\text{Var}\left(\widehat{\theta}-\theta^{*}\right) = A^{-1}\,\Omega\,A^{-1\prime}$$

where we have defined the MxM matrices

$$\begin{aligned} A &= \left[\frac{\partial m(\theta)}{\partial \theta}\right] \\ \Omega &= E\left\{\left[m\left(\widehat{\theta}\right)-m\left(\theta^{*}\right)\right]\left[m\left(\widehat{\theta}\right)-m\left(\theta^{*}\right)\right]'\right\}. \end{aligned}$$

To determine the matrix A, we change the value of each parameter one at a time by 1%, simulate the model, and record how each of the M moments change. For Ω, since we are drawing from many different data sets, we place the square of the reported standard errors on the diagonal elements and assume the off-diagonal elements are zero.

We estimate the following 10 parameters using the first 10 moments we describe earlier: A_ι^h/A_ι^b for $\iota=1,2$, $a_{2,\iota}$ for $\iota=1,\ldots,4$, χ_ι for $\iota=1,2$, $\mathcal{Z}$, and ρ.[21] We estimate the remaining 9 parameters directly using the last 9 moments: Z_ι for $\iota=1,\ldots,4$, t_n for $n=1,2$, τ_n for $n=1,2$, and ζ^{-1}. Each of the 19 parameters can influence any moment, so all 19 columns of the first 10 rows of A will be populated. Each of the moments corresponding to parameters 11-19 is trivial in the sense that the parameter is set to directly match the estimate of that parameter taken from outside of the model. We capture this simplicity by setting the diagonal elements of A from rows 11-19 equal to one and setting the off-diagonals in those rows to 0.

[21] See Section 4.5 for intuition on identification.

F Pandemic Counterfactuals

In both the COVID-19 and hypothetical 2009 pandemic counterfactuals, we restrict hours worked at the office for all four types to be equal to 40% of their baseline hours. Denote baseline hours for type ι households living in zone n that are not at a WFH firm as $\bar{b}_{n\iota}$. For households that are not at a WFH firm, in the COVID counterfactuals we set

$$\begin{aligned} b_{n\iota} &= 0.4 \cdot \bar{b}_{n\iota} \\ \ell_{n\iota} &= 1 - (1 + t_n)\, b_{n\iota}. \end{aligned}$$

Note that expressions (8) through (11) continue to hold. Given the wage as determined by these equations, and given $b_{n\iota}$, labor income is determined. Given labor income and leisure, the household optimally chooses consumption and housing to maximize utility.

For households that are at a WFH firm, the process to determine labor income is a little more involved. Denote $\bar{l}^b_{n\iota}$ as the baseline pre-pandemic time at the office for households at a WFH firm. Then for the COVID counterfactuals, we restrict

$$l^b_{n\iota} = 0.4 \cdot \bar{l}^b_{n\iota} \tag{A.25}$$

For convenience, we drop the location and type subscripts. To determine the remaining endogenous variables, we assume (as before) that households own the WFH firm and find quantities that solve

$$\max_{c,h,\ell,y,y^b,y^h,l^h,s^b,s^h,k^b,k^h} \left\{ \quad (1-\alpha)\ln c + \alpha \ln h + \psi \ln \ell \quad \right\}$$

subject to

$$0 = \mu_c \left[y - r^k k^b - r^s s^b - \tau l^b - c - r\left(h + s^h\right) - r^k k^h \right] \tag{A.26}$$

$$0 = \mu_l \left[1 - (1+t)\, l^b - l^h - \ell \right] \tag{A.27}$$

$$0 = \mu_y \left[\left[\left(y^b\right)^\rho + \left(y^h\right)^\rho \right]^{1/\rho} - y \right] \tag{A.28}$$

$$0 = \mu_b \left[A^b \left(l^b\right)^{\theta_b} \left(k^b\right)^{\theta_k} \left(s^b\right)^{\theta_s} - y^b \right] \tag{A.29}$$

$$0 = \mu_h \left[A^h \left(l^h\right)^{\theta_b} \left(k^h\right)^{\theta_k} \left(s^h\right)^{\theta_s} - y^h \right]. \tag{A.30}$$

The first-order conditions are

$$
\begin{array}{llrcl}
1a & y: & \mu_y & = & \mu_c \\
2a & y^b: & \mu_b & = & y^{1-\rho}\left(y^b\right)^{\rho-1}\mu_y \\
3a & y^h: & \mu_h & = & y^{1-\rho}\left(y^h\right)^{\rho-1}\mu_y \\
5a & l^h: & \mu_\ell & = & \mu_h\theta_b\left(y^h/l^h\right) \\
6a & k^b: & \mu_c r^k & = & \mu_b\theta_k\left(y^b/k^b\right) \\
7a & k^h: & \mu_c r^k & = & \mu_h\theta_k\left(y^h/k^h\right) \\
8a & s^b: & \mu_c r^s & = & \mu_b\theta_s\left(y^b/s^b\right) \\
9a & s^h: & \mu_c r & = & \mu_h\theta_s\left(y^h/s^h\right) \\
10a & c: & \mu_c & = & \left(1-\alpha\right)/c \\
11a & h: & \mu_c r & = & \alpha/h \\
12a & \ell: & \mu_\ell & = & \psi/\ell.
\end{array}
$$

In the numbering of the FOCs, we have skipped "4a" so the numbering of the FOCs exactly corresponds to the numbering in the unconstrained problem of the previous section, making comparisons of mathematics in this section and the previous section straightforward.

To make progress, we derive the solution for all other variables given a guess of a solution for l^h (and thus ℓ) and then confirm that the guess for l^h is correct. To do this, we divide the FOC 6a by FOC 8a and FOC 7a by FOC 9a and rearrange terms to get

$$\frac{k^b}{k^h} = \frac{r^s s^b}{r s^h}.$$

Divide FOC 8a by FOC 9a and use the results of FOCs 2a and 3a to get

$$\frac{y^b}{y^h} = \left(\frac{r^s s^b}{r s^h}\right)^{\frac{1}{\rho}}.$$

Using the mathematics from the previous section, we can derive an expression for s_b/s_h as a function of l_b/l_h

$$
\begin{aligned}
\left(\frac{y^b}{y^h}\right) &= \frac{A^b}{A^h}\left(\frac{l^b}{l^h}\right)^{\theta_b}\left(\frac{k^b}{k^h}\right)^{\theta_k}\left(\frac{s^b}{s^h}\right)^{\theta_s} \\
\rightarrow \left(\frac{s^b}{s^h}\right) &= \left[\left(\frac{r^s}{r}\right)^{\frac{\rho\theta_k-1}{\rho}}\left(\frac{A^b}{A^h}\right)\left(\frac{l^b}{l^h}\right)^{\theta_b}\right]^{\frac{\rho}{1-\rho\theta_k-\rho\theta_s}}.
\end{aligned}
$$

Given l^b/l^h, we can determine s^b/s^h, k^b/k^h and y^b/y^h.

To pin down levels, note that FOCs 7a and 9a imply

$$k^h \;=\; \left(\frac{\theta_k}{\theta_s}\right)\left(\frac{r}{r^k}\right)s^h$$

so given a value of s^h, we know k^h; and given s^h and k^h, we know s^b and k^b and thus y^b and y^h (given we know the ratios s^b/s^h, k^b/k^h and y^b/y^h). Then, using mathematics from the previous section, note that FOCs 8a and 9a imply[22]

$$r^s s^b + r s^h \;=\; \theta_s y.$$

After rearranging terms, this becomes

$$s^h \;=\; \frac{\theta_s y}{r^s\left(s^b/s^h\right)+r}$$

The results of the previous section show that we can derive

$$s^h \;=\; \left[\frac{\theta_s\left[\left(\widetilde{A}^b\right)^{\rho}\left(l^b\right)^{\frac{\rho\theta_b}{1-\rho\theta_k}}\left(\frac{s^b}{s^h}\right)^{\frac{\rho\theta_s}{1-\rho\theta_k}} \;+\; \left(\widetilde{A}^h\right)^{\rho}\left(l^h\right)^{\frac{\rho\theta_b}{1-\rho\theta_k}}\right]^{\frac{1-\rho\theta_k}{\rho(1-\theta_k)}}}{r^s\left(\dfrac{s^b}{s^h}\right)+r}\right]^{\frac{1-\theta_k}{1-\theta_k-\theta_s}}.$$

where, as before,

$$\widetilde{A}^b \;=\; \left(A^b\right)^{\frac{1}{1-\rho\theta_k}}\left(\theta_k/r^k\right)^{\frac{\theta_k}{1-\rho\theta_k}} \quad\text{and}\quad \widetilde{A}^h \;=\; \left(A^h\right)^{\frac{1}{1-\rho\theta_k}}\left(\theta_k/r^k\right)^{\frac{\theta_k}{1-\rho\theta_k}}.$$

Finally, we have to confirm that we have guessed the correct value of l^h. Combine the FOCs for 5a and 12a to get

$$\psi\left(\frac{l^h}{\ell}\right) \;=\; \theta_b\mu_h y_h \;=\; \theta_b\mu_c y^{1-\rho}\left(y^h\right)^{\rho} \;=\; \frac{\theta_b y^{1-\rho}\left(y^h\right)^{\rho}}{c+rh}$$

where the last equality comes from combining FOCs 10a and 11a. After imposing the

[22]As before, we have used the implications of FOCs 1a, 2a, and 3a and the definition of y from equation (A.35) to derive that $\mu_h y^h + \mu_b y^b = \mu_c y$.

budget constraint and rearranging terms, this becomes

$$l^h = \frac{\ell\theta_b}{\psi}\left(\frac{y^{1-\rho}\left(y^h\right)^\rho}{y - r^k k^b - r^s s^b - \tau l^b - r s^h - r^k k^h}\right).$$

Given what we have derived, all of the terms on the right hand side have been determined given a value of l^h. To find the solution, we search for the value of l^h such that the above equation holds.

G Additional Results for Dynamic Counterfactuals

Table A.1: Dynamics of Distribution of Incomes and Population

Row		Pre-COVID	Post-COVID Scenarios				
		Baseline	SR	Year 3	Year 5	Year 7	LR Putty-Clay
		(1)	(2)	(3)	(4)	(5)	(6)
	Technology:						
(1)	A_1^h/A_1^b	0.365	0.665	0.665	0.665	0.665	0.665
(2)	A_2^h/A_2^b	0.348	0.515	0.515	0.515	0.515	0.515
(3)	A_1^b	9330	9254	9251	9250	9248	9245
	Incomes:						
(4)	Type 1 avg. ann. income per worker	$ 108,862	$ 141,424	$ 142,924	$ 143,876	$ 144,794	$ 146,114
(5)	Type 2 avg. ann. income per worker	$ 77,776	$ 84,921	$ 85,466	$ 85,822	$ 86,172	$ 86,685
(6)	Type 3 avg. ann. income per worker	$ 93,135	$ 94,170	$ 94,173	$ 94,176	$ 94,179	$ 94,184
(7)	Type 4 avg. ann. income per worker	$ 60,176	$ 61,630	$ 61,647	$ 61,658	$ 61,670	$ 61,688
(8)	High-skill avg. ann. income per worker	$ 103,620	$ 125,673	$ 126,674	$ 127,309	$ 127,923	$ 128,804
(9)	Low-skill avg. ann. income per worker	$ 64,486	$ 67,334	$ 67,480	$ 67,576	$ 67,670	$ 67,810
(10)	High-skill to low-skill avg. income	1.61	1.87	1.88	1.88	1.89	1.90
	Consumption:						
(11)	Type 1 avg. non-housing consumption	$ 80,664	$ 94,557	$ 95,244	$ 95,683	$ 96,108	$ 96,721
(12)	Type 2 avg. non-housing consumption	$ 48,463	$ 50,634	$ 50,779	$ 50,877	$ 50,976	$ 51,125
(13)	Type 3 avg. non-housing consumption	$ 71,074	$ 71,925	$ 71,915	$ 71,910	$ 71,906	$ 71,902
(14)	Type 4 avg. non-housing consumption	$ 37,457	$ 38,468	$ 38,462	$ 38,460	$ 38,459	$ 38,459
(15)	High-skill avg. non-housing consumption	$ 77,467	$ 87,013	$ 87,468	$ 87,759	$ 88,041	$ 88,448
(16)	Low-skill avg. non-housing consumption	$ 40,152	$ 41,447	$ 41,479	$ 41,501	$ 41,525	$ 41,561
(17)	High-skill to low-skill avg. consumption	1.93	2.10	2.11	2.11	2.12	2.13
	Population Location:						
(18)	Total high-skill	51.0%	51.0%	51.0%	51.0%	51.0%	51.0%
(19)	Living in Zone 1	35.6%	34.0%	33.3%	32.9%	32.5%	32.0%
(20)	Living in Zone 2	64.4%	66.0%	66.7%	67.1%	67.5%	68.0%
(21)	Total low-skill	49.0%	49.0%	49.0%	49.0%	49.0%	49.0%
(22)	Living in Zone 1	34.8%	36.5%	35.6%	35.1%	34.7%	34.1%
(23)	Living in Zone 2	65.2%	63.5%	64.4%	64.9%	65.3%	65.9%

Table A.2: Dynamics of Work Location, Space, and Rents

Row		Pre-COVID Baseline (1)	SR (2)	Year 3 (3)	Year 5 (4)	Year 7 (5)	LR Putty-Clay (6)
			Post-COVID Scenarios				
	Labor supply:						
(24)	Type 1	0.411	0.427	0.428	0.428	0.428	0.429
(25)	Type 2	0.407	0.416	0.416	0.416	0.417	0.417
	Labor Supply of WFH:						
(26)	Type 1	0.041	0.164	0.168	0.17	0.172	0.176
(27)	Type 2	0.018	0.073	0.077	0.08	0.082	0.086
	Days WFH to Total Days Worked:						
(28)	Type 1	0.099	0.383	0.392	0.397	0.403	0.41
(29)	Type 2	0.045	0.176	0.185	0.191	0.197	0.205
	Extensive Margin of WFH:						
(30)	Share of type 1 choosing WFH firm	0.697	0.974	0.976	0.978	0.979	0.981
(31)	Share ot type 2 choosing WFH firm	0.322	0.646	0.663	0.674	0.683	0.697
	Intensive Margin of WFH:						
(32)	Days worked WFH to total days for type 1 at WFH firm	0.14	0.39	0.4	0.41	0.41	0.42
(33)	Days worked WFH to total days for type 2 at WFH firm	0.14	0.27	0.28	0.28	0.29	0.29
	Demand for Space:						
(34)	Office space per worker in CBD	21,403	21,403	21,403	21,403	21,403	21,403
(35)	Total space per household in Zone 1	26,680	26,681	28,160	29,134	30,100	31,535
(36)	Housing per household in Zone 1	25,904	23,331	24,564	25,374	26,176	27,366
(37)	Home office per household in Zone 1	775	3,350	3,596	3,760	3,924	4,169
(38)	Total space per household in Zone 2	42,092	42,091	46,159	48,860	51,554	55,584
(39)	Housing per household in Zone 2	39,995	34,240	37,334	39,378	41,410	44,435
(40)	Home office per household in Zone 2	2,097	7,852	8,825	9,482	10,145	11,149
	Rent per Unit of Space:						
(41)	CBD	1.000	0.928	0.925	0.923	0.921	0.919
(42)	Zone 1	0.810	0.945	0.899	0.871	0.846	0.810
(43)	Zone 2	0.470	0.601	0.554	0.527	0.502	0.470

H Misallocation: WFH Firms Where Households Are Constrained

In this section, we solve for the optimal allocation for households that work at constrained WFH firms. At these firms, time spent working at home and at the office are each constrained to equal some pre-determined value that can depend on the zone in which the household lives, i.e.,

$$\text{(A.31)} \qquad l^b_{n\iota} = \bar{l}^b_{n\iota}$$

$$\text{(A.32)} \qquad l^h_{n\iota} = \bar{l}^h_{n\iota}$$

$$\text{(A.33)} \qquad \ell_{n\iota} = 1 - (1 + t_n)\,\bar{l}^b_{n\iota} - \bar{l}^h_{n\iota}$$

Conditional on these constraints, and after eliminating the n and ι subscripts, the household chooses all other variables optimally, including quantity of capital and space at the firm. The household's problem is thus

$$\max_{c,h,\ell,y,y^b,y^h,s^b,s^h,k^b,k^h} \left\{ \; (1-\alpha)\ln c + \alpha \ln h + \psi \ln \ell \; \right\}$$

subject to

$$\text{(A.34)} \qquad 0 = \mu_c \left[y - r^k k^b - r^s s^b - \tau l^b - c - r\left(h + s^h\right) - r^k k^h \right]$$

$$\text{(A.35)} \qquad 0 = \mu_y \left[\left[\left(y^b\right)^\rho + \left(y^h\right)^\rho \right]^{1/\rho} - y \right]$$

$$\text{(A.36)} \qquad 0 = \mu_b \left[A^b \left(l^b\right)^{\theta_b} \left(k^b\right)^{\theta_k} \left(s^b\right)^{\theta_s} - y^b \right]$$

$$\text{(A.37)} \qquad 0 = \mu_h \left[A^h \left(l^h\right)^{\theta_b} \left(k^h\right)^{\theta_k} \left(s^h\right)^{\theta_s} - y^h \right].$$

The first-order conditions are

$$\begin{array}{llrcl}
1b & y: & \mu_y & = & \mu_c \\
2b & y^b: & \mu_b & = & y^{1-\rho}\left(y^b\right)^{\rho-1}\mu_y \\
3b & y^h: & \mu_h & = & y^{1-\rho}\left(y^h\right)^{\rho-1}\mu_y \\
6b & k^b: & \mu_c r^k & = & \mu_b\theta_k\left(y^b/k^b\right) \\
7b & k^h: & \mu_c r^k & = & \mu_h\theta_k\left(y^h/k^h\right) \\
8b & s^b: & \mu_c r^s & = & \mu_b\theta_s\left(y^b/s^b\right) \\
9b & s^h: & \mu_c r & = & \mu_h\theta_s\left(y^h/s^h\right) \\
10b & c: & \mu_c & = & \left(1-\alpha\right)/c \\
11b & h: & \mu_c r & = & \alpha/h \\
12b & \ell: & \mu_\ell & = & \psi/\ell.
\end{array}$$

In the numbering of the FOCs, we have skipped "4b" and "5b" so that the numbering of the FOCs exactly corresponds to the numbering in the unconstrained problem in Appendix C.2 making comparisons of mathematics in this section and Appendix C.2 straightforward.

We can divide 6b by 8b and 7b by 9b and rearrange terms to get

$$\frac{k^b}{k^h} = \frac{r^s s^b}{r s^h}.$$

Divide FOC 8b by FOC 9b and use the results of FOCs 2b and 3b to get

$$\frac{y^b}{y^h} = \left(\frac{r^s s^b}{r s^h}\right)^{\frac{1}{\rho}} = \left[\left(\frac{r^s}{r}\right)^{\frac{\rho\theta_k-1}{\rho}}\left(\frac{A^b}{A^h}\right)\left(\frac{l^b}{l^h}\right)^{\theta_b}\right]^{\frac{\rho}{1-\rho\theta_k-\rho\theta_s}}.$$

Given l^b/l^h, we can determine s^b/s^h, k^b/k^h, and y^b/y^h. To pin down levels, note that FOCs 7b and 9b imply

$$k^h = \left(\frac{\theta_k}{\theta_s}\right)\left(\frac{r}{r^k}\right)s^h$$

so given a value of s^h, we know k^h. Given s^h and k^h, we know s^b and k^b and thus y^b and y^h (given we know the ratios s^b/s^h, k^b/k^h, and y^b/y^h). Using mathematics from earlier, note that we can derive

$$
\begin{aligned}
s^h &= \frac{\theta_s y}{r^s\left(s^b/s^h\right)+r} \\
&= \left[\frac{\theta_s\left[\left(\widetilde{A}^b\right)^\rho\left(l^b\right)^{\frac{\rho\theta_b}{1-\rho\theta_k}}\left(\frac{s^b}{s^h}\right)^{\frac{\rho\theta_s}{1-\rho\theta_k}} \;+\; \left(\widetilde{A}^h\right)^\rho\left(l^h\right)^{\frac{\rho\theta_b}{1-\rho\theta_k}}\right]^{\frac{1-\rho\theta_k}{\rho\left(1-\theta_k\right)}}}{r^s\left(\dfrac{s^b}{s^h}\right)+r}\right]^{\frac{1-\theta_k}{1-\theta_k-\theta_s}} .
\end{aligned}
$$

where, as before,

$$
\widetilde{A}^b = \left(A^b\right)^{\frac{1}{1-\rho\theta_k}}\left(\theta_k/r^k\right)^{\frac{\theta_k}{1-\rho\theta_k}} \quad \textbf{and} \quad \widetilde{A}^h = \left(A^h\right)^{\frac{1}{1-\rho\theta_k}}\left(\theta_k/r^k\right)^{\frac{\theta_k}{1-\rho\theta_k}} .
$$