

The Work-from-Home Technology Boon and its Consequences*

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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 indicate that the pandemic induced a large change to the relative productivity of WFH that substantially increased home prices and 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 0.998 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 83% 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 8% decline in office rents in the central business district (CBD) when the supply of office space is fixed. Residential rents rise, especially in the outer suburbs, due to increased demand for home office space. Our counterfactual simulations suggest these rent increases translate into a rise in home prices of 14% in areas near the CBD and 25% in the outer suburbs. 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. Dutcher (2012), Bartik, Cullen, Glaeser, Luca, and Stanton (2020), Morikawa (2020), Barber, Jiang, Morse, Puri, Tookes, and

Werner (2021), Behrens, Kichko, and Thisse (2021), PwC (2021), Gibbs, Mengel, and Siemroth (forthcoming), and Kruger, Maturana, and Nickerson (forthcoming), provide additional evidence and discussion of the productivity of WFH before and during the pandemic.

The three papers studying WFH that are most closely related to ours are Kaplan, Moll, and Violante (2020), Delventhal, Kwon, and Parkhomenko (2022), and Delventhal and Parkhomenko (2021). Kaplan, Moll, and Violante (2020) abstract from urban form but specify disutility from WFH, home production, and work at the office. They 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.

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. In contrast to an increase in productivity, Delventhal and Parkhomenko (2021) argue that workers received disutility from the option to WFH prior to the pandemic and that a preference shift over the course of the pandemic caused the increase in WFH. Delventhal, Kwon, and Parkhomenko (2022) assume that working from home and working at the office are perfect substitutes in production such that the main spatial implications of their model regard movements of people across rather than within cities. Our empirical evidence is inconsistent with Delventhal, Kwon, and Parkhomenko (2022)'s assumption of perfect substitutes.

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.

Finally, our work relates to how cities respond to shocks in the short run and the long run. Ouazad (2021) surveys this literature. Our model predicts that the trend towards suburbanization will continue, which is consistent with Ouazad (2021).¹ The evidence suggests that natural disasters tend to have only transitory effects on city structure (Davis and Weinstein, 2002; Ouazad, 2021), 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 EOS 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

¹Brueckner, Kahn, and Lin (forthcoming), Gupta, Mittal, Peeters, and Van Nieuwerburgh (2022a), Haslag and Weagley (forthcoming), Li and Su (2021), Liu and Su (2021), and Ramani and Bloom (2022) also document an increased tendency toward suburbanization.

years just prior to the pandemic and of longer-term trends in the frequency of full 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 sub-modules. 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 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.

²We 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.

Table 2 provides more detail on the frequency of WFH as reported in the GSS. Only about 6% 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 15% 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, and explains the slowly moving positive trend in 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 Overview

Households make a set of choices in a given sequence to maximize expected utility. First, they choose where to live from one of $n = 1, \dots, N$ locations. Next, households in a teleworkable occupation choose whether to work for a firm that allows workers to work full days at home, a WFH firm, or a firm that does not allow WFH, a non-WFH firm. Wages at WFH and non-WFH firms may differ. Furthermore, wages at WFH firms vary depending on the mix of days worked at home and days worked at the office. 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.

Each day worked at the office involves a commute to the CBD that costs time and resources. 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 of 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.

The production technologies for WFH firms and non-WFH firms differ. This allows the quantity of WFH to change in multiple ways over time, even when the fraction of households that work in telecommutable occupations is fixed. The fraction of households that choose a WFH firm is the extensive margin of WFH. How much households at a WFH firm work from home is the intensive margin of WFH. Thus, a change in the relative productivity of WFH can change both the extensive and intensive margins.

Labor markets are frictionless and perfectly competitive such that workers' wages reflect their marginal product of labor. Households have different preferences for WFH and non-WFH firms. Therefore, if workers have a positive preference for being able to WFH, competitive labor markets imply the wages will be lower at firms that allow WFH. However, the production technology at WFH firms combines the output workers produce at home and at the office in a way that allows for the possibility that

the two types of work are complementary.

3.2 Household Environment

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 $\pi_\iota, \iota \in 1, \dots, 4$.

3.2.1 Location Preferences

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

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

$a_{n\iota}$ 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 .³ We assume $e_{n\iota j}$ is drawn i.i.d 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 $e_{n\iota j}$.

³To focus on the implications of WFH for city structure, we abstract from the potential for endogenous amenities due to neighborhood sorting emphasized by Diamond (2016), Couture and Handbury (2020), and Couture, Gaubert, Handbury, and Hurst (forthcoming).

3.2.2 Determining X_{nl} for Households in Telecommuting Occupations

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

$$(2) \quad X_{nlj}^\kappa = X_{nl}^\kappa + (1/\zeta) \epsilon_{nlj}^\kappa.$$

As specified, the utility of households living in n and working for a firm of type κ has two components: a deterministic one, X_{nl}^κ , and a stochastic one, $(1/\zeta) \epsilon_{nlj}^\kappa$. We will precisely define the deterministic component of utility later, but for now note that it includes utility from consumption, housing, and leisure, all of which may vary across type of firm κ , given location n and household type ι . ϵ_{nlj}^κ is drawn i.i.d. 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 .⁴

Utility when employed by a non-WFH firm. Households of type $\iota = 1$ or 2 that live in n and work for a firm operating in the CBD that does not allow WFH ($\kappa = 0$) receive utility from consumption (c_{nl}^0), housing (h_{nl}^0), leisure (ℓ_{nl}^0), and the fraction of discretionary time to spend at the office (b_{nl}^0) according to

$$(3) \quad X_{nl}^0 = (1 - \alpha_\iota) \ln c_{nl}^0 + \alpha_\iota \ln h_{nl}^0 + \psi_\iota \ln \ell_{nl}^0.$$

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_{nl}^0 fraction of a full year of labor thus earns a net annual income of $(w_\iota^0 - \tau_n) b_{nl}^0$. The household spends this labor income on consumption, c_{nl}^0 , and housing, h_{nl}^0 . The rental price per unit of housing in location n is r_n . Given a total endowment of time in the year of 1, the quantity of leisure enjoyed by a household spending b_{nl}^0 percentage of the year working is $1 - (1 + t_n) b_{nl}^0$, where t_n is the round-trip time spent commuting

⁴Delventhal 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.

from location n .

They thus face the budget and time constraints of

$$(4) \quad \begin{aligned} 0 &= (w_\iota^0 - \tau_n) b_{n\iota}^0 - c_{n\iota}^0 - r_n h_{n\iota}^0 \\ 0 &= 1 - (1 + t_n) b_{n\iota}^0 - \ell_{n\iota}^0. \end{aligned}$$

In equations (3) and (4), the 0 superscripts denote that the household works at a non-WFH firm ($\kappa = 0$), and w_ι^0 denotes the wage paid by non-WFH firms to type ι households that spend 100% of their discretionary time at work.

Utility when employed by a WFH firm. Households of type $\iota = 1$ or $\iota = 2$ living in n and working at a WFH firm ($\kappa = 1$) receive

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

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 B, 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.

They face budget and time constraints modified to account for the fact that WFH takes time, commuting costs only apply to time spent at the office, and renting a home office and home equipment is costly. Further, the gross compensation function for workers at WFH firms, $\omega_\iota(l_{n\iota}^b, l_{n\iota}^h, s_{n\iota}^h, k_{n\iota}^h)$, depends on (a) the percentage of total time in the year to worked at the firm in the CBD, $l_{n\iota}^b$, (b) the percentage of total time in the year worked at home, $l_{n\iota}^h$, (c) the size of the home office, $s_{n\iota}^h$, and (d) the amount of equipment and software the household rents for use in the home office, $k_{n\iota}^h$. Their

constraints are thus

$$\begin{aligned} \text{budget :} \quad 0 &= \omega_\iota (l_{n\iota}^b, l_{n\iota}^h, s_{n\iota}^h, k_{n\iota}^h) - \tau_n l_{n\iota}^b - c_{n\iota}^1 - r_n (h_{n\iota}^1 + s_{n\iota}^h) - r^k k_{n\iota}^h \\ \text{time :} \quad 0 &= 1 - (1 + t_n) l_{n\iota}^b - l_{n\iota}^h - \ell_{n\iota}^1. \end{aligned}$$

3.2.3 $X_{n\iota}$ for Households in Non-Telecommuting Occupations

Households of type $\iota = 3$ or 4 work in an occupation that does not allow telecommuting receive utility from consumption, housing, and leisure according to

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

They face the budget and time constraints of

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

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 work for a non-WFH firm.

3.3 Firms and Production

Non-WFH Firms. Each firm in the model employs one worker 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, a firm employing labor, $b_{n\iota}$, capital in the form of both equipment and software, $k_{n\iota}$, and office space, $s_{n\iota}$, receives profits

$$(5) \quad \begin{aligned} &y_{n\iota} - w_\iota b_{n\iota} - r^k k_{n\iota} - r^s s_{n\iota} \\ \text{where} \quad &y_{n\iota} = Z_\iota b_{n\iota}^{\theta_b} k_{n\iota}^{\theta_k} s_{n\iota}^{\theta_s}. \end{aligned}$$

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.⁵

⁵While 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 vari-

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

$$(6) \quad y_{n\iota} = \left[(y_{n\iota}^b)^\rho + (y_{n\iota}^h)^\rho \right]^{1/\rho}$$

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

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

$k_{n\iota}^b$ 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 .⁶

3.4 Technology

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

$$\begin{aligned} \text{non-WFH firm TFP, } \iota = 1, 3 & \quad Z_\iota = \bar{Z}_\iota \mathcal{H}^{\delta_b} \\ \text{WFH firm TFP while at the office for type 1} & \quad A_1^b = \bar{A}_1^b \mathcal{H}^{\delta_b}. \end{aligned}$$

ables in equation (5) is necessary. 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.

⁶Note 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.

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}_ι and \bar{A}_ι^b .⁷

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

$$(7) \quad A_\iota^h = \bar{A}_\iota^h L_h^{\delta_n}$$

where

$$(8) \quad \bar{A}_\iota^h = \mathcal{A}_\iota^h [(L_h^{max})^{\delta_{\iota,h}}] .$$

L_h^{max} is the maximum amount of time that households in aggregate spent working at home in any previous year and L_h is the current aggregate amount of WFH. Equation (7) specifies that A_ι^h can change over time due to exogenously increasing TFP, i.e., changes to \mathcal{A}_ι^h , changes to how much other workers are working from home, or changes to the adoption externality if the total amount of time that households spent working at home in any previous year increases.

Equation (7) allows for both adoption and network externalities. The network externality is akin to a standard agglomeration externality as it depends on the current amount of WFH. This implies that if there is a large drop in the amount of WFH being done, its productivity falls. In contrast, the adoption externality in equation (8) is due to households learning how to use the technology. It 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. Consistent with the earlier literature on technology adoption (Greenwood, Seshadri, and Yorukoglu, 2005; Brock and Durlauf, 2010, e.g.), this specification implies that people do not forget how to use a technology once they have adopted it.

Commuting Speed. Denote \mathcal{L}_n as the aggregate quantity of work at the office in the CBD by households living in location n during the year and define d_n as the dis-

⁷Gould (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.

tance from location n to the CBD. We define aggregate distance commuting, \mathcal{V} , as

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

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 $\gamma = -0.15$.

3.5 The Decision Problems

3.5.1 Household Choices

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

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

Decisions of Type 1 and 2 Households After choosing where to live, households working in teleworkable occupations choose whether to work for a non-WFH firm or a WFH firm. 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_{nij}^κ . Before the values of ϵ_{nij}^κ are

realized, the probability that a household living in n works for a particular firm of type κ' , $g_{n\iota}^{\kappa'}$, is equal to

$$(9) \quad g_{n\iota}^{\kappa'} = \frac{e^{\zeta X_{n\iota}^{\kappa'}}}{e^{\aleph_{n\iota}}} \quad \text{where} \quad \aleph_{n\iota} = \ln \sum_{\kappa=0}^1 e^{\zeta X_{n\iota}^{\kappa}}.$$

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

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

where Γ is Euler's constant.

In Appendix C, we show that optimal household choices for households at non-WFH firms satisfy

$$\begin{aligned} \ell_{n\iota}^0 &= \frac{\psi_{\iota}}{1 + \psi_{\iota}} \\ b_{n\iota}^0 &= \left(\frac{1}{1 + \psi_{\iota}} \right) \left(\frac{1}{1 + t_n} \right) \\ c_{n\iota}^0 &= (1 - \alpha_{\iota}) (w_{\iota}^0 - \tau_n) b_{n\iota}^0 \\ r_n h_{n\iota}^0 &= \alpha_{\iota} (w_{\iota}^0 - \tau_n) b_{n\iota}^0. \end{aligned}$$

Households that choose a WFH firm then choose $l_{n\iota}^b$, $l_{n\iota}^h$, $s_{n\iota}^h$, and $k_{n\iota}^h$. These choices determine the gross compensation offered by a WFH firm to the household, $\omega_{\iota} (l_{n\iota}^b, l_{n\iota}^h, s_{n\iota}^h, k_{n\iota}^h)$.

As shown in Appendix D.1, for workers at WFH firms 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

$$\begin{aligned} c_{n\iota}^1 &= (1 - \alpha_{\iota}) [\omega_{\iota} (l_{n\iota}^b, l_{n\iota}^h, s_{n\iota}^h, k_{n\iota}^h) - \tau_n l_{n\iota}^b - r_n s_{n\iota}^h - r^k k_{n\iota}^h] \\ r_n h_{n\iota}^1 &= \alpha_{\iota} [\omega_{\iota} (l_{n\iota}^b, l_{n\iota}^h, s_{n\iota}^h, k_{n\iota}^h) - \tau_n l_{n\iota}^b - r_n s_{n\iota}^h - r^k k_{n\iota}^h] \\ \ell_{n\iota}^1 &= \frac{\psi_{\iota}}{1 + \psi_{\iota}} \end{aligned}$$

Additionally, the marginal impact on income of an extra unit of home office space must be equal to the rent on that space, $\partial \omega_{\iota} / \partial s_{n\iota}^h = r_n$. Finally, the impact on income, less commuting costs of an extra day at the office and adjusted for time spent com-

muting that extra day, must be equal to the impact on income of an extra day working from home, i.e.,

$$(10) \quad \left(\frac{1}{1+t_n} \right) \left[\frac{\partial \omega_\iota}{\partial l_{n\iota}^b} - \tau_n \right] = \frac{\partial \omega_\iota}{\partial l_{n\iota}^h}.$$

In Appendices C and D we derive optimal quantities and choices for all types of households and firms. 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.

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

$$(11) \quad \left(\frac{l_{n\iota}^b}{l_{n\iota}^h} \right) = \left(\frac{r^s}{r_n} \right)^{\frac{-\rho\theta_s}{1-\rho}} \left(\frac{A_\iota^b}{A_\iota^h} \right)^{\frac{\rho}{1-\rho}} \left[(1+t_n) + \frac{\tau_n}{(1+\psi)(c_{n\iota} + r_n h_{n\iota})} \right]^{\frac{-(1-\rho\theta_k - \rho\theta_s)}{1-\rho}}.$$

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 locations, and as both types of commuting costs rise.

3.5.2 Firm Choices

Non-WFH Firms Under competitive labor and factor markets, the firm maximizes profits by setting

$$(12) \quad w_\iota b_{n\iota} = \theta_b y_{n\iota},$$

$$(13) \quad r^k k_{n\iota} = \theta_k y_{n\iota},$$

$$(14) \quad r^s s_{n\iota} = \theta_s y_{n\iota}.$$

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

$$(15) \quad y_{n\iota} = \left[\left(\frac{\theta_k}{r^k} \right)^{\frac{\theta_k}{\theta_b}} \left(\frac{\theta_s}{r^s} \right)^{\frac{\theta_s}{\theta_b}} (Z_\iota)^{\frac{1}{\theta_b}} \right] b_{n\iota}.$$

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

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

Since 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. We characterize the solutions for the optimal quantities of these variables in Appendix D.2.⁸

3.6 Equilibrium and Solution

An equilibrium in this economy is a vector of prices for business capital r^k , office space in the CBD r^s , housing and home office space in locations $1, \dots, N$, r_n ; a wage rate for each type of worker $\iota = 1, \dots, 4$ working at a non-WFH firm, w_ι ; a wage function $\omega_\iota(l_{n\iota}^b, l_{n\iota}^h, s_{n\iota}^h, k_{n\iota}^h)$ for each type of worker $\iota = 1, 2$ able to work at a WFH firm; and commute times t_n for locations $1, \dots, N$ such that

- type $\iota = 3, 4$ households choose the location in which to live and consumption, housing, and labor supply to maximize utility given all commute times, wages and prices subject to budget and time constraints,
- type $\iota = 1, 2$ households maximize utility by choosing the location in which to

⁸To be specific, in Appendix D.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.

live and whether to work at a firm that allows WFH. If they choose to work for a non-WFH firm, they then choose consumption, housing, and labor supply to maximize utility given commute times and all wages and prices and subject to budget and time constraints. If they choose to work for a WFH firm, they choose consumption, housing, labor supply at the office, labor supply at home, business capital at home and home office space to maximize utility given the wage function, commute times, and all prices and subject to budget and time constraints,

- non-WFH firms take all wages and prices as given and choose labor, business capital, and office space to maximize profits,
- WFH firms take all prices and the wage function and its inputs for each type of worker and location where the worker lives as given and choose business capital at the office and office space to maximize profits,
- the total demand for housing inclusive of home office space in each location is equal to the supply of housing in each location and the total demand for office space is equal to the supply of office space, and
- aggregate quantities are consistent with the externalities affecting all wages and commute times.

For each location and type of household, we compute the model solution by finding the value of the ratio in equation (11) that is consistent with annual income and the optimal choice of c_{ni} and h_{ni} ; see Appendices C and D for details. We then use the implications of equations (1) and (2) to identify the fraction of households of each type that live in each location 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 location 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 the model parameters, we use data from seven sources: 1) the 2018 GSS, 2) the 2017-2018 LJF (ATUS 2020 as compiled by Hofferth et al. (2020)), 3) the 2019 5-year American Community Survey (ACS) as compiled by Ruggles et al. (2021) which pools data collected in 2015-2019, 4) the 2019 American Housing Survey (AHS), 5) office rents derived from RCA (2020), 6) residential listing prices per square foot by county compiled by Realtor.com available via FRED at the Federal Reserve Bank of St. Louis, and 7) the Dingel and Neiman (2020) occupation codes (ONET) classified by telecommutable status combined with Census 2010 occupation classifications as our ACS data contains only Census occupation codes.

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 ($uhrswork \geq 30 \& uhrswork < 99$), not living in group quarters, who worked at least 40 weeks ($wkswork \geq 40$) 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.⁹

⁹While 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 occupations. See Mongey, Pilosopph, and Weinberg (forthcoming) for a discussion of the demographic composition of workers in remote-capable occupations.

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 Core-Based Statistical Area (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 Federal Information Processing Standards (FIPS) code in the 2015-2019 ACS data for the CBD county for Miami (Miami-Dade) or Denver (Denver).¹⁰ Our final sample thus includes 21 cities.

Zones. We allow for two residential locations which we refer to hereafter as 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 CBSA. 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 $\nu \rightarrow \infty$. 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.¹¹ These

¹⁰We identify the CBSA, county FIPS code, and state FIPS code using the variables *met2013*, *countyfip*, and *statefip* in the IPUMS data.

¹¹The average home sizes for non-college-educated and college-educated households are 1,582 and

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.¹²

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_i , 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 RCA by multiplying the average transaction price psf for office space in that city by the cap rate specific to that city.¹³ 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. 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.

2,025 square feet.

¹²Many 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).

¹³The 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.¹⁴

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 .¹⁵

Given values of θ_k , θ_s , θ_b , r^k , and r^s and estimates of hourly wages by ι , we use equations (15) and (12) to solve for Z_ι . Denote \tilde{w}_ι 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 $w_\iota = \tilde{w}_\iota \cdot 15 \cdot 365$. Then the model implies for all type 3 and 4 workers and type 1 and 2 workers at non-WFH firms

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

¹⁴We 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.

¹⁵See Gutiérrez-i-Puigarnau and van Ommeren (2010), Black, Kolesnikova, and Taylor (2014), and Pabilonia and Vernon (2022) for discussions of the demographic differences in the relationship between commuting time and work. Since we cannot identify workers at WFH firms in the ACS, we include all workers to estimate wages.

where the constant is equal to

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

Importance of Idiosyncratic Preferences for WFH Firm Choice. To estimate $1/\zeta$, note that equation (9) implies the following relationship of the difference in the log probability of choosing a WFH firm and a non-WFH firm

$$(16) \quad \log g_{ni}^1 - \log g_{ni}^0 = \zeta [X_{ni}^1 - X_{ni}^0].$$

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

$$\begin{aligned} \mathcal{W}_{ni}^0 &= (w_i^0 - \tau_n) b_{ni}^0 \\ \mathcal{W}_{ni}^1 &= (\omega_i (l_{ni}^b, l_{ni}^h, s_{ni}^h, k_{ni}^h) - \tau_n l_{ni}^b - r_n s_{ni}^h - r^k k_{ni}^h). \end{aligned}$$

The optimal choices for housing and consumption imply that equation (16) can be written as

$$(17) \quad \log g_{ni}^1 - \log g_{ni}^0 = \zeta [\chi_i + \log \mathcal{W}_{ni}^1 - \log \mathcal{W}_{ni}^0]$$

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 (17) for each of these data points and then evaluate the difference, we get

$$(18) \quad \log(0.75/0.25) - \log(0.25/0.75) = \zeta \left[\log \left(1 - \frac{\$0.20}{\$17.50} \right) - \log \left(1 - \frac{\$2.45}{\$17.50} \right) \right]$$

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.¹⁶

¹⁶Mas 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_i when computing the difference.

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 understanding 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 2.¹⁷ 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%.

¹⁷We 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.

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 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_ι^h/A_ι^b and ρ . From equation (11), 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_ι^h/A_ι^b and ρ , given estimates of r^s , r_n , and θ_s . Since A_ι^h/A_ι^b is fixed for each type, as commuting costs and rental prices change, equation (11) shows that ρ determines how the optimal allocation of time changes. The response of $l_{n\iota}^b/l_{n\iota}^h$ to variation in A_ι^h/A_ι^b , t_n , τ_n , and r_n identifies ρ . Given ρ , the level of $l_{n\iota}^b/l_{n\iota}^h$ is determined by A_ι^h/A_ι^b , conditional on all other variables and parameters.

To identify the remaining parameters, we impose $A_1^b = \mathcal{Z}Z_1$ and $A_2^b = \mathcal{Z}Z_2$. 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_ι^h/A_ι^b , \mathcal{Z} pins down the levels of A_ι^b and therefore A_ι^h . 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_1^h/A_1^b and A_2^h/A_2^b , 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_1^h/A_1^b and A_2^h/A_2^b 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 3.55. Using the delta method, we calculate a 95% confidence interval on the EOS of 0.998 (essentially Cobb-Douglas) to 6.105 confirming that WFH and work at the office are imperfect substitutes in production, consistent with the descriptive evidence in Section 2. While not complements in the sense of having an EOS below 1, as the term complements is often used with regard to preferences over two consumption goods, we use the term complement to distinguish our findings regarding the production function from research modeling WFH as a perfect substitute with work at the office (e.g., Delventhal, Kwon, and Parkhomenko, 2022; Bick, Blandin, and Mertens, 2022; Brueckner, Kahn, and Lin, forthcoming). 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. Imperfect substitutability is also consistent with survey evidence. PwC (2021) reports that most firms anticipate a hybrid work week post-pandemic rather than many firms switching to becoming 100% remote. Figure 11 of Bick, Blandin, and Mertens (2022) similarly illustrates that a much larger fraction of workers anticipate doing some WFH than being entirely remote post-pandemic.

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_{2i} , 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).¹⁸ 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).¹⁹ We set δ_n to 0.04 in the interest of symmetry. Section 5.4 uses our counterfactuals to calculate δ_{1h} and δ_{2h} . In Section 5.4, we compute an upper bound for δ_n based on the share of the overall increase in WFH productivity that can feasibly arise from the network externality and compare the predictions of the model at that upper bound as compared to $\delta_n = 0.04$.

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. All of the change in WFH is driven by a change in its productivity. 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, \mathcal{A}_t^h , 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

¹⁸The 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.

¹⁹Our concept of an agglomeration externality in production corresponds to a city-level parameter such that the Davis, Fisher, and Whited (2014) estimate is appropriate. See Rosenthal and Strange (2003), Ahlfeldt, Redding, Sturm, and Wolf (2015), and Baum-Snow, Gendron-Carrier, and Pavan (2021) for measures of more localized agglomeration economies.

and type 2 households. Noting that Barrero, Bloom, and Davis (2021) 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 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 work at the office prior to the pandemic, consistent with the share of work done at home during the pandemic reported by Barrero, Bloom, and Davis (2021). 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 6 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.

5.2 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 7 and 8, 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_t^h/A_t^l increases from 0.365 to 0.666 (83%) for high-skill workers and from 0.348 to 0.516 (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 8).

Comparing columns 1 and 2 of Table 7 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 18%, from 1.59 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 8% (row 41). Residential rents rise in both zones, with the increase larger in Zone 2 (29%, 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.

5.3 Long-Run Counterfactuals

Our two long-run counterfactuals allow the stock of space to adjust in contrast to the SR counterfactual where rents do all of the adjusting. We assume that there is a construction sector outside the model that collects all rents and constructs residential units according to the following constant-elasticity supply equations:

$$\begin{aligned}\log S_n^{LR BSH} - \log S_n^{Base} &= \mathcal{E}_n^{LR BSH} [\log r_n^{LR BSH} - \log r_n^{Base}] \\ \log S_n^{LR} - \log S_n^{Base} &= \mathcal{E}_n^{LR} [\log r_n^{LR} - \log r_n^{Base}]\end{aligned}$$

where $S_n^{LR BSH}$ is the supply of space in zone n in the LR BSH counterfactual, S_n^{Base} is the supply of space in zone n in the pre-COVID Baseline, $r_n^{LR BSH}$ and r_n^{Base} are the prices of space in the LR BSH counterfactual and Baseline in zone n , and $\mathcal{E}_n^{LR BSH}$ is the elasticity of supply in zone n in the LR BSH counterfactual. Similarly, S_n^{LR} , r_n^{LR} , and \mathcal{E}_n^{LR} are the supply of space, residential rents, and supply elasticity in the LR counterfactual.

We set $\mathcal{E}_n^{LR BSH}$ equal to the relevant zone elasticities from Baum-Snow and Han (2022) and assume the stock of office space is subject to putty-clay dynamics such that it cannot contract despite the decreased demand.²⁰ 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. 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. That is, we set $\mathcal{E}_n^{LR} = \infty$ and allow the supply

²⁰Based on the recommendations of Baum-Snow and Han (2022), we use the Finite Mixture Model (FMM) quadratic estimates (gamma11b_units.FMM). We use the 2011 predictions to get elasticities as close as possible to the end of the pandemic and weight by the population in our sample. The resulting elasticities are 0.229 and 0.263 for Zones 1 and 2.

of office space to contract or expand as needed to keep r^s at its pre-pandemic value.

Column 3 of Tables 7 and 8 shows the results of the LR BSH counterfactual. Office rents remain at 92% of their pre-pandemic level (row 41) while residential rents moderate somewhat as supply increases. Residential rents in Zones 1 and 2 remain 13% and 23% above their pre-pandemic levels. Because of the moderation in residential rents, the share of days worked from home rises slightly.

Once the quantity of space has adjusted, the share of days worked from home rises even further, to 43% 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 12% relative to its pre-pandemic level (row 34). The demand for space for all uses increases by 17% in Zone 1 (row 35) and 32% 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 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.

5.4 The Adoption and Network Externalities of WFH

We can combine equations (7) and (8) to show the sources of possible change to WFH productivity:

$$A_t^h = \underbrace{\mathcal{A}_t^h}_{\text{Exogenous TFP}} \times \underbrace{(L_h^{max})^{\delta_{lh}}}_{\text{Adoption Externality}} \times \underbrace{L_h^{\delta_n}}_{\text{Network Externality}}$$

Growth in the productivity of WFH between any two points in time is the sum of contributions from growth in exogenous TFP, growth in the adoption externality, and growth in the network externality according to

$$(19) \quad \Delta \log A_t^h = \Delta \log \mathcal{A}_t^h + \delta_{lh} \Delta \log L_h^{max} + \delta_n \Delta \log L_h.$$

Now consider the growth in WFH productivity between the pre-COVID baseline and the SR counterfactual. Assuming \mathcal{A}_t^h did not change during this two year period, then

growth in WFH productivity either arises from changes to the adoption or network externalities, i.e.,

$$\Delta \log A_t^h = \delta_{th} \Delta \log L_h^{max} + \delta_n \Delta \log L_h.$$

In our baseline specification, we set $\delta_n = 0.04$ and $\Delta \log L_h = \log 4$ given WFH in the SR is set to equal to 4 times WFH in the pre-COVID baseline. This gives $\delta_n \Delta \log L_h = 0.0555$. The log change in A_t^h for type 1 households over this period was 0.593 and was 0.394 for type 2 households. Thus when $\delta_n = 0.04$, for type 1 (type 2) households the change in the density externality accounted for about 9.4% (14.1%) of productivity growth and the change in the adoption externality accounted for the other 90.6% (85.9%).

We can use estimates from the COVID simulations of the model to uncover the implied value of δ_{th} for each type. Specifically, we compute the change in the log of L_h^{max} by comparing $L_h^{max} = 0.0966$, the aggregate quantity of WFH in the COVID pandemic counterfactual, with $L_h = 0.0170$, the aggregate quantity in the pre-pandemic baseline.²¹ This gives $\Delta \log L_h^{max} = 1.74$, enabling us to calculate

$$\begin{aligned} \text{type 1: } \delta_{1h} &= (0.593 - 0.0555) / 1.74 = 0.309 \\ \text{type 2: } \delta_{2h} &= (0.394 - 0.0555) / 1.74 = 0.195. \end{aligned}$$

Finally, although there are no available estimates of δ_n , we can provide an upper bound for δ_n that we denote as $\bar{\delta}_n$. Referring to equation (19), if A_t^h did not decline during the pandemic, and if the adoption externality is always non-negative, then at $\delta_n = \bar{\delta}_n$ the change in the network externality accounts for *all* of the change in WFH productivity. Thus, $\bar{\delta}_n$ satisfies

$$\bar{\delta}_n = \Delta \log A_t^h / \Delta \log L_h.$$

The right-hand side of this equation is 0.427 for type 1 households and 0.284 for type 2 households. Since both types are subject to the same sized network externality, it must be the case that $\bar{\delta}_n = 0.284$; any larger value of δ_n implies a decline in A_t^h during the pandemic. At $\delta_n = 0.284$, the change in the network externality accounts

²¹We compute total WFH labor supply in the pre-pandemic baseline as $\pi_1 * 0.041 + \pi_2 * 0.018$ (see rows 26 and 27 of Table 8). Total WFH labor supply is computed similarly for the SR and COVID counterfactuals.

for all WFH productivity growth between the pre-COVID baseline and SR for type 2 households, but only accounts for about two thirds ($0.394/0.593$) of WFH productivity growth for type 1 households. In other words, even when δ_n is at its upper bound, the adoption externality plays an important role for type 1 workers, increasing their WFH productivity by about 20 percent during the pandemic: $\delta_{1h}\Delta \log L_h^{max} = \Delta \log A_1^h - \bar{\delta}_n\Delta \log L_h = 0.593 - 0.394 = 0.20$. Note that an implication of such a high value of δ_n is that productivity of WFH for type 2 workers was highest during the pandemic and declines substantially immediately post-pandemic.

We redo the model simulations at $\delta_n = \bar{\delta}_n$ to understand the sensitivity of our main results. Table 9 shows the results. In summary, the LR BSH results barely change and the LR simulations change modestly. When housing supply is completely elastic, the sizes of home offices and the predicted quantity of WFH rise a bit more when $\delta_n = \bar{\delta}_n$ compared to our baseline results when $\delta_n = 0.04$. With larger home offices and more WFH, the larger network externality increases the productivity of WFH and therefore provides incentives for even more WFH.

5.5 A Hypothetical 2009 Pandemic

In Columns (4)-(6) of Table 6, 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 6, 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 10 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_t^h/A_t^b , 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 (2022), however, document that low-skill workers did not move nearly as much as high-skill workers during the pandemic. In Table 11, 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 $V_{nlj} = a_{nl} + e_{nlj}$ 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 im-

mobile 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 LR BSH 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. In each counterfactual, we assume that the economy is in steady state for the given level of housing supply.

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. To compute prices, we assume that households have perfect foresight about the path of housing supply. We thus compute prices as the present discounted value of future rents for each of the steady states computed in the ten-year adjustment period. 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 92.1% to 92.2% of their pre-pandemic level. Assuming a 7% discount rate, the prices of residential space in Zones 1 and 2 are 14% and 25% 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 (2022a).

As predicted by our model, there was a substantial increase in home prices between the start of 2020 and the end of 2021 (see Figure 4). REIT pricing indicates that apartment prices rose 13% over this time while single-family home prices rose 36%. While apartments and single-family homes are not a perfect mapping to our Zone 1 and 2 residences, and the model abstracts from pandemic-related changes to

the US labor force that may have raised construction costs, the model’s consistency with current real estate price data provides confidence in its longer term predictions regarding moments that cannot yet be measured (e.g., long-term income inequality).

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., $A_t^h/A_t^b < 1$. 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 (10)).

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 something in the economic environment other than the productivity of WFH constrained 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 two 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 increase in the productivity of WFH over the course of the pandemic but,

rather, it was already high and there was some shift in preferences over the pandemic. To explore the implications of this hypothesis, we reestimate the model with all the productivity parameters governing WFH (\bar{A}_1^h , \bar{A}_2^h , \mathcal{Z} , and ρ) at their post-pandemic values. That is, instead of using moments on the frequency of WFH to estimate these parameters as we did in our baseline, we take the values of these parameters as given by what we found to generate our SR counterfactual. We then reestimate the model on a smaller set of moments to understand what the other parameters of the model must be to generate the data we observed pre-pandemic. Specifically, we estimate the six remaining parameters of the model, $a_{2\iota}$ for $\iota = 1, \dots, 4$ and χ_ι for $\iota = 1, 2$, using pre-pandemic moments on the fraction of each type living in Zone 1 for $\iota = 1, \dots, 4$ and the share of all work that is WFH for each type $\iota = 1, 2$.²²

Table 12 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 WFH, χ_1 and χ_2 become negative, implying that 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 (2021) that workers value the option to work from home. Further, the surveys by Barrero, Bloom, and Davis (2021) 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 indicating that productivity change is a more plausible explanation for the increase in WFH than a preference shift.

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-

²²For $\iota = 1, 2$ we compute the share of all work that is WFH as

$$\sum_n f_{n\iota} \left(\frac{g_{n\iota}^1 l_{n\iota}^h}{g_{n\iota}^1 (l_{n\iota}^h + l_{n\iota}^b) + (1 - g_{n\iota}^1) b_{n\iota}^0} \right).$$

where the notation follows that from Section 3.

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 0.49 — 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%.²³

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.²⁴

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%. While Gupta, Mittal, and Van Nieuwerburgh (2022b) predict larger changes in office prices based on NYC leases executed through 2021, some of the change in prices they predict is due to changes in discount rates rather than rents. Furthermore, NYC has a steeper rent gradient, longer commutes, and a higher share of workers in remote-capable occupations than most US cities. Our model predicts that, because of these three factors, NYC will have a more pronounced decline in office prices than the US as a whole.

²³We 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.

²⁴The 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.

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 important details that may be fruitful directions for future research. Although we capture heterogeneity in WFH productivity by occupation and by skill level, there are likely important demographic differences in both the preference for WFH and its productivity that our model abstracts from. 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. Finally, our estimation approach aggregates data from across the entire United States based on our model of a single monocentric city. This approach ignores heterogeneity across cities in the composition of the labor force (Althoff, Eckert, Ganapati, and Walsh, 2022) and in rent gradients as well as how WFH may affect flows of households and firms across cities.

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Table 1: Frequency of WFH by Demographics and Definition

Group	(1)	(2)	(3)	(4)
	Any WFH	ATUS Only WFH	Only WFH Full Days	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	58%	60%	61%
A few times a year	9%	8%	7%
About once a month	7%	5%	6%
About once a week	8%	7%	8%
More than once a week	13%	13%	11%
Worker works mainly at home	6%	6%	7%
Share of workers that WFH that work mainly at home	14%	15%	18%

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_k	Structures share in production	Fixed	0.18	
θ_s	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	0.17	
π_3	Share of workers of type 3	Fixed	0.12	
π_4	Share of workers of type 4	Fixed	0.37	
r^b	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	Distance from Zone 1 to CBD	Estimated	0.0953	0.0001
t_2	Distance 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 ($A_i^b = \mathcal{Z}Z_i$ for $i = 1, 2$)	Jointly Est.	0.890	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.	0.157	0.035
χ_2	Pref. for WFH firm for type 2	Jointly Est.	0.063	0.038
ρ	EOS between WFH and work at the office = $\frac{1}{1-\rho}$	Jointly Est.	0.718	0.103
$\frac{A_1^b}{A_2^b}$	Relative productivity of WFH for type 1 at a WFH firm	Jointly Est.	0.365	0.141
$\frac{A_2^b}{A_3^b}$	Relative productivity of WFH for type 2 at a WFH firm	Jointly Est.	0.348	0.130
<i>Parameters only used in or determined by counterfactuals:</i>				
δ_b	Agglomeration externality	Fixed	0.04	
δ_n	Network externality	Fixed	0.04	
\bar{Z}_1	Base level of TFP for type 1 at non-WFH firm	Fixed	11,251	
\bar{Z}_3	Base level of TFP for type 3 at non-WFH firm	Fixed	9,918	
\bar{A}_1^b	Base level of TFP for type 1 at WFH firm	Fixed	10,010	
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{S}	Commuting speed parameter	Fixed	40.8	
δ_{1h}	Adoption externality for type 1	Fixed	0.309	
δ_{2h}	Adoption externality for type 2	Fixed	0.195	

Notes: A type 1 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. All parameters correspond to an annual frequency; see Appendix A for how \mathcal{T} maps into an annual frequency and how τ_1 and τ_2 map into annual pecuniary commuting costs of \$2,226 and \$5,565.

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., $P(WFH=1—iota=1)$	0.697	0.001	ACS & GSS 2018 (for scaling ACS WFH)
Share of type 2 working at WFH firms, i.e., $P(WFH=1—iota=2)$	0.322	0.001	ACS & GSS 2018 (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	0.037	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 1 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}	0.890	0.029	0.890	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	0.157	0.035	0.157	0.035
χ_2	0.063	0.038	0.063	0.038
ρ	0.718	0.103	0.718	0.103
$\frac{A_1^b}{A_1^b}$	0.365	0.141	0.365	0.141
$\frac{A_2^b}{A_2^b}$	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: Pandemic Counterfactuals

	COVID-19 Pandemic			Hypothetical 2009 Pandemic		
	Pre-COVID (1)	COVID Start (2)	Ratio (3)	Pre-COVID (4)	COVID Start (5)	Ratio (6)
<i>Technology:</i>						
$\frac{A_1^h}{A_1^b}$	0.365	0.406		0.289	0.326	
$\frac{A_2^h}{A_2^b}$	0.348	0.373		0.306	0.332	
<i>Incomes:</i>						
Type 1 avg. ann. income per worker	\$ 108,918	\$ 88,193	81.0%	\$ 109,444	\$ 80,600	73.6%
Type 2 avg. ann. income per worker	\$ 77,794	\$ 59,696	76.7%	\$ 78,508	\$ 58,737	74.8%
Type 3 avg. ann. income per worker	\$ 93,135	\$ 42,664	45.8%	\$ 93,065	\$ 42,753	45.9%
Type 4 avg. ann. income per worker	\$ 60,176	\$ 29,181	48.5%	\$ 60,168	\$ 29,278	48.7%
High-skill avg. ann. income per worker	\$ 104,801	\$ 76,315	72.8%	\$ 105,171	\$ 70,727	67.2%
Low-skill avg. ann. income per worker	\$ 65,722	\$ 38,788	59.0%	\$ 65,941	\$ 38,552	58.5%
<i>Consumption:</i>						
Type 1 avg. non-housing consumption	\$ 80,706	\$ 58,968	73.1%	\$ 82,252	\$ 55,081	67.0%
Type 2 avg. non-housing consumption	\$ 48,474	\$ 33,725	69.6%	\$ 49,092	\$ 33,505	68.2%
Type 3 avg. non-housing consumption	\$ 71,074	\$ 32,769	46.1%	\$ 70,992	\$ 32,830	46.2%
Type 4 avg. non-housing consumption	\$ 37,457	\$ 18,423	49.2%	\$ 37,448	\$ 18,485	49.4%
High-skill avg. non-housing consumption	\$ 78,193	\$ 52,133	66.7%	\$ 79,314	\$ 49,277	62.1%
Low-skill avg. non-housing consumption	\$ 40,925	\$ 23,240	56.8%	\$ 41,114	\$ 23,214	56.5%

Notes: 1) In our pandemic counterfactuals, we keep \bar{A}_1^h and \bar{A}_2^h fixed at the pre-pandemic level and force the amount of labor that can be worked at the office to 40% of the pre-pandemic level.

Table 7: Model Prediction for Distribution of Incomes and Population

Row		Pre-COVID	Post-COVID Scenarios		
		Baseline (1)	SR (2)	LR BSH (3)	LR (4)
	<i>Technology:</i>				
(1)	$\frac{A_1^h}{A_1^b}$	0.365	0.666	0.667	0.671
(2)	$\frac{A_2^h}{A_2^b}$	0.348	0.516	0.517	0.519
(3)	A_1^b	9335	9249	9247	9231
	<i>Incomes:</i>				
(4)	Type 1 avg. ann. income per worker	\$ 108,918	\$ 141,534	\$ 142,440	\$ 145,185
(5)	Type 2 avg. ann. income per worker	\$ 77,794	\$ 85,099	\$ 85,429	\$ 85,702
(6)	Type 3 avg. ann. income per worker	\$ 93,135	\$ 94,165	\$ 94,175	\$ 91,598
(7)	Type 4 avg. ann. income per worker	\$ 60,176	\$ 61,726	\$ 61,748	\$ 60,176
(8)	High-skill avg. ann. income per worker	\$ 104,801	\$ 129,176	\$ 129,849	\$ 131,206
(9)	Low-skill avg. ann. income per worker	\$ 65,722	\$ 69,084	\$ 69,203	\$ 68,212
(10)	Ratio of high-skill to low-skill Income	1.59	1.87	1.88	1.92
	<i>Consumption:</i>				
(11)	Type 1 avg. non-housing consumption	\$ 80,706	\$ 94,632	\$ 95,053	\$ 95,482
(12)	Type 2 avg. non-housing consumption	\$ 48,474	\$ 50,744	\$ 50,841	\$ 50,174
(13)	Type 3 avg. non-housing consumption	\$ 71,074	\$ 71,921	\$ 71,925	\$ 69,846
(14)	Type 4 avg. non-housing consumption	\$ 37,457	\$ 38,533	\$ 38,542	\$ 37,457
(15)	High-skill avg. non-housing consumption	\$ 78,193	\$ 88,707	\$ 89,020	\$ 88,794
(16)	Low-skill avg. non-housing consumption	\$ 40,925	\$ 42,377	\$ 42,414	\$ 41,461
(17)	Ratio of high-skill to low-skill avg. consumption	1.91	2.09	2.10	2.14
	<i>Population Location:</i>				
(18)	Total high-skill	46.0%	46.0%	46.0%	46.0%
(19)	Living in Zone 1	35.7%	33.8%	33.6%	31.6%
(20)	Living in Zone 2	64.3%	66.2%	66.4%	68.4%
(21)	Total low-skill	54.0%	54.0%	54.0%	54.0%
(22)	Living in Zone 1	34.6%	36.2%	35.9%	33.8%
(23)	Living in Zone 2	65.4%	63.8%	64.1%	66.2%

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 levels 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 the SR counterfactual shown in column (2). In the LR BSH counterfactual shown in column (3), we adjust the supply of residential space consistent with the elasticities in Baum-Snow and Han (2022) and keep the stock of office space fixed at its pre-pandemic level. In the LR counterfactual shown in column (4), we adjust the supply of both residential and office space such that rents are equal to their pre-COVID benchmark in column (1).

Table 8: Model Predictions for Work Location, Space, and Rents

Row		Pre-COVID	Post-COVID Scenarios		
		Baseline	SR	LR BSH	LR
		(1)	(2)	(3)	(4)
	<i>Labor supply:</i>				
(24)	Type 1	0.411	0.427	0.428	0.429
(25)	Type 2	0.407	0.416	0.416	0.417
	<i>Labor Supply of WFH:</i>				
(26)	Type 1	0.041	0.164	0.166	0.184
(27)	Type 2	0.018	0.073	0.075	0.093
	<i>Days WFH to Total Days Worked:</i>				
(28)	Type 1	0.099	0.383	0.388	0.428
(29)	Type 2	0.045	0.176	0.181	0.224
	<i>Extensive Margin of WFH:</i>				
(30)	Share of type 1 choosing WFH firm	0.697	0.974	0.976	0.985
(31)	Share of type 2 choosing WFH firm	0.322	0.646	0.656	0.728
	<i>Intensive Margin of WFH:</i>				
(32)	Days worked WFH to total days for type 1 at WFH firm	0.140	0.390	0.400	0.430
(33)	Days worked WFH to total days for type 2 at WFH firm	0.140	0.270	0.270	0.310
	<i>Demand for Space:</i>				
(34)	Office space per worker in CBD	21,150	21,150	21,150	18,664
(35)	Total space per household in Zone 1	27,109	27,124	28,132	31,679
(36)	Housing per household in Zone 1	26,305	23,661	24,493	27,203
(37)	Home office per household in Zone 1	804	3,462	3,640	4,476
(38)	Total space per household in Zone 2	42,830	42,818	45,015	56,392
(39)	Housing per household in Zone 2	40,644	34,700	36,355	44,362
(40)	Home office per household in Zone 2	2,186	8,117	8,660	12,029
	<i>Rent per Unit of Space:</i>				
(41)	CBD	1.000	0.923	0.921	1.000
(42)	Zone 1	0.810	0.948	0.917	0.810
(43)	Zone 2	0.470	0.604	0.578	0.470

Notes: 1) Labor supply is the fraction of total discretionary time spent working. 2) See notes to Table 7.

Table 9: Sensitivity to Greater Network Economies in WFH

	(1) Pre-COVID Baseline	(2) Post-COVID Scenarios SR	(3) LR BSH	(4) LR
<i>A. Rents</i>				
		$\delta_n = 0.04$		
CBD	1.00	0.92	0.92	1.00
Zone 1	0.81	0.95	0.92	0.81
Zone 2	0.47	0.60	0.58	0.47
		$\delta_n = 0.28$		
CBD	1.00	0.92	0.92	1.00
Zone 1	0.81	0.95	0.92	0.81
Zone 2	0.47	0.60	0.58	0.47
<i>B. Incomes</i>				
		$\delta_n = 0.04$		
High-skill avg. income	\$ 104,801	\$ 129,176	\$ 129,849	\$ 131,206
Low-skill avg. income	\$ 65,722	\$ 69,084	\$ 69,203	\$ 68,212
High-skill/low-skill avg. income	1.59	1.87	1.88	1.92
		$\delta_n = 0.28$		
High-skill avg. income	\$ 104,801	\$ 129,176	\$ 130,533	\$ 138,061
Low-skill avg. income	\$ 65,722	\$ 69,084	\$ 69,332	\$ 69,455
High-skill/low-skill avg. income	1.59	1.87	1.88	1.99
<i>C. Population Location</i>				
		$\delta_n = 0.04$		
Share of high-skill living in Zone 1	35.7%	33.8%	33.6%	31.6%
Share of low-skill living in Zone 1	34.6%	36.2%	35.9%	33.8%
		$\delta_n = 0.28$		
Share of high-skill living in Zone 1	35.7%	33.8%	33.5%	31.0%
Share of low-skill living in Zone 1	34.6%	36.2%	35.9%	33.5%

Notes: 1) In our benchmark specification, we set $\delta_n = 0.04$. 2) $\delta_n = 0.28$ is an upper bound for the network externality.

Table 10: Sensitivity to Greater Agglomeration Economies

	(1) Pre-COVID Baseline	(2) Post-COVID SR	(3) Post-COVID Scenarios LR BSH	(4) LR
<i>A. Rents</i>				
		$\delta_b = 0.04$		
CBD	1.00	0.92	0.92	1.00
Zone 1	0.81	0.95	0.92	0.81
Zone 2	0.47	0.60	0.58	0.47
		$\delta_b = 0.10$		
CBD	1.00	0.92	0.91	1.00
Zone 1	0.81	0.94	0.91	0.81
Zone 2	0.47	0.60	0.57	0.47
<i>B. Incomes</i>				
		$\delta_b = 0.04$		
High-skill avg. income	\$ 104,801	\$ 129,176	\$ 129,849	\$ 131,206
Low-skill avg. income	\$ 65,722	\$ 69,084	\$ 69,203	\$ 68,212
High-skill/low-skill avg. income	1.59	1.87	1.88	1.92
		$\delta_b = 0.10$		
High-skill avg. income	\$ 104,801	\$ 126,775	\$ 127,379	\$ 128,151
Low-skill avg. income	\$ 65,722	\$ 69,244	\$ 69,362	\$ 68,214
High-skill/low-skill avg. income	1.59	1.83	1.84	1.88
<i>C. Population Location</i>				
		$\delta_b = 0.04$		
Share of high-skill living in Zone 1	35.7%	33.8%	33.6%	31.6%
Share of low-skill living in Zone 1	34.6%	36.2%	35.9%	33.8%
		$\delta_b = 0.10$		
Share of high-skill living in Zone 1	35.7%	33.8%	33.6%	31.6%
Share of low-skill living in Zone 1	34.6%	36.2%	35.9%	33.8%

Table 11: Sensitivity to Immobility for Low-Skill Workers

	(1) Pre-COVID Baseline	(2) Post-COVID Scenarios SR	(3) LR BSH	(4) LR
<i>A. Rents</i>				
		$\nu = 3.3$		
CBD	1.00	0.92	0.92	1.00
Zone 1	0.81	0.95	0.92	0.81
Zone 2	0.47	0.60	0.58	0.47
		$\nu_2 = \nu_4 = 0$		
CBD	1.00	0.92	0.92	1.00
Zone 1	0.81	0.94	0.91	0.81
Zone 2	0.47	0.61	0.58	0.47
<i>B. Incomes</i>				
		$\nu = 3.3$		
High-skill avg. income	\$ 104,801	\$ 129,176	\$ 129,849	\$ 131,206
Low-skill avg. income	\$ 65,722	\$ 69,084	\$ 69,203	\$ 68,212
High-skill/low-skill avg. income	1.59	1.87	1.88	1.92
		$\nu_2 = \nu_4 = 0$		
High-skill avg. income	\$ 104,801	\$ 129,214	\$ 129,890	\$ 131,248
Low-skill avg. income	\$ 65,722	\$ 69,013	\$ 69,143	\$ 68,204
High-skill/low-skill avg. income	1.59	1.87	1.88	1.92
<i>C. Population Location</i>				
		$\nu = 3.3$		
Share of high-skill living in Zone 1	35.7%	33.8%	33.6%	31.6%
Share of low-skill living in Zone 1	34.6%	36.2%	35.9%	33.8%
		$\nu_2 = \nu_4 = 0$		
Share of high-skill living in Zone 1	35.7%	34.2%	33.8%	31.6%
Share of low-skill living in Zone 1	34.6%	34.6%	34.6%	34.6%

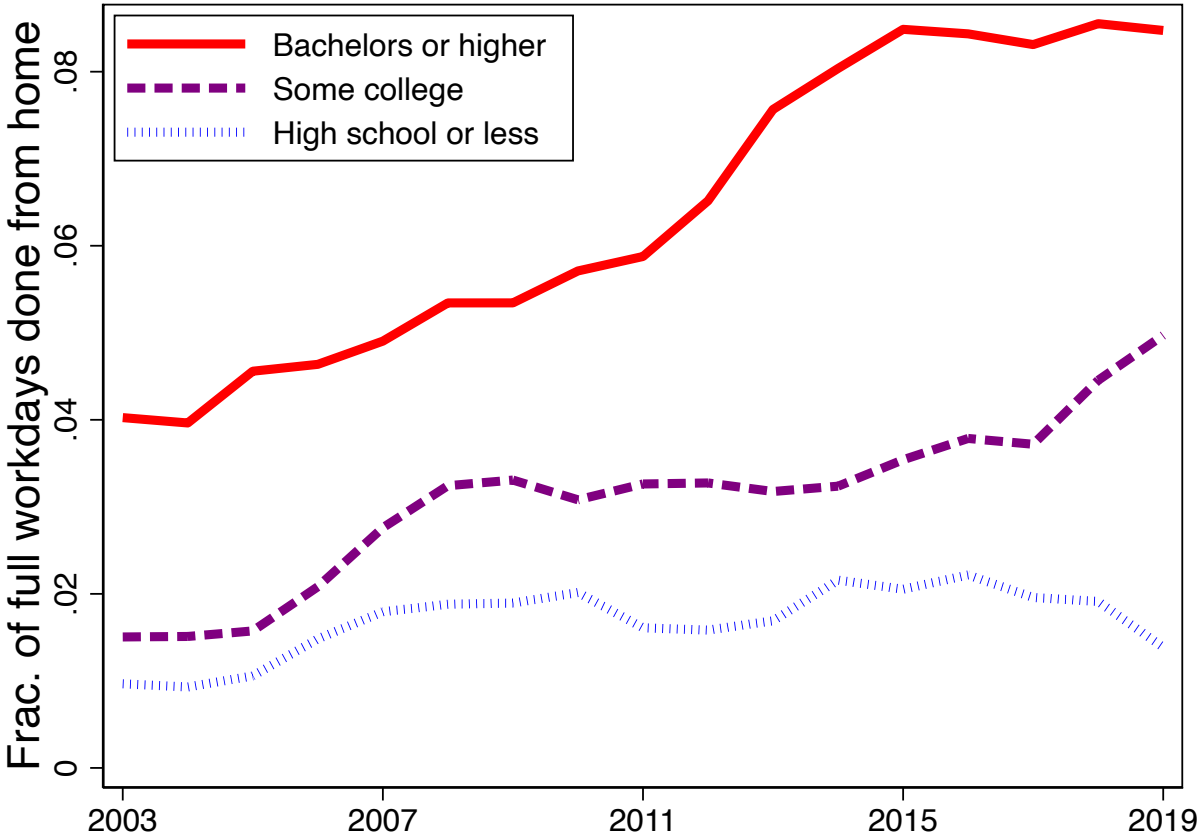
Notes: 1) In our benchmark specification, we set $\nu = 3.3$ for all worker types. 2) $\nu_2 = \nu_4 =$ counterfactuals correspond to setting $\nu = 0$ for type 2 and type 4 workers and keeping $\nu = 3.3$ for type 1 and type 3 workers.

Table 12: Misallocation Parameter Estimates

Parameter	Value	Benchmark	Misallocation
\mathcal{Z}		0.890	0.890
a_{21}		0.149	0.150
a_{22}		0.146	0.144
a_{23}		0.191	0.191
a_{24}		0.132	0.131
χ_1		0.157	-0.160
χ_2		0.063	-0.075

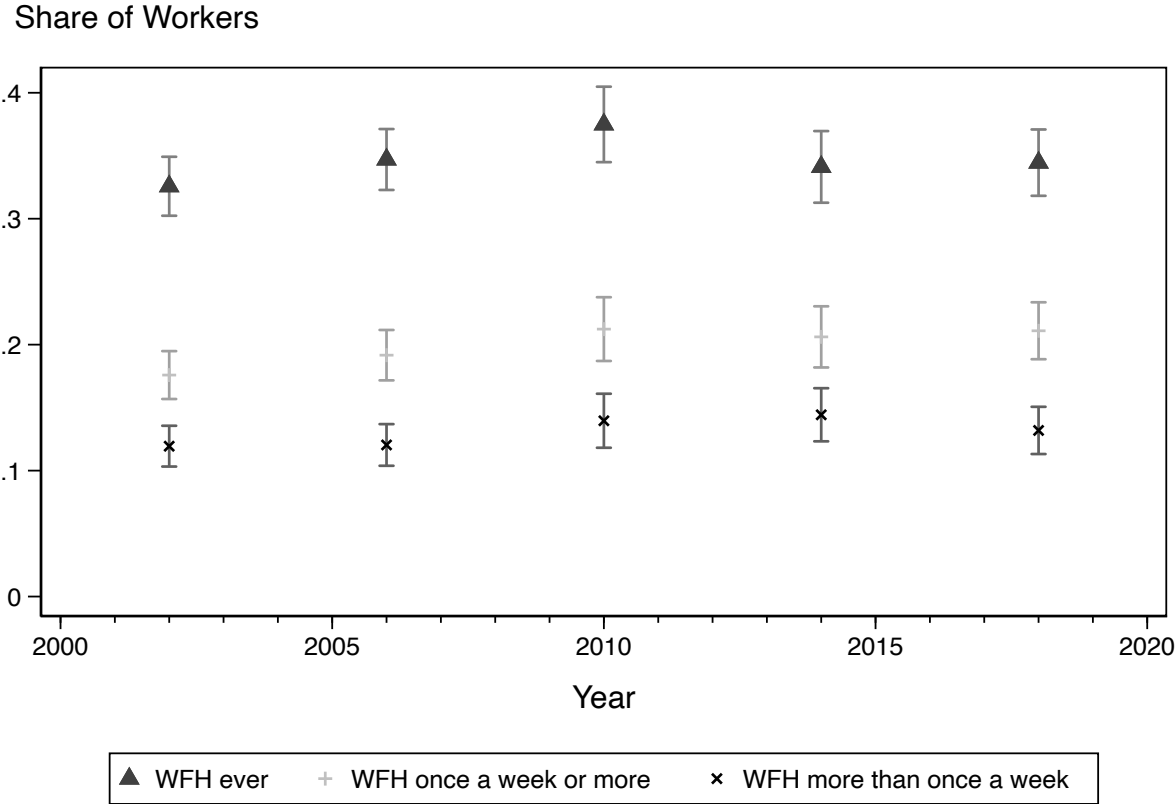
Notes: 1) The productivity parameters in this exercise are held fixed at their post-pandemic values, 2) Moments used to estimate the model are the share of each of the four types of workers living in Zone 2, the share of days of WFH done by type 1, and the share of days of WFH done by type 2.

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



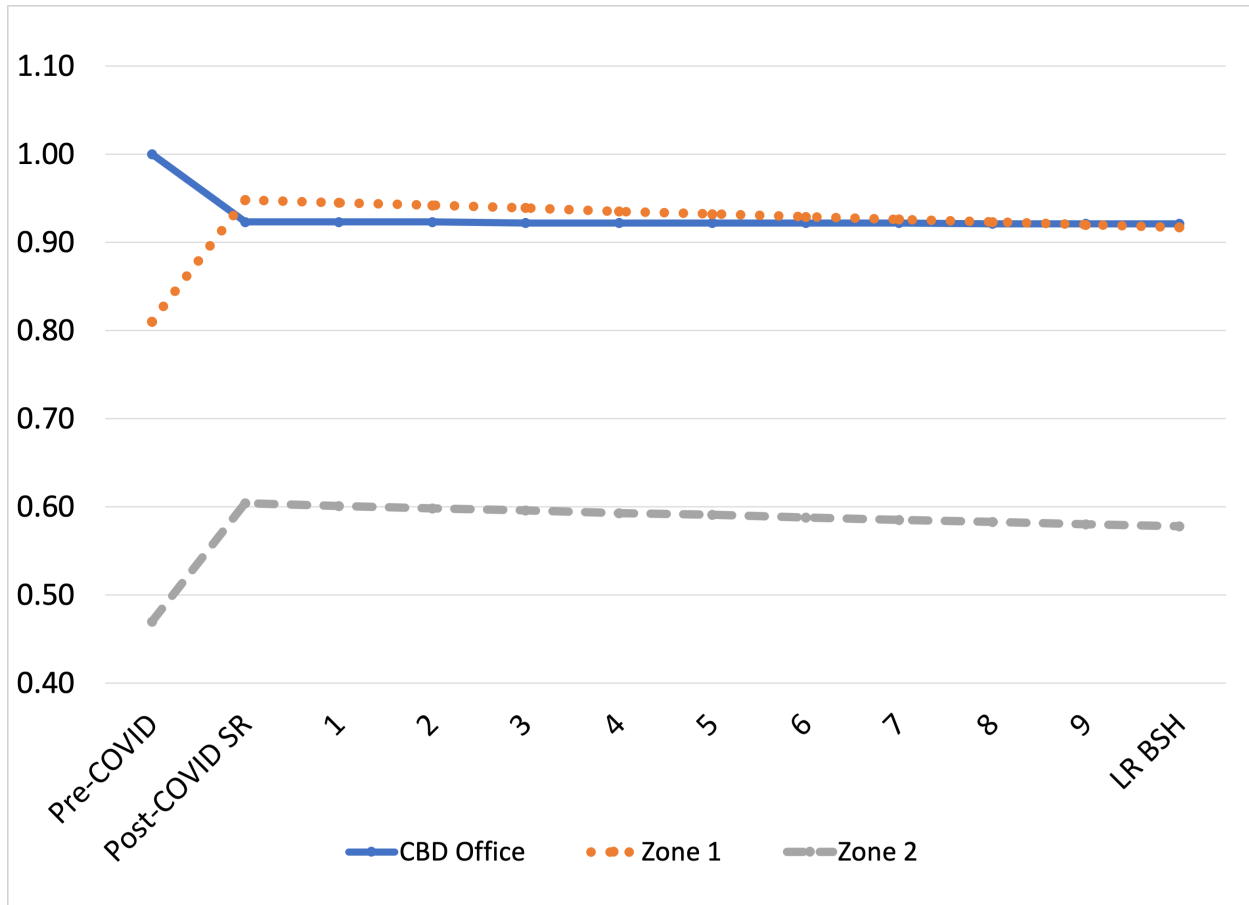
Notes: All data from American Time Use Survey (ATUS).

Figure 2: Intensity of WFH Over Time



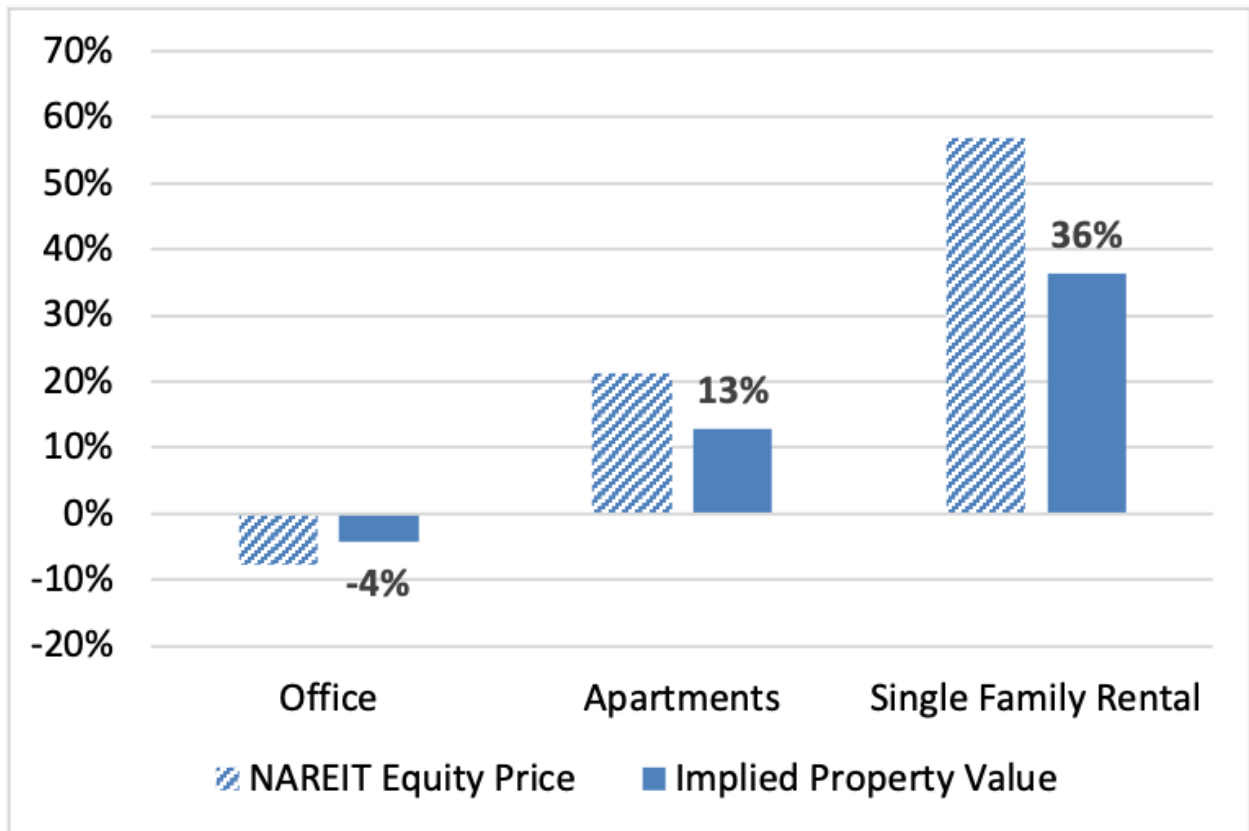
Notes: 1) GSS data. 2) Survey asks respondents “How often do you work at home as part of your job?”
3) Error bands are 95% confidence intervals. 4) Figure extends Figure 1 of Mas and Pallais (2020).

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 pre-COVID and ending with the LR BSH experiment assuming the supply of office space does not adjust and the stock of residential space expands to its LR value based on the Baum-Snow and Han (2022) elasticities 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}

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

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

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

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

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

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

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

Now replace the term in brackets with b defined as

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

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, \dots , 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

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

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

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

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.,

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

Now define l^b and l^h as

$$(A.3) \quad l^b = \frac{\eta^b \hat{b}}{365 \mathcal{T}} \quad l^h = \frac{\eta^h \hat{b}}{365 \mathcal{T}}$$

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 $\eta^b [\hat{w} - \hat{\tau}] + \eta^h \hat{w} - r^k k^h - r s^h$. Now use equation (A.3) to replace η^b and η^h to yield

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

If we define

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

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

$$w (l^b + l^h) - \tau l^b - r^k k^h - r s^h.$$

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

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

B 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

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

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

$$(A.4) \quad \mathbf{a}_0 \ln c^m + [\mathbf{a}_1 \ln A^n + \mathbf{a}_1 \theta_n \ln h + \mathbf{a}_1 (1 - \theta_n) \ln l^n] + \mathbf{a}_2 \ln \ell.$$

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

$$\underbrace{\mathbf{a}_1 \ln A^n}_A + \underbrace{\mathbf{a}_0 \ln c^m}_B + \underbrace{\mathbf{a}_1 \theta_n \ln h}_C + \underbrace{\mathbf{a}_2 \ln \ell}_D + \underbrace{\mathbf{a}_1 (1 - \theta_n) \ln l^n}_E.$$

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 \mathbf{a}_0 in term B is equal to $1 - \alpha$ and the coefficient $\mathbf{a}_1 \theta_n$ is equal to α . The coefficient \mathbf{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.

B.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.4) subject to the following two constraints

$$\begin{aligned} \text{budget:} & \quad \mu_c [(w - \tau) b - c^m - r h] \\ \text{time:} & \quad \mu_l [1 - (1 + t) b - l^n - \ell] \end{aligned}$$

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

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

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

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

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

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

Inserting this second equation into the first gives

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

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

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

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

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

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 $\mathbf{a}_0 = 0.75$, $\mathbf{a}_1 = 0.758$, and $\mathbf{a}_2 = 0.492$.

B.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

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

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

The first-order conditions are

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

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

$$(A.5) \quad \mu_c = \frac{\mathbf{a}_0 + \mathbf{a}_1 \theta_n}{\omega(l^b, l^h, k^h, s^h) - \tau l^b - r s^h - r^k k^h}.$$

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

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

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

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

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

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

Now use the results from equation (A.5) to get

$$(A.6) \quad \frac{\left(\frac{\partial \omega}{\partial l^b} \right) l^b + \left(\frac{\partial \omega}{\partial l^h} \right) l^h + \left(\frac{\partial \omega}{\partial k^h} \right) k^h + \left(\frac{\partial \omega}{\partial s^h} \right) s^h - \tau l^b - r s^h - r^k k^h}{\omega(l^b, l^h, k^h, s^h) - \tau l^b - r s^h - r^k k^h} = \frac{\mathbf{a}_2 / \ell - \hat{\mathbf{a}}}{\mathbf{a}_0 + \mathbf{a}_1 \theta_n}.$$

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

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

then equation (A.6) 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 $\hat{\mathbf{a}}$ into equation (A.6) to get

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

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

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

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 $\omega(l^b, l^h, k^h, s^h)$.

C 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

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

subject to

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

The first-order conditions are

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

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

$$(A.7) \quad 1 = \mu_c (w - \tau) b.$$

We can substitute μ_c into the FOC for b using equation (A.7), multiply by b , and then use the FOC for ℓ to get

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

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

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

D Solution: Households at WFH Firms

D.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

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

subject to

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

The first-order conditions are

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

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

$$(A.8) \quad 1 = \mu_c [\omega(l^b, l^h, k^h, s^h) - \tau l^b - r s^h - r^k k^h]$$

which implies

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

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

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

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

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

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 $(\partial\omega / \partial k^h) k^h$ and $(\partial\omega / \partial s^h) s^h$ 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.8):

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

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

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

such that

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

D.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

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

subject to

$$(A.9) \quad 0 = \mu_c [y - r^k k^b - r^s s^b - \tau l^b - c - r(h + s^h) - r^k k^h]$$

$$(A.10) \quad 0 = \mu_l [1 - (1+t)l^b - l^h - \ell]$$

$$(A.11) \quad 0 = \mu_y \left[[(y^b)^\rho + (y^h)^\rho]^{1/\rho} - y \right]$$

$$(A.12) \quad 0 = \mu_b \left[A^b (l^b)^{\theta_b} (k^b)^{\theta_k} (s^b)^{\theta_s} - y^b \right]$$

$$(A.13) \quad 0 = \mu_h \left[A^h (l^h)^{\theta_b} (k^h)^{\theta_k} (s^h)^{\theta_s} - y^h \right].$$

The first-order conditions are

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

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

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

Adding these three equations together and imposing (A.9) implies

$$(A.14) \quad \mu_c (y - \tau l^b) = 1 + (1 - \theta_b) (\mu_b y^b + \mu_h y^h)$$

$$(A.15) \quad = 1 + (1 - \theta_b) \mu_c y$$

$$(A.16) \quad \rightarrow \theta_b \mu_c y = 1 + \mu_c \tau l^b$$

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

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

where the third line uses (A.16). 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:

$$\begin{aligned} \text{(A.17)} \quad k^b &= y^{1-\rho} (y^b)^\rho \theta_k / r^k \\ k^h &= y^{1-\rho} (y^h)^\rho \theta_k / r^k. \end{aligned}$$

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

(A.18)

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

where we have defined

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

We can rewrite the production function using equation (A.18) as follows

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

Combining terms gives

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

and thus

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

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

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

which yields the expression

$$(A.20) \quad \begin{aligned} r^s s^b + r s^h &= \theta_s y \\ \rightarrow s^h \left[r^s \left(\frac{s^b}{s^h} \right) + r \right] &= \theta_s y. \end{aligned}$$

Now insert the expression for y from equation (A.19) to get

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

which gives

$$(A.21) \quad s^h = \left[\frac{\theta_s \left[\left(\tilde{A}^b \right)^\rho (l^b)^{\frac{\rho\theta_b}{1-\rho\theta_k}} \left(\frac{s^b}{s^h} \right)^{\frac{\rho\theta_s}{1-\rho\theta_k}} + \left(\tilde{A}^h \right)^\rho (l^h)^{\frac{\rho\theta_b}{1-\rho\theta_k}} \right]^{\frac{1-\rho\theta_k}{\rho(1-\theta_k)}}}{r^s \left(\frac{s^b}{s^h} \right) + r} \right]^{\frac{1-\theta_k}{1-\theta_k-\theta_s}}.$$

If we know l^b/l^h , we know (a) s^b/s^h (from A.17) and (b) l^b and l^h separately given that leisure is a constant. Equation (A.21) implies we then know s^h . This gives s^b and then y from equation (A.19), which then gives y^b and y^h from equation (A.18) and therefore k^b and k^h from equation (A.17).

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

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

We can then use FOCs 4 and 5 to derive

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

From earlier, we know

$$\begin{aligned}
\left(\frac{y^b}{y^h}\right)^\rho &= \left(\frac{r^s}{r}\right) \left(\frac{s^b}{s^h}\right) \\
&= \left(\frac{r^s}{r}\right) \left[\left(\frac{r^s}{r}\right)^{\frac{\rho\theta_k-1}{\rho}} \left(\frac{A^b}{A^h}\right) \left(\frac{l^b}{l^h}\right)^{\theta_b} \right]^{\frac{\rho}{1-\rho\theta_k-\rho\theta_s}} \\
\text{(A.22)} \quad &= \left(\frac{r^s}{r}\right)^{\frac{-\rho\theta_s}{1-\rho\theta_k-\rho\theta_s}} \left[\left(\frac{A^b}{A^h}\right) \left(\frac{l^b}{l^h}\right)^{\theta_b} \right]^{\frac{\rho}{1-\rho\theta_k-\rho\theta_s}}.
\end{aligned}$$

Inserting equation (A.22) gives

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

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

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

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 $M \times 1$ vector of moments to match and let θ be a $K \times 1$ vector of parameters. Denote $\hat{\theta}$ as the estimator of θ , where $\hat{\theta}$ satisfies

$$(A.23) \quad \hat{\theta} = \arg \min [m(\theta) - m(\theta^*)]' [m(\theta) - m(\theta^*)].$$

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.²⁵

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

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

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

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

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

²⁵The value of the minimized objective function at our reported estimates is 2.12E-11.

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

$$\text{Var}(\hat{\theta} - \theta^*) = A^{-1} \Omega A^{-1'}$$

where we have defined the $M \times M$ matrices

$$A = \left[\frac{\partial m(\theta)}{\partial \theta} \right]$$

$$\Omega = E \left\{ \left[m(\hat{\theta}) - m(\theta^*) \right] \left[m(\hat{\theta}) - m(\theta^*) \right]' \right\}.$$

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 $\iota = 1, \dots, 4$, χ_ι for $\iota = 1, 2$, \mathcal{Z} , and ρ .²⁶ We estimate the remaining 9 parameters directly using the last 9 moments: Z_ι for $\iota = 1, \dots, 4$, 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.

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

²⁶See Section 4.5 for intuition on identification.

we set

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

Note that expressions (12) through (15) continue to hold. Given the wage as determined by these equations, and given b_{ni} , 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}_{ni}^b as the baseline pre-pandemic time at the office for households at a WFH firm. Then for the COVID counterfactuals, we restrict

$$(A.25) \quad l_{ni}^b = 0.4 \cdot \bar{l}_{ni}^b$$

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

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

subject to

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

$$(A.27) \quad 0 = \mu_l [1 - (1 + t) l^b - l^h - \ell]$$

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

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

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

The first-order conditions are

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

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 imply²⁷

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

After rearranging terms, this becomes

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

The results of the previous section show that we can derive

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

where, as before,

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

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

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

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

²⁷As before, we have used the implications of FOCs 1a, 2a, and 3a and the definition of y from equation (A.28) to derive that $\mu_h y^h + \mu_b y^b = \mu_c y$.

budget constraint and rearranging terms, this becomes

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

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.