

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. A key parameter is the elasticity of substitution between working at home and in the office that we estimate using cross-sectional time-use data. The model indicates that the pandemic induced a large change to the relative productivity of working at home which will permanently affect incomes, income inequality, and city structure.

Keywords: Technology Adoption. Coronavirus. Telecommuting.

JEL codes: O33, O41, R12, R33.

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1 Introduction

The work-from-home (WFH) revolution has been slowly brewing for more than 30 years. Distinct technological advances have contributed to our ability to work effectively at home. In the early 1990s, affordable PCs running Microsoft Word and Excel became widely available. In the mid 1990s, we embraced email as a useful way to communicate and the Netscape IPO led a rush to explore the possibilities of the World Wide Web. In the early 2000s, high-speed internet became widely available and by 2010 cellphones turned to smartphones. Finally, between 2010 and 2020 video conferencing technology became useable and cloud-computing became cheap and convenient, facilitating remote meetings and data sharing across the world.

A common theme of these technological innovations is that their impact on productivity depends, at least in part, on the prevalence of adoption. There is no point to writing an email if no one reads it, video conferencing is very difficult if the person on the receiving end has slow internet, and so forth. While many WFH technologies have been around for a while, the technologies became much more useful after widespread adoption.

We postulate that the COVID pandemic accelerated the widespread adoption of technologies that enabled households to work from home, which, in turn, permanently raised the productivity of working from home relative to working at the office. We investigate this change in relative productivity on incomes, where and how we work, where we live, and the demand and price of office space and housing. To do so, we specify a model where high-skill workers 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, saving time, but productivity of working from home may be lower than at the office. High-skill workers 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.

A key parameter in the model is the elasticity of substitution (EOS) between market work created at home and market work created in the office. With a high EOS, small changes in technology can lead to a large shift in behavior. For example, consider a world in which working from home and at the office are perfect substitutes in production. This can lead to “bang-bang” behavior, where little time is spent working at home up to a certain level of WFH technology, after which a lot of time is spent

working at home. Conversely, if working at the office and at home are not perfect substitutes, once the pandemic subsides workers will continue to work some in the office and some at home, rather than choose a corner solution. Thus, our understanding of how changes to WFH technology will affect outcomes is intimately related to the EOS in production between work done at home and work in the office.

The first-order conditions of the model yield an exact relationship between time spent commuting, the share of time households spend working at home as compared to at the office, and the EOS between working at home and at the office. The intuition for this relationship is simple: As commuting time rises, workers spend more time working at home at a rate that depends on the EOS. We use this relationship to estimate the EOS from a cross-section of data on high-skill workers from the 2017-2018 Leave and Job Flexibility (LJF) module of the American Time Use Survey (ATUS) which includes information on the frequency of working from home. We use a GMM procedure to correct for measurement error in reported commuting times.

We find that working from home and at the office are not perfect substitutes in production. We consider a variety of identifying assumptions in estimation and bracket our estimate of the EOS between 3 and 7, with our preferred estimate equal to 5. We do not find any evidence that working from home and at the office are perfect substitutes. In fact, data from prior to the pandemic suggests this cannot be the case: Prior to the pandemic, people that worked from home rarely did so on a full-time basis. Since working from home and at the office are not perfect substitutes implying some commuting to the office will occur once the pandemic ends, workers and firms should not move en masse to remote areas with low taxes and a low cost of living. Rather, we expect, and our model predicts, that many workers will move farther out in their current metro area, to places with longer (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 high-skill workers work at home 10 percent of the time. Given the model structure, this pins down the level of WFH technology prior to the onset of the pandemic. We then study an “after” period, call it 2022, where high-skill workers spend 30 percent of their time spent working at home. This tripling in time spent working from home is consistent with survey evidence reported in Barrero, Bloom, and Davis (2020) 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 hours worked at home allows us to size the gain in WFH productivity that occurred during the pandemic. Finally, we study the pandemic period itself, a period in which we assume productivity at the office falls by 50 percent, reflecting the impact of social distancing.

The model suggests the widespread adoption of WFH technology increased the productivity of working from home relative to the productivity of working in the office by 46 percent between the onset and the end of the pandemic. This change in relative productivity leads to an approximately 15 percent decline in office rents in the central business district (CBD) if the supply of office space is constrained to not fall below pre-pandemic levels. Residential rents rise in the short run, especially in the outer suburbs, due to increased demand for home office space. Hours worked at home increase even more in the long run after the supply of space in residential areas has a chance to adjust. Since only high-skill workers can work at home in our model, the large improvement in WFH technology widens income inequality. Finally, the model forecasts a small decline in productivity in work at the office due to a decrease in agglomeration economies.

We also simulate outcomes if the COVID pandemic had occurred in 1990, prior to the existence of many WFH technologies. We assume that in 1989, relative home productivity is 1/3 its 2019 value and that it does not change after the onset of the pandemic in 1990. As with the 2020 pandemic, we characterize the 1990 pandemic by a 50 percent drop in relative productivity in working at the office. During this hypothetical 1990 pandemic, people continue to work at the office at the same rate and do not substitute into working at home. Incomes and prices fall, but there is no increased demand to work from home in the suburbs. According to this calibration of the model, in 1990 working at home is not a practical alternative to working in the office.

As this 1990 counterfactual simulation indicates, the long-term effects of COVID depend critically on WFH technology being available but not yet fully adopted. Overall, our model suggests the COVID pandemic will lead to higher lifetime income for the working population because it forced many households to work at home which raised WFH productivity. While the measured gains to productivity we report of working at home likely would have happened eventually, the pandemic accelerated the process.

Related Literature

Our paper relates to five distinct literatures. The first is 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. We postulate that COVID radically accelerated the use of WFH technology due to a large positive externality in 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 what 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, arising 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 and working on home production over the business cycle; see, for example, McGrattan, Rogerson, and Wright (1997).

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 working from home. We study a broader class of workers whose work is less routine on average such that working 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 is a complement to face-to-face interaction, rather than a substitute, our estimates use more recent technologies and suggest WFH is an imperfect substitute for face-to-face. Our findings also demonstrate how the COVID shock could make us permanently more productive in aggregate. Instead of studying the productivity of WFH, Mas and Pallais (2017) study how workers value it and find that prospective call “center” employees are willing to take an 8% cut in pay to work from home. This finding suggests welfare benefits from the WFH technology boon beyond higher consumption.

Our paper also relates to a more recent literature investigating the long-term effects of the COVID crisis on work and cities. Bick, Blandin, and Mertens (2021) document increased WFH during the pandemic and present a model of work in which

working from home and at the office are perfect substitutes. Consistent with our findings, they argue that there was increased adoption of working from home during the pandemic but do not specify the technological process nor does their model have implications for rents. Kaplan, Moll, and Violante (2020) study the effect of pandemic policies by specifying an endogenous Susceptible-Infected-Recovered (SIR) model where people can do market work from home or at the office. Kaplan, Moll, and Violante (2020) specify disutility from WFH, home production, and work at the office and, in particular, allow for imperfect substitution between WFH and work at the office. While our concern in this paper is not with pandemic policies, the imperfect substitution in the disutility of WFH and work at the office would likely also predict a hybrid post-pandemic office rather than a corner solution.

One of the predictions of our model is that the improvement in WFH productivity arising from both changes to technology as well as mass adoption will lead to a further widening of income inequality. This occurs because the WFH technology is only available to high-skill workers in our model so any improvement to that technology directly affects the productivity and wages of only high-skill workers. Our assumption, while stark, is consistent with the evidence shown in Figure 1 of Dingel and Neiman (2020), that demonstrates that the share of jobs that can be done at home, on average, rises with median hourly wages. Our assumption is also 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 on wages and income inequality of the endogenous adoption of a skill-biased invention, the personal computer, within a model of urban economics.

The two papers that are most closely related to ours are Delventhal, Kwon, and Parkhomenko (2020) and Delventhal and Parkhomenko (2021). Delventhal, Kwon, and Parkhomenko (2020) and Delventhal and Parkhomenko (2021) model the geography of a city and firm and worker location choices in considerable detail, but take as exogenously pre-determined changes in WFH behavior. We consider a simpler structure of a city, in the spirit of Favilukis and Van Nieuwerburgh (2021), but allow high-skill 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 required to generate an expected tripling of time worked from home once the

pandemic subsidies. Delventhal, Kwon, and Parkhomenko (2020) and Delventhal and Parkhomenko (2021) assume that working from home and at the office are perfect substitutes in production.

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

We present our model in the next section. Section 3 describes how we estimate the elasticity of substitution of working at home and working at the office and calibrate the other parameters of the model. In section 4 we run counterfactual experiments of the model, showing how changes to WFH technology affect the allocation of time of high-skill, incomes of high- and low-skill workers, and rents. Section 5 concludes.

2 Model

A measure π of households live in a metropolitan area that we call a city. A fraction π of workers are high skill and $1 - \pi$ are low skill. Low-skill workers differ from high-skill workers in along a number of dimensions. The most important difference is that high-skill workers are assumed to optimally allocate their time between working at the office and working at home, but low-skill workers only work at the office. This difference is extreme but it highlights the fact that working from home is much more common among college-educated workers.² Unless otherwise specified, variables and parameters specific to high-skill workers have a superscript of 1 and variables and parameters specific to low-skill workers have a superscript of 0.

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

²See, for example, Arbogast, Gascon, and Spewak (2019), Dingel and Neiman (2020), Mas and Pallais (2020), and Papanikolaou and Schmidt (2020).

2.1 Low-Skill Workers

All low-skill workers work for firms operating in the CBD. Low-skill workers choose where to live and how much labor to supply. Firms pay w^0 per unit of low-skill labor that is supplied, so low-skill workers living in location n working b_n hours in the CBD earn annual income of $w^0 b_n$.

Households receive utility from consumption, housing, leisure, and location-specific amenities. Denote these variables for low-skill workers living in location n as n as c_n^0 , h_n^0 , ℓ_n^0 , and χ_n^0 , respectively. The utility of a low-skilled worker living in n is

$$\nu^0 [\log \chi_n^0 + (1 - \alpha^0) \log c_n^0 + \alpha^0 \log h_n^0 + \psi^0 \log \ell_n^0].$$

Non-housing consumption is equal to labor income less housing expenditures, $c_n^0 = w^0 b_n - r_n h_n^0$, where r_n is the rental price of one unit of housing at location n . Leisure is equal to time not spent commuting or working in the CBD, $\ell_n^0 = 1 - (1 + t_n^0) b_n$, where t_n^0 is the commuting time required for each unit of work in the CBD for low-skill workers. We discuss ν^0 later; for now it can be ignored. α^0 captures the benefit of more housing relative to non-housing consumption and ψ^0 captures the benefit of more leisure.

The optimal quantities of housing and time spent working in the CBD solve

$$\max_{h_n^0, b_n} \nu^0 [\log \chi_n^0 + (1 - \alpha^0) \log (w^0 b_n - r_n h_n^0) + \alpha^0 \log h_n^0 + \psi^0 \log (1 - (1 + t_n^0) b_n)].$$

The first-order conditions are

$$\begin{aligned} b_n &= \left(\frac{1}{1 + t_n^0} \right) \left(\frac{1}{1 + \psi^0} \right) \\ h_n^0 &= \alpha^0 w^0 b_n / r_n \end{aligned}$$

implying $c_n^0 = (1 - \alpha^0) w^0 b_n$. Optimized utility for low-skill workers living in location n is thus

$$u_n^0 = \nu^0 [\log \chi_n^0 - \log(1 + t_n^0) - \alpha^0 \log r_n + \zeta^0]$$

where ζ^0 is a constant that depends on α^0 , ψ^0 , and w^0 . Utility is therefore increasing in amenities χ^0 , decreasing in commute times t_n^0 , and decreasing in rental prices r_n .

We allow low-skill workers to vary in their preferences for living in location n . For

a particular low-skill worker i , the utility of living in n is

$$u_{ni}^0 = u_n^0 + e_{ni}.$$

e_{ni} is assumed to vary across households i and locations n . Since e_{ni} is additive, it does not affect any decisions conditional on residing in location n . We assume that e_{ni} is drawn from the Type 1 Extreme Value distribution.

Household i chooses its optimal location of residence n_i^* to satisfy

$$n_i^* = \arg \max_{n=1, \dots, N} \{u_{ni}^0\}$$

where N is the number of locations in the city where the agent can live. Define the variable U^0 , proportional to expected utility for low-skill workers, as

$$U^0 = \log \sum_{n=1}^N e^{u_n^0}.$$

Due to the properties of the Type 1 Extreme Value distribution, the probability low-skill worker i lives in specific location n' is

$$f_{n'}^0 = e^{u_{n'}^0} / e^{U^0}$$

and log relative probabilities over location choice between locations n' and n has the simple expression

$$\begin{aligned} \log (f_{n'}^0 / f_n^0) &= u_{n'}^0 - u_n^0 \\ &= \nu^0 \left[\log (\chi_{n'}^0 / \chi_n^0) - \log \left(\frac{1 + t_{n'}^0}{1 + t_n^0} \right) - \alpha^0 \log (r_{n'} / r_n) \right]. \end{aligned}$$

The population of low-skill workers is decreasing in commuting costs, decreasing in rental prices, and increasing in amenities. The parameter ν^0 pins down the responsiveness of the low-skill population with respect to differences in amenities or commuting costs and, given this, α^0 pins down the responsiveness of the population with respect to rental prices.

2.2 High-Skill Workers

High-skill workers can work from home or in the office which is located in the CBD. The total amount of effective labor that a high-skill worker living in location n supplies to a firm, y_n , is a CES aggregate of effective labor while working from home, y_n^h , and effective labor while working at the office, y_n^b , specifically

$$(1) \quad y_n = [(y_n^b)^\rho + (y_n^h)^\rho]^{1/\rho}.$$

$\rho \leq 1$ determines the elasticity of substitution of effective labor at home and at the office in creating units of total effective labor. Firms pay w^1 per unit of total effective high-skill labor and total income to high-skill workers supplying y_n units of effective labor is $w^1 y_n$.

Effective labor at home and in the CBD are generated using raw hours worked l and space s according to

$$(2) \quad y_n^b = A^b (s_n^b)^\theta (l_n^b)^{1-\theta}$$

$$(3) \quad y_n^h = A^h (s_n^h)^\theta (l_n^h)^{1-\theta}$$

where s_n^b and s_n^h refer to space rented in the CBD and space rented at home that is strictly dedicated to work (such as a home office), respectively, and l_n^b and l_n^h refer to hours worked at the office in the CBD and hours worked at home. θ is the share of space in the production process, which is identical for the home and the CBD. A^b and A^h are total factor productivity for effective labor at the firm and at home for high-skill workers. Households take the values of A^b and A^h as given.

Denote consumption, housing, leisure, and amenities in location n for high-skill workers as c_n^1 , h_n^1 , ℓ_n^1 , and χ_n^1 . Utility over these variables for high-skill workers is³

$$(4) \quad \nu^1 [\log \chi_n^1 + (1 - \alpha^1) \log c_n^1 + \alpha^1 \log h_n^1 + \psi^1 \log \ell_n^1].$$

High-skill workers maximize utility by choosing consumption, housing, leisure, hours

³In our calibration we set $\alpha^0 > \alpha^1$. This is an analytically tractable way to capture non-homothetic preferences in housing consumption, i.e., that poor people spend a larger fraction of their income on housing. Although Davis and Ortalo-Magné (2011) argue that the expenditure share on rent for the median renter is constant across cities and over time, a large number of studies find that, in the cross-section of people, a 1 percent increase in income results in a much less than 1 percent increase in housing expenditure. See, for example, Rosen (1979), Green and Malpezzi (2003), Glaeser, Kahn, and Rappaport (2008), and Rosenthal (2014).

to work in the CBD and at home, and office space to rent at the CBD and at home given the production technologies listed in equations (1) -(3) and subject to the following time and budget constraints (where we temporarily suppress location subscripts (the n) and high-skill superscripts (the 1) to keep notation manageable)

$$\begin{aligned} 1 &= (1+t)l^b + l^h + \ell \\ wy &= c + r^b s^b + r(s^h + h). \end{aligned}$$

Appendix A contains the derivation of the optimal solution when households take all wages and prices as given; here we list results. To start, the model predicts how commuting time (t) maps to the allocation of time spent working at home and in the office given relative productivity (A^b/A^h), relative rents (r^b/r), the structures share of output (θ) and the parameter that determines the elasticity of substitution between working at home and at the office (ρ) as follows:

$$(5) \quad \frac{l^b}{l^h} = \left(\frac{A^b}{A^h}\right)^{\frac{\rho}{1-\rho}} \left(\frac{r^b}{r}\right)^{\frac{-\rho\theta}{1-\rho}} (1+t)^{\frac{-(1-\rho\theta)}{1-\rho}}.$$

We use equation 5 to estimate the EOS in the next section. Additionally, the model predicts leisure is a constant and independent of n .

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

These two equations completely determine the allocation of time (ℓ , l^b , and l^h).

The model implies that the relationship between effective hours at the office and at home is

$$(6) \quad \frac{y^b}{y^h} = \left(\frac{A^b}{A^h}\right)^{\frac{1}{1-\rho\theta}} \left(\frac{r^b}{r}\right)^{\frac{-\theta}{1-\rho\theta}} \left(\frac{l^b}{l^h}\right)^{\frac{1-\theta}{1-\rho\theta}}.$$

The model also implies that the ratio of structures used for working at the office and at home is

$$(7) \quad \frac{s^b}{s^h} = \left(\frac{y^b}{y^h}\right)^{\rho} \left(\frac{r^b}{r}\right)^{-1}.$$

Given l^b/l^h from equation (5), this determines y^b/y^h via equation (6) which then determines s^b/s^h from equation (7).

We solve for consumption, housing, and spending on office space in the CBD and at home as a function of labor income:

$$\begin{aligned}
 c &= (1 - \theta)(1 - \alpha)wy \\
 rh &= (1 - \theta)\alpha wy \\
 (8) \quad r^b s^b + r s^h &= \theta wy.
 \end{aligned}$$

Rewrite (8) as

$$s^h \left[r^b \left(\frac{s^b}{s^h} \right) + r \right] = \theta wy.$$

From the production function equations (1), (2) and (3), we can write

$$\theta wy = \theta w (s^h)^\theta \left[\left(A^b \left(\frac{s^b}{s^h} \right)^\theta (l^b)^{1-\theta} \right)^\rho + \left(A^h (l^h)^{1-\theta} \right)^\rho \right]^{1/\rho}.$$

Combining these last two equations gives an expression for s^h that is a function of all terms that are known,

$$s^h = \left\{ \frac{\theta w \left[\left(A^b \left(\frac{s^b}{s^h} \right)^\theta (l^b)^{1-\theta} \right)^\rho + \left(A^h (l^h)^{1-\theta} \right)^\rho \right]^{1/\rho}}{\left[r^b \left(\frac{s^b}{s^h} \right) + r \right]} \right\}^{\frac{1}{1-\theta}}.$$

Once we know s^h , we also know s^b . Given knowledge of l^b , s^b , l^h , and s^h , we therefore know income wy and the entire allocation and utility for high-skill workers at any location n .

To continue, we reintroduce location subscripts and worker-skill superscripts. Denote maximized utility for high-skill workers at location n as u_n^1 . Similar to low-skill workers, each high-skill worker j has a specific additive preference for living in location n , e_{nj} , such that utility of living in n for worker j is

$$u_{nj}^1 = u_n^1 + e_{nj}.$$

Since e_{nj} is an additive shock, it does not affect any decisions conditional on residing in location n . As with low-skill workers, we assume that e_{nj} is drawn iid from the Type 1 Extreme Value distribution. Worker j chooses his or her optimal location of

residence n_j^* to satisfy

$$n_j^* = \arg \max_{n=1, \dots, N} \{u_{nj}^1\}.$$

Denote the probability a high-skill worker optimally chooses to live in location n as f_n^1 . The log relative probability high-skill workers choose location n' as compared to n is equal to

$$\log (f_{n'}^1 / f_n^1) = u_{n'}^1 - u_n^1$$

which we cannot reduce further analytically.

2.3 Wage Rates per Effective Hour

Define the total hours of all low-skill workers as $B = (1 - \pi) \sum_n f_n^0 b_n$ and the total effective hours of all high-skill workers as $Y = \pi \sum_n f_n^1 y_n$. A representative firm aggregates these quantities and produces a final good according to

$$\mathcal{O} = [B^\omega + \lambda Y^\omega]^{\frac{1}{\omega}}.$$

The firm chooses B and Y to maximize profits according to

$$[B^\omega + \lambda Y^\omega]^{\frac{1}{\omega}} - w^0 B - w^1 Y.$$

The first-order conditions of this problem yield an expression for payment per unit of effective hours for both low- and high-skill workers

$$\begin{aligned} w^0 &= \mathcal{O}^{1-\omega} (B)^{\omega-1} \\ w^1 &= \mathcal{O}^{1-\omega} \lambda (Y)^{\omega-1} \end{aligned}$$

implying

$$\frac{w^1}{w^0} = \lambda \left(\frac{Y}{B} \right)^{\omega-1}. \quad (9)$$

2.4 Technology and Commuting Processes

We allow commuting time to be subject to a negative externality from aggregate commuting miles. Define the distance to the CBD from zone n as d_n . Define aggregate commuting miles, \mathcal{V} , as

$$\mathcal{V} = \sum_n d_n [(1 - \pi) f_n^0 b_n + \pi f_n^1 l_n^b]$$

As in Couture, Duranton, and Turner (2018), we assume the speed of each commuter, \mathcal{S} , is determined as

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

The time spent commuting in each zone for both low- and high- skill workers is $t_n = d_n/\mathcal{S}$.

Although our model is static, in counterfactual experiments we solve for different states of the world in which the variables governing the relative technology of working at home and in the office, A_h and A_b , may differ from our baseline calibration. One important consideration is whether we should expect the level of WFH technology, A_h , to change in response to a surge in the quantity of people that have worked at home due to the pandemic. To accommodate this possibility, we specify

$$(10) \quad A^h = \bar{A}^h (L_h^{max})^{\delta_h}$$

where L_h^{max} is the maximum amount of time in aggregate that high-skill workers spent working at home in any previous year.⁴ This captures 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. For example, a home fitness equipment salesperson will find more value in adopting WFH technology if she expects to be able to exhibit her product via teleconference than if she only anticipates other salespeople to have had experience with videoconference technology. Similarly, a tax preparer may invest in WFH technology if he anticipates that most of his clients will be willing to meet virtually and transmit documents electronically.

Additionally, high-skill worker productivity at the office, A_b , may be subject to agglomeration externalities, such that the quantity of workers at the CBD directly

⁴ L_h^{max} is bounded below by 0 and above by $\pi/(1 + \psi^1)$.

affects A_b .⁵ Define the aggregate quantity of hours of high-skill workers in the CBD as $L_b = \pi \sum_n f_n^1 l_b^n$.⁶ We specify

$$A^b = \bar{A}^b L_b^{\delta_b} \quad (11)$$

with $\delta_b \geq 0$.

An equilibrium in this model is a set of prices – w^0 , w^1 , r^b and r_n for $n = 1, \dots, N$ – such that the market for office space clears, housing demand is equal to housing supply in each location n , firms maximize profits and households maximize utility taking all prices and wages as given, and wage rates for low- and high-skill workers are equal to marginal products. Note that in the presence of externalities, the equilibrium we compute is likely inefficient because the household does not consider the impact of his or her decisions on the productivity of others. If agglomeration economies are exclusively at the level of the firm, the firm can internalize the externality. However, if there are significant externalities at the city-level, such as the sort documented by Atkin, Chen, and Popov (2020), there may be a role for public policy to improve expected utility. A large body of earlier work suggests agglomeration economies operate across firms within the same industry and across industries, and many of these agglomeration economies require face-to-face interaction. See Glaeser (2012) and Combes and Gobillon (2015) for a review of this literature.

3 Parameterizing the Model

With the exception of δ_h , we estimate or calibrate the parameters of the model to data prior to the onset of COVID.

3.1 Estimating the Elasticity of Substitution between Home and Office Work

The parameter ρ determines the EOS between home and office work and is new to the literature. Our estimation strategy for ρ builds on Equation (5), which implies that

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

⁶Similar to L_h^{max} , L_b is bounded below by 0 and above by $\pi / (1 + \psi^1)$.

for any given household the log-odds of commuting are linear in log-commuting costs, $\log(1+t)$,

$$(12) \quad \log\left(\frac{l^b}{l^h}\right) = \frac{\rho}{1-\rho} \log\left(\frac{A^b}{A^h}\right) + \frac{-\rho\theta}{1-\rho} \log\left(\frac{r^b}{r}\right) + \frac{-(1-\rho\theta)}{1-\rho} \log(1+t)$$

with a slope coefficient (third term) of $\Psi \equiv \frac{\partial \log(l^b/l^h)}{\partial \log(1+t)} = \frac{-(1-\rho\theta)}{1-\rho}$.

Conceptually, one can think of l^b as typical days worked in the office per week or month and l^h as typical days worked at home over the same period. If we define $x = l^b/l^h$, then the probability that a person works in the office on any given day is equal to $x/(1+x)$. This transformation allows us to use survey data on the fraction of days spent working from home versus in the office to estimate ρ for reasons we explain next.

Define \bar{C}_i as the fraction of days individual i reports working in the office. Then, we can write the estimating version of Equation (12) as

$$(13) \quad \begin{aligned} E(\bar{C}_i) &= \frac{\exp\left(\log\left(\frac{l^b}{l^h}\right)\right)}{1 + \exp\left(\log\left(\frac{l^b}{l^h}\right)\right)} \\ E(\bar{C}_i) &= \Lambda\left(\log\left(l^b/l^h\right)\right) \\ E(\bar{C}_i) &\approx \Lambda\left(\beta_0 + X_i'\beta_1 + \Psi \log(1+t_i)\right) \end{aligned}$$

where $\Lambda(\cdot)$ is the logistic function. The transformation is required because some individuals in our data report that they never work at home. Even if our theory predicts everyone spends at least some time at home, when surveyed over a small enough time window a respondent may not have worked at home at all. For these individuals, \bar{C}_i is well defined but $\log(l^b/l^h)$ is not.

The main regressor of interest is $\log(1+t_i)$, which must vary across households (conditional on X_i) to identify Ψ . A key threat to identification arises if the value of A^b/A^h varies unobservably in the population and people with unobservably high values of A^b/A^h choose, all else equal, locations with short commute times. In this scenario, the commute time is endogenous and correlated with an unobserved variable.⁷

⁷In the model, A^b/A^h is the same for all high-skill workers. That said, if the model were to include groups of high-skill workers with different values of A^b/A^h , the presence of the e_{nj} terms implies the groups would not perfectly sort into locations.

We imagine that variation in A^b/A^h is largely explained by differences in occupation, industry, and demographic variables, consistent with the evidence in Dingel and Neiman (2020). The observable characteristics (X_i) we include in (13) are age, age², a female indicator, age-female and age²-female interactions, race, marital status, two-digit industry dummies, and two-digit occupation dummies. Our identifying assumption is that variation in $\log(1+t)$ is uncorrelated with A^b/A^h conditional on these occupation, industry, and demographic variables. We show later that our estimate of Ψ does not depend on the inclusion of these observable characteristics. This suggests that for omitted variables to bias our estimate of Ψ , sorting for commute-time reasons on any unobserved component of relative productivity would need to be substantially more important than sorting on the component of relative productivity explained by important observables (Altonji, Elder, and Taber, 2005).

3.1.1 Data

We estimate the parameters of (13) using data from the 2017-2018 Current Population Survey (CPS), the American Time Use Survey (ATUS), and the Leave and Job Flexibility (LJF) module of the CPS. The ATUS and LJF are both CPS submodules. Respondents provide a time diary of activities on one randomly chosen day. The ATUS data provide a record of commute duration for cases where a commute occurs on the observation day. The LJF sample is a subsample of ATUS respondents. The LJF asks questions focusing on workplace leave policies and job flexibility, including whether respondents have the ability to work from home and the frequency of home work. We restrict our sample to college-educated workers (i.e., those that have at least a four-year college degree) that report working at least four days per week.

We merge ATUS and LJF records at the individual level to create a dataset containing both commute times and frequencies of working from home. There are two main challenges with using these data. First, following the merge, we restrict our sample to individuals who were observed commuting on their randomly selected ATUS observation day. This necessary restriction introduces non-representativeness to our merged sample. Given that we exclude observations where people are not commuting on the ATUS observation day, the probability of an individual i being represented in our sample is increasing in the probability that i commutes on any given day; we correct for this by reweighting the sample. The LJF survey collects information that enables us to compute the fraction of days in each month that each survey respon-

dent works at the office; denote this fraction as \bar{C}_i .⁸ Given the probability that the respondent is included in our sample is (effectively) equal to the fraction of that individual's days that involve a commute, we reweight to undo this selection by setting sampling weights equal to the inverse of this fraction, $IPW_i = 1/\bar{C}_i$. After applying these weights, the mean and standard deviation of \bar{C}_i for our sample of 1,771 high-skill, full-time workers are 0.913 and 0.209, respectively.

Second, there is likely significant measurement error in the reporting of commute times. For example, over 90 percent of people report a commute time that is a multiple of 5 minutes, and there is a large percentage of respondents reporting commutes exactly equal to 15 or 30 minutes. We use two approaches to correct for any bias resulting from measurement error. The first is an instrumental variables approach that exploits the fact that we observe multiple reported commute times for the majority of individuals in our sample. We compute the two measures of commuting cost using $t_{i1} = \frac{2 \times \text{commute time}_{i1} \text{ (minutes)}}{8 \times 60}$ and $t_{i2} = \frac{2 \times \text{commute time}_{i2} \text{ (minutes)}}{8 \times 60}$ defining the "commute times" as the lengths of the two longest-duration activity intervals classified as "time spent traveling for work" in the ATUS time diary. For individuals who report only one "time spent traveling for work" interval, t_{i2} is missing. Using one measure as an IV for the other is a common approach to addresses measurement errors under the assumption that the measurement errors from the two measures are uncorrelated. Our use of the other commute time as an instrument relates to the concept of Obviously Related Instrumental Variables (ORIV) of Gillen, Snowberg, and Yariv (2019).

Two striking patterns in the commute-time data, shown in Figure 1, cause us to suspect that the measurement errors may, in fact, be correlated. First, shown in the top panel of the figure, 51 percent of individuals with two observed commutes report the exact same commute time. Second, shown in the bottom panel, most commute times appear to be rounded, with 91 percent being a multiple of 5 minutes (as mentioned earlier) and 46 percent being a multiple of 15 minutes. Based on this evidence, the measurement error of two reported commutes is likely positively correlated. For example, a person with realized commutes of 26 and 27 minutes might report 30 minutes for both commutes. Therefore, our second approach to addressing measurement error involves correcting non-IV estimates of ψ using an analytically derived adjustment that is based on an assumed value of the correlation of the measurement errors of the two reported commutes. With this approach, we are able to assess the sensitivity of our estimates of ψ to the correlation of the measurement errors.

⁸In Appendix B.1 we detail the mapping of the responses to survey questions to our estimate of \bar{C}_i .

3.1.2 Estimation Details

We use a GMM approach to estimate Ψ . We first compute estimates that do not correct for measurement error in reported computing times. We then use a related IV version of the estimator to compute measurement-error-corrected estimates. The moments we target for estimation are based on the error term given by the difference between each individual's reported fraction of days spent in the office and the prediction given by Equation (13). Under a given parameterization (Ψ, β) this prediction error can be written

$$\epsilon_i(\Psi, \beta) = \bar{c}_i - \Lambda\left(\beta_0 + X_i' \beta_1 + \Psi \log(1 + t_{i1})\right).$$

The GMM estimator with no measurement error correction is based on the moments

$$(14) \quad \begin{aligned} \hat{m}_0(\Psi, \beta) &= \sum_i \epsilon_i(\Psi, \beta) \\ \hat{m}_1(\Psi, \beta) &= \sum_i X_{i1} \epsilon_i(\Psi, \beta) \\ &\vdots \\ \hat{m}_K(\Psi, \beta) &= \sum_i X_{iK} \epsilon_i(\Psi, \beta) \\ \hat{m}_{K+1}(\Psi, \beta) &= \sum_i \log(1 + t_{i1}) \epsilon_i(\Psi, \beta) \end{aligned}$$

where K is the length of X_i . Estimation is based on the moment condition, $E[\hat{m}(\Psi, \beta)] = 0$, where

$$\hat{m}(\Psi, \beta) = \begin{bmatrix} \hat{m}_0(\Psi, \beta) \\ \hat{m}_1(\Psi, \beta) \\ \vdots \\ \hat{m}_{K+1}(\Psi, \beta) \end{bmatrix}$$

and the GMM estimator is

$$(15) \quad (\hat{\Psi}^{GMM}, \hat{\beta}^{GMM}) = \arg \min_{(\Psi, \beta)} \hat{m}'(\Psi, \beta) \mathcal{W} \hat{m}(\Psi, \beta)$$

where \mathcal{W} is an optimal weighting matrix.

This GMM framework also directly facilitates our IV strategy for accounting for

measurement error. We correct for measurement error using two approaches, both of which rely on the bias due to measurement error in our logistic setting being similar to that which arises in the linear regression framework. In Appendix B.2, we show that over the relevant range of commute times and a high probability of commuting similar to what we observe in the data, the logistic function is close to linear such that a linear approximation is reasonable.

Both approaches exploit the fact that many people report more than one commute. We use one commute for the same individual as an instrument for the other commute. This corrects for the measurement error within an individual that is uncorrelated across trips. For example, suppose an individual recalls that the afternoon commute was 18 minutes while only recalling that the morning commute was approximately 20 minutes. Alternatively, suppose an individual runs an errand on the way home from work and thus misreports the afternoon commute time because of inclusion of the errand. The morning commute is correlated with the true commute time but uncorrelated with the extra errand time.

Our first approach to correcting for measurement error constructs the GMM-IV estimator by replacing the orthogonality condition, moment $K + 1$, with the IV analog,

$$(16) \quad \widehat{m}_{K+1}(\Psi, \beta) = \sum_i \log(1 + t_{i2}) \epsilon_i(\Psi, \beta).$$

That is, identification of Ψ is based on the orthogonality of the second commute time IV $\log(1 + t_{i2})$ with the prediction error calculated using $\log(1 + t_{i1})$. To maximize efficiency, we allow each individual in our sample to contribute two observations for the IV estimator. For one observation, we treat the first commute time measurement as the regressor $\log(1 + t_{i1})$ and the second commute time measurement as the instrument $\log(1 + t_{i2})$, and for the second observation we reverse the roles of the two measures.

Our second strategy to account for measurement error involves applying an analytical correction to the estimate of Ψ from the GMM moments in Equation (14). We derive the correction by applying the analytical expression for the magnitude of

attenuation bias in the linear regression framework,

$$(17) \quad E[\widehat{\Psi}^{GMM}] \approx \Psi \times \begin{pmatrix} \text{true value} \\ \frac{\text{var}(x_i^*)}{\text{var}(x_{i1})} \\ \text{measured value} \end{pmatrix}$$

where, for compactness of notation, we have substituted $x_i^* = \log(1 + t_i)$ for the true value of the mismeasured covariate and $x_{i1} = \log(1 + t_{i1})$ and $x_{i2} = \log(1 + t_{i2})$ for the measurements. We write the measurements as

$$\begin{aligned} x_{i1} &= x_i^* + e_{i1} \\ x_{i2} &= x_i^* + e_{i2} \end{aligned}$$

$$\text{var} \begin{pmatrix} e_{i1} \\ e_{i2} \end{pmatrix} = \begin{bmatrix} \sigma_e^2 & \rho_e \sigma_e^2 \\ \rho_e \sigma_e^2 & \sigma_e^2 \end{bmatrix}.$$

The measurement errors e_{i1} and e_{i2} are uncorrelated with x_i^* but are potentially correlated with one another with correlation coefficient $\rho_e > 0$.

We construct the bias-corrected estimator by multiplying the naive GMM estimator by the inverse of an estimate of the attenuation bias

$$\begin{aligned} \widehat{\Psi}^{BC} &= \widehat{\Psi}^{GMM} \left(\frac{\widehat{\text{var}}(x_1)}{\widehat{\text{var}}(x^*)} \right) \\ &= \widehat{\Psi}^{GMM} \left(\frac{\widehat{\text{var}}(x_1)}{\widehat{\text{var}}(x_1) - \widehat{\text{var}}(e)} \right). \end{aligned}$$

Finally, noting that

$$\begin{aligned} \text{var}(x_{i1}) &= \sigma_{x^*}^2 + \sigma_e^2 \\ \text{cov}(x_{i1}, x_{i2}) &= \sigma_{x^*}^2 + \rho_e \sigma_e^2 \end{aligned}$$

which imply that

$$\text{var}(e_i) = \frac{\text{var}(x_{i1}) - \text{cov}(x_{i1}, x_{i2})}{1 - \rho_e}$$

the bias-corrected estimator is

$$(18) \quad \hat{\Psi}^{BC} = \hat{\Psi}^{GMM} \left(\frac{\widehat{var}(x_{i1})}{\widehat{var}(x_{i1}) - \left(\frac{\widehat{var}(x_{i1}) - \widehat{cov}(x_{i1}, x_{i2})}{1 - \rho_e} \right)} \right).$$

In Appendix B.3, we present evidence from Monte Carlo experiments showing that the correction based on this approximation performs well in simulated datasets that match key moments of the commute data and with a range of correlations between the measurement errors in two reported commutes.

Before showing GMM results, we provide evidence that the WFH share rises with commute times such that it is unlikely that working from home and at the office are perfect substitutes. Figure 2 shows how the percentage of time spent working from home varies with commute time in our sample. In this graph, we sort each worker in our estimation sample into a bin based on reported commute time and then graph the frequency with which workers in each commute-time bin work at home at least one day per month (solid line), at least two days per month (dashed line), at least one day per week (dotted line) and at least three days per week (dot-dash line).⁹ Outcomes are not mutually exclusive, for example a person that works from home at least three days per week also works from home at least one day per month.

Two results emerge from this graph. First, abstracting from the impact of sampling variability, the percentage of workers working from home in every category (at least one day per month, at least two days per month, etc.) rises with commute times. Ultimately, we use a GMM procedure to estimate the slope, but there is an obvious relationship in the data.

Second, the graph strongly suggests working from home and at the office are not perfect substitutes. In the case of perfect substitutes, we would expect workers to either work 100 percent of the time at home or 100 percent of the time at the office. In this case, the four lines shown in Figure 2 would overlap, as everyone that works at home at least one day per month also works at home at least three days per week. The gap between the solid line, at least one day per month, and the dot-dash line, at least three days per week, shows the fraction of workers who work some from home that choose an interior solution, i.e., some allocation of working from home less than

⁹We bin based on the average commute time of each worker in the event the worker reports multiple commute times.

100 percent.

Table 1 reports GMM estimates of ψ , the value of ρ after imposing $\theta = 0.18$ from Valentinyi and Herrendorf (2008), and the implied EOS = $1/(1 - \rho)$ between working at home and in the office. Columns 1 and 2 report GMM estimates without correcting for measurement error excluding (column 1) and including demographic controls and industry and occupation fixed effects (column 2). The sample in these columns is anyone that reports at least one commute. For the 1,203 commuters that report two commutes, we create two records, one for each commute time reported. We include both these records in our estimation and allocate 50 percent of the IPW to each of them. These columns show that when we do not correct estimates for measurement error, the estimate of the EOS is about 3.0 and does not depend on the inclusion of important demographic or occupation and industry controls. Following the logic of Altonji, Elder, and Taber (2005), selection on unobservables would need to be substantially stronger than selection on important observables for our estimate of Ψ to be significantly biased by selection.

Column 3 shows estimation results resulting from a simple attempt to remove observations that may obviously be contaminated with measurement error: We remove from the sample individuals who report two commutes that differ by at least 20 minutes. This removes 147 observations, 8.3 percent of the sample, and boosts the estimate of the EOS to about 3.5.

Column 4 shows our GMM estimate when we restrict the sample to individuals who report at least two commutes, 1,203 respondents, and column 5 shows our IV-corrected GMM estimates from this sample based on the moment condition shown in equation (16). The IV correction increases the coefficient estimate by a factor of nearly 1.6, from -2.54 to -3.85, raising the EOS from 2.9 to 4.5.

Columns 6-9 show the results of the analytic correction for measurement error shown in equation (18) when we use as a baseline the GMM estimates shown in column 2. When we assume the two measurement errors are uncorrelated, column 6, the estimate of ψ increases by a factor of 1.39, from -2.78 to -3.85, and the associated EOS rises from 3.18 to 4.47. As the assumed correlation of the measurement error rises, from 0.1 in column 7 to 0.25 in column 8 to 0.50 in column 9, the estimate of ψ increases in absolute value and the EOS increases from 4.68 (column 7) to 5.16 (column 8) to 7.37 (column 9).

While our assumptions admit a range of possibilities for the EOS, the implication

of our estimates is that working from home is not a perfect substitute with work at the office. In what follows, we set our baseline estimate of $\rho = 0.80$, implying an EOS of 5, corresponding to a correlation of the two measurement error terms of about 0.2. We explore the sensitivity of our results by considering alternative values for ρ of 0.667 and 0.857. This corresponds to elasticities of substitution between work at home and in the office of 3, our estimate when we do not correct for measurement error, and 7, our estimate when the correlation of measurement errors is about 0.5.

3.2 Other Parameters

3.2.1 Parameters Set Outside of Model

Table 2 summarizes our parameterization of the model. We allow for two residential zones. 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) but consider the sensitivity of our results to a higher level of δ_b in Section 4.6. We set $\omega = 0.33$ such that the EOS between low-skill and high-skill workers is 1.5. This is in the middle of the range reported by Autor, Katz, and Krueger (1998).

We set π , the fraction of workers that are high skill, to 0.33 which is the share of US adults that are college educated as of 2019 according to data from the U.S. Census Bureau. We set $\alpha^0 = 0.33$ and $\alpha^1 = 0.20$ to roughly match the relative size of housing of college- and non-college-educated workers in the 2019 American Housing Survey.¹⁰ These values of α bracket the estimate of Davis and Ortalo-Magné (2011) of 0.24 for the median expenditure share on rents for all renting households in the United States.¹¹ The preference for leisure, ψ , does not impact our results since with log separable preferences leisure is a constant, independent of wage and location. We set the preference for leisure to 0.25 for both low- and high-skill workers ($\psi^0 = \psi^1 = 0.25$).

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

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

¹¹As a check, we compute the median of the ratio of annual gross rent to household income using data from the 2018 5-year American Community Survey, for non-college-educated and college-educated household-head, with the household head aged 21-65 and with positive rent and household income. These estimates are 0.31 and 0.23, respectively.

on average because they get a good random draw of household-specific preferences e_{ni} or e_{nj} from living in that location. We set $\nu^0 = \nu^1 = 3.3$ based on the estimates in Monte, Redding, and Rossi-Hansberg (2018).

γ measures the elasticity of driving speed with respect to aggregate commuting miles. We set $\gamma = -0.15$ based on estimates in Couture, Duranton, and Turner (2018).

In our benchmark calibration, 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 solve for new quantities holding rental prices fixed. We use data from the New York City CBSA in 2015 to compute rents per square foot in the CBD and in zones 1 and 2 in the benchmark. According to Real Capital Analytics Trends, average rents per year per square foot on office property in Manhattan were \$37.89 per year. We apply a 5 percent cap rate to the median price per square foot residential prices by county in Galka (2016) to compute residential rents per square foot in each zone. We consider the Bergen NJ, Bronx NY, Hudson NJ, Kings NY, Richmond NY, Queens NY as Zone 1, \$13.26 rent per square foot per year, and all other counties as Zone 2, \$9.09 per square foot per year. We normalize r^b to 1.0 giving us rents of $r^b = 1.0$, $r_1 = 0.35$ and $r_2 = 0.24$.

3.2.2 Calibrated Parameters

We normalize \bar{A}^b to 1 such that A^h captures the relative productivity of WFH for high-skill workers. Similarly, the model implicitly normalizes the labor productivity of low-skill workers to 1 such that the parameter λ in Equation (9) determines relative wages.

χ_1^0 , χ_1^1 , χ_2^0 , and χ_2^1 describe the relative average amenities low- and high-skill workers receive when living in Zones 1 and 2. We normalize $\chi_1^0 = \chi_1^1 = 1$. We calibrate the remaining free parameters of the model (χ_2^0 , χ_2^1 , d_1 , d_2 , λ , and A^h) to match the following moments that we exactly match in our benchmark parameterization:

1. Share of low-skill workers living in Zone 2 (χ_2^0): 35.8 percent
2. Share of high-skill workers living in Zone 2 (χ_2^1): 40.4 percent
3. Commute time to CBD for workers living in Zone 1 (d_1): 30 minutes per trip each way

4. Commute time to CBD for workers living in Zone 2 (d_2): 50 minutes per trip each way
5. Total age-adjusted income of high-skill relative to low-skill (λ): 1.8. We measure labor income for high-skill workers as $wy - r^b s^b$ to account for the fact that in the data, unlike in our model, firms pay for office space directly rather than workers.
6. Fraction of time spent working at home relative to time spent working in our benchmark for high-skill workers (A^h): 10 percent

We include in parentheses the parameter that is most closely related to the moment we are targeting although we estimate all parameters jointly.

We calculate the first five moments using the ATUS-CPS data for residents living in New York City, Washington DC, Charlotte, Pittsburgh, St. Louis, Denver, Detroit, Columbus OH, and Louisville metropolitan areas. We select these cities because they are approximately monocentric and have sufficient population to identify the county of residency in the ATUS data. We set Zone 1 to the counties that are adjacent to the CBD and Zone 2 includes as counties not adjacent to the CBD but included in the CBSA. We calculate moment (6) based on our estimates from the ATUS. In the sample from the ATUS we use to estimate the EOS, on average 91.3 percent of worker time is spent at the office and 8.7 percent at home. We round this up to 10 percent to account for the fact that our sample does not include any workers that always work from home due to the requirement for estimation that sample respondents have a reported commute. Furthermore, the LJF questionnaire only asks about full days spent working at home.

4 Counterfactuals

We use the model to understand how the pandemic affected the economy and to forecast its long-term effects. At the onset of the pandemic, we assume productivity of working at the office, \bar{A}^b , falls significantly as workers require more space (and time) to produce output due to social distancing and other precautionary responses. This decline in office productivity leads to more work at home, which we assume increases A^h via Equation (10). At this new, higher level of A^h much more work occurs at home after the pandemic ends, even when productivity of working at the office returns to its pre-pandemic value.

4.1 Effects During the Pandemic

Column 1 of Tables 3 and 4 show simulations of the benchmark economy prior to the onset of the pandemic. We consider two counterfactual simulations for understanding how the pandemic affected the economy. In the first, we hold A^h at its baseline level but reduce \bar{A}^b by 50 percent. This corresponds to the beginning of the pandemic when office productivity declines markedly but workers have not significantly increased their experience with working at home. Column 2 of Tables 3 and 4 displays the results of this first counterfactual. The overall decrease in A^b , shown in row (1), is slightly larger than the 50 percent decline in \bar{A}^b . This occurs because high-skill work at the office declines, reducing the contribution of agglomeration effects on office productivity. Hours worked at home for high-skill workers rise from 10 percent to 52 percent of total hours, shown in row (25), and rent for office space in the CBD falls to 41 percent of its pre-pandemic level, row (37). Residential rents, rows (38) and (39), fall: Households significantly increase their demand for home offices, rows (30) and (34), but incomes fall substantially, rows (4) and (7). Low-skill workers move from Zone 2 to Zone 1 (rows 12 and 13) and high-skill workers do the opposite, rows (15) and (16). Note that we hold the stock of space fixed in the CBD (row 28) and both zones (rows 29 and 33) in this counterfactual.

Next we consider a counterfactual simulation of the economy at the end of the pandemic, column 3 of Tables 3 and 4. In this counterfactual, \bar{A}^b is still depressed due to social distancing but A^h (row 2) increases by 46 percent, from 0.371 to 0.543, such that the percentage of high-skill work that occurs from home triples from 10 to 30 percent (row 25, column 4) once \bar{A}^b returns to its pre-pandemic level. Row 25 shows that hours worked at home rises to 77 percent (column 3), from 52 percent at the start of the pandemic (column 2) and 10 percent prior to the pandemic, column 1. Comparing columns 1 and 3 for rows (30) and (34), the model predicts a huge increase in demand for home offices in both Zones 1 and 2. Since the supply of space in each zone is assumed fixed in this counterfactual, the increase in the size of home offices is accommodated by a decrease in space used for housing, rows (31) and (32) and (35) and (36). Rents for office space in the CBD fall to just 25 percent of their pre-pandemic level, row (37), and residential rents in both zones rise (rows 38 and 39). Shown in row (7), measured income per high-skill worker falls by less than one-half percent, from 5.52 to 5.51, as the increase in A^h mitigates the steep decline in the productivity of work from the office and workers allocate a larger fraction of their incomes to rent on their home offices.

4.2 Effects After the Pandemic

We consider three counterfactual experiments that bracket the possible changes to city form and the use of space after the health-related impacts of the pandemic subside such that people can start freely interacting again. In all three counterfactuals, people can adjust where they live, how much they spend on housing, office space, and home-office space, and how much they choose to work in the CBD or (for high skill) in their home office. 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.

In the first post-COVID counterfactual, called SR in Tables 3 and 4, we hold fixed the supply of office space in the CBD and the aggregate amount of available structures for use in housing and home-office work in each of Zones 1 and 2 (separately) at the baseline levels. In this counterfactual, we search for three market clearing prices, r^b , r_1 , and r_2 , such that the demand for space is equal to the supply 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 for space has not yet responded.

In this and our other two post-COVID experiments, we keep $A^h = 0.543$, its value during the experiment for the end of the pandemic. As discussed earlier, this value of A^h generates a tripling of the share of time high-skill workers spend working the CBD relative to the baseline, from 0.1 to 0.3. We believe this change in the share of high-skill work done from home is consistent with expectations reported by Barrero, Bloom, and Davis (2020) and Mortensen and Wetterling (2020).

Comparing columns 1 and 4 of Table 3 shows that, while incomes for both types of workers rise (rows 4 and 7), the rise is more pronounced for high-skill workers such that the ratio of high-skill to low-skill income rises by 6.7 percent, from 1.80 to 1.92 (row 3). Low-skill wages rise because low-skill and high-skill effective hours are complementary in production: As high-skill effective hours rises, low-skill output becomes more valuable. Although high-skill workers work in the office less, there is only a slight increase in the share of high-skill workers living in Zone 2 in this counterfactual (row 16) as space has not yet had a chance to adjust. Relative to the pre-pandemic benchmark, rent for office space in the CBD falls by 15 percent (row 37) and residential rents rise in both zones with the increase larger in Zone 2 (17 percent, row 39) than in Zone 1 (9 percent, row 38). The change in residential rents is

driven by a large increase in demand for home offices (rows 30 and 34); the quantity of housing not used for home offices modestly declines for both high- and low-skill workers, rows (31) and (32) and (35) and (36).

In the second post-COVID counterfactual experiment, shown in column 5 as LR, we hold rental prices in the CBD and in both zones fixed at their baseline levels and allow the supply of space in each zone to flexibly accommodate any change in demand. We think of this as a long-run response in most areas. Once the quantity of space has adjusted, the share of high-skill hours worked from home rises even further, to 35 percent from 30 percent immediately after the pandemic (row 25). The demand for office space in the CBD declines by about 20 percent, row (28); the demand for space for all uses in Zone 1 increases by 7.7 percent, from 1.95 to 2.10 (row 29); and the demand for space for all uses in Zone 2 increases by 20 percent, from 1.63 to 1.95 (row 33). Housing for both types of workers increases from the benchmark, as both types earn more income, but high-skill workers build larger home offices in this environment and this makes high-skill workers 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 of space is fixed and quantity is flexible. In the SR, home office space approximately triples from the pre-pandemic level, shown in rows (30) and (34). In the LR, space for home offices increases by about a factor of four relative to pre-pandemic levels.

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 triples 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 log expenditure share on housing for renting households where at least one member is working remotely is 0.063 to 0.135 larger compared to the log expenditure share of otherwise similar households where no one works remotely. The equivalent calculation for high-skill residents living in Zones 1 and 2 in our baseline calibration is 0.075 and 0.116, respectively.¹²

In our final post-COVID counterfactual, we hold the quantity of office space in the

¹²In the case of high-skill residents in Zone 1, we compute this as the log of the sum of space for home offices and other housing, rows 30 and 31 of column 1, less the log of space on other housing, row 31 of column 1. For Zone 2 high-skill residents, we do an equivalent calculation. These calculations assume that high-skill workers that never work at home would have zero expenditures on home office space.

CBD fixed and find the rent r^b such that demand is equal to supply, but fix rents in Zones 1 and 2 at their baseline levels assuming that additional development in these zones is feasible at current prices. Column 6 shows the results of this experiment, LR Putty-Clay. This experiment recognizes that depreciation rates are sufficiently low on structures 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 quite some time. In this experiment, rents on office space in the CBD fall to 84 percent of their pre-pandemic level, row (37), and relative to the LR experiment, a smaller share of hours are worked at home, row (25), because office space is cheap in the CBD. For related reasons, the migration of high-skill workers to Zone 2 is a bit less pronounced in column 6 than in column 5, row (16). The increase in income inequality, row (3), persists.

In all the experiments we have reported so far, consumption inequality (row 10) increases by less than income inequality (row 3). We measure consumption as the sum of expenditures on consumption and expenditures on housing not including home offices. In the post-COVID counterfactuals, wy rises for high-skill workers because they have become relatively more productive. The increase in productivity arises due to (i) the increase in A^h as well as (ii) the expansion of home offices. Workers are compensated for the increase in their productivity, but some of the gains in income directly offset additional expenses incurred from renting larger home offices. To match the model with data, we do not subtract expenditures on home offices from labor income as typical survey questions measuring wage and salary income do not ask respondents to net out expenditures on home offices. Measured consumption inequality does not increase as much as income inequality because rent for these home offices reduces income available for consumption for high-skill workers, and low-skill workers do not rent home offices.

4.3 A 1990 Pandemic

In Table 5 we consider a counterfactual that corresponds to the effect of the COVID pandemic if A^h is so low that working from home is not a viable alternative for high-skill workers. This scenario corresponds to the effects of a pandemic had it happened in, say, 1990 prior to current WFH technology being widely available. Indeed, despite the 1918-1920 flu pandemic being an order of magnitude more lethal than that of COVID, particularly for prime-age workers, there was much less social distancing

during the 1918-1920 pandemic.¹³ Column 1 shows simulated outcomes of our model economy prior to the onset of the pandemic, call it 1989, and column 2 shows results once the pandemic hits. In both columns 1 and 2 we set A^h to 0.11, about 30 percent of its 2019 level, and then compare outcomes when we reduce \bar{A}^b by 50 percent at the onset of the pandemic, row 1 of Table 5.

Had the pandemic occurred in 1990, the model predicts hours worked at home would have increased from 0 percent to 1 percent, row (6). Incomes for both low- and high-skill workers (rows 7 and 8) would have declined by much more than implied by the counterfactual experiments for the current (2020-2021) pandemic, shown in columns 3 and 4, because workers in 1990 cannot offset the decline in productivity at the CBD by working from home. In this scenario, office rents in the CBD (row 12) and in both zones (rows 13 and 14) decline significantly due to the drop in income, although the rental price of office space in the CBD in the 1990 pandemic does not decline as sharply as in the 2020 pandemic. These simulations show that worker behavior after the onset of a pandemic in 1990 would not have changed much, and the virus would have been much more lethal and costly in terms of income.¹⁴

4.4 Quantifying the Impact of Experience on A^h

In Equation (10), we specify the level of A^h as equal to $\bar{A}^h (L_h^{max})^{\delta_h}$. Denote the pre-pandemic level of A^h as A_0^h and the (immediate) post-pandemic level of A^h as A_1^h . Assuming that \bar{A}^h is fixed during the COVID pandemic, which is reasonable given the pandemic lasted about 12 months, we can use the simulated maximum number of hours worked from home before and during the pandemic, row (22) of Table 4, to solve for δ_h

$$\frac{A_1^h}{A_0^h} = \frac{0.543}{0.371} = \left(\frac{0.59}{0.07} \right)^{\delta_h}$$

This yields $\delta_h = 0.179$, implying a 10 percent increase in aggregate hours (ever) worked at home boosts productivity of working at home for all high-skill workers by 1.79 percent.

¹³See Barry (2004) for a discussion of the lethality and lack of social distancing during the 1918-1920 pandemic.

¹⁴Eichenbaum et al. (2020) find that approximately 17 percent of virus transmissions occur in workplaces.

4.5 The Role of the EOS between Home and Office Work

Table 6 shows how predictions of our model change depending on the EOS we choose: 3, 5, or 7. For each value of the EOS, we set A^h pre- and post-COVID such that high-skill workers spend 10 percent of their time working at home pre-COVID and 30 percent of their time working at home after COVID in the SR counterfactual. In all simulations, we assume that \bar{A}^b declines by 50 percent during the pandemic.

Rows (2), (4), and (6) of Table 6 show the levels of A^h required to match the target values of the share of work done at home. With a lower value of the EOS, such that working from home and at the office are more complementary than we assume in our benchmark, the relative productivity of working from home must be lower relative to its benchmark value for the household to choose a small fraction of time to work from home. When the EOS is 5, we find the pre-pandemic level of A^h is 0.37 but when the EOS is 3 we have to set $A^h = 0.21$ to replicate that only 10 percent of high-skill hours are worked from home. When the EOS is 5, A^h has to rise by 46 percent (from 0.37 to 0.54) to triple hours worked from home after the pandemic ends. When the EOS is 3 A^h has to double and when the EOS is 7, A^h must increase by 31 percent.

Given our method for setting A^h before and after the pandemic, Table 6 shows that the long-run implications of the COVID shock are similar regardless of the value chosen for the EOS: 1) CBD rents fall by approximately 12-18 percent in both the SR and LR Putty-Clay scenarios; 2) incomes rise for both types of workers but more for high-skill workers such that income inequality increases; and 3) A^b declines due to lower agglomeration economies.

4.6 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 when we set δ_b to a much higher value of 0.10. Table 7 presents these results. As with the previous counterfactual experiments, we set A^h pre- and post-COVID such that high-skill workers spend 10 percent of their time working at home pre-COVID and 30 percent of their time working at home after COVID in the SR counterfactual. Table 7 shows that this

change in δ_b does not materially affect any of our main results.

4.7 Long-term Trend for Office: The Effect of Upskilling

While COVID induced a permanent change in the productivity of working from home that reduced the demand for office space in the CBD, the long-term rise in the share of the workforce with a college degree has the opposite effect on demand for office space as skilled workers demand more office space. To understand the effect of this upskilling on rents, we conduct an additional experiment in which we hold the supply of CBD office space fixed in the long run, as in our LR Putty-Clay counterfactual in column 6 of Table 4, but increase the share of high-skill workers in the population to 40 percent. In this scenario, we find that office rents fall to 90 percent of their pre-pandemic level rather than 84 percent. Thus, we expect an increase in the share of high-skill workers to offset less than half of the decline in CBD office rents that we report in Table 4.

5 Conclusions

We have investigated long-run changes to urban form, rents, and income inequality resulting from an increase in WFH technology. Our model suggests the ability of high-skill workers to work from home significantly cushioned the impact of the COVID-19 pandemic on incomes; expectations about future time spent working from home as compared to the office have permanently changed as a result. Surveys suggest that once the pandemic subsides, workers expect to approximately triple their time spent working from home relative to pre-pandemic levels. We use the model to infer the change in WFH productivity that occurred during the pandemic such that workers will optimally choose to triple their time working from home once the pandemic ends. At our estimated elasticity of substitution between working from home and at the office in the production of output, we estimate WFH productivity increased by 46% during the pandemic. We believe this increase in productivity is a direct consequence of the pandemic, as quarantining and social distancing forced a large fraction of the high-skill workforce to learn how to effectively work from home.

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Table 1: GMM Estimates of the Elasticity of Substitution

	Drop					with Analytic Bias Correction			
	(1)	(2)	$ x_{i1} - x_{i2} \geq 20$ mins	IV Sample	IV	$\rho_e = 0$	$\rho_e = 0.1$	$\rho_e = 0.25$	$\rho_e = 0.50$
log(1+t)	-2.63**	-2.78**	-3.06**	-2.54*	-3.85*	-3.85**	-4.02**	-4.41**	-6.22**
	(1.21)	(1.20)	(1.53)	(1.39)	(2.11)	(1.66)	(1.74)	(1.91)	(2.69)
Implied ρ	0.67	0.69	0.72	0.65	0.78	0.78	0.79	0.81	0.86
EOS	2.99	3.18	3.51	2.87	4.47	4.47	4.68	5.16	7.37
Demog. controls	no	yes	yes	yes	yes	yes	yes	yes	yes
Industry FEs	no	yes	yes	yes	yes	yes	yes	yes	yes
Occupation FEs	no	yes	yes	yes	yes	yes	yes	yes	yes
N	1,771	1,771	1,624	1,203	1,203	1,771	1,771	1,771	1,771

Table 2: Parameterization

Param.	Description	Value	Determined
<i>Technology:</i>			
ρ	EOS bw home and office work = $\frac{1}{1-\rho}$	0.80	Midpoint estimate
θ	Structures share in production	0.18	Fixed
ω	EOS bw type 0 and 1 labor = $\frac{1}{1-\omega}$	0.33	Fixed
δ_b	Agglomeration economies	0.04	Fixed
κ	Relative commuting speed for type 0	1.0	Fixed
\bar{A}^b	Productivity of working at CBD for type 1	1	Normalized
A^h	Relative productivity of work from home	0.371	Calibrated
λ	Relative productivity of high-skill worker	1.33	Calibrated
γ	Congestion externality	-0.15	Fixed
d_1	Distance to CBD from Zone 1	0.168	Calibrated
d_2	Distance to CBD from Zone 2	0.280	Calibrated
<i>Rents:</i>			
r^b	Office rent in CBD	1.0	Normalized
r_1	Residential rent in Zone 1	0.35	Fixed
r_2	Residential rent in Zone 2	0.24	Fixed
<i>Demographics:</i>			
π	Fraction high-skill	0.33	Fixed
<i>Preferences:</i>			
α^0	Housing exp. share for type 0	0.33	Fixed
α^1	Housing exp. share for type 1	0.20	Fixed
ψ^0	Pref. for leisure	0.25	Fixed
ψ^1	Pref. for leisure	0.25	Fixed
ν^0	Importance of Deterministic Utility for n	3.3	Fixed
ν^1	Importance of Deterministic Utility for n	3.3	Fixed
χ_1^0	Amenities in Zone 1	1.0	Normalized
χ_1^1	Amenities in Zone 1	1.0	Normalized
χ_2^0	Amenities in Zone 2	0.795	Calibrated
χ_2^1	Amenities in Zone 2	0.876	Calibrated

Notes: 1) Superscript 0 denotes low-skill household, superscript 1 denotes high-skill (college graduate) household.

Table 3: Model Prediction for Distribution of Incomes and Population

Row		Pre-COVID	COVID Scenarios		Post-COVID Scenarios		
		Baseline (1)	Start (2)	End (3)	SR (4)	LR (5)	LR Putty-Clay (6)
<i>Technology:</i>							
(1)	A^b	0.940	0.459	0.447	0.931	0.929	0.930
(2)	A^h	0.371	0.371	0.543	0.543	0.543	0.543
<i>Incomes:</i>							
(3)	Type 1/0 Ratio of Labor Income	1.80	1.67	1.92	1.92	1.93	1.94
(4)	Type 0 Income per Worker	3.07	2.63	2.88	3.17	3.15	3.18
(5)	Living in Zone 1	3.15	2.69	2.94	3.25	3.23	3.26
(6)	Living in Zone 2	2.93	2.51	2.75	3.02	3.01	3.03
(7)	Type 1 Income per worker	5.52	4.39	5.51	6.10	6.07	6.15
(8)	Living in Zone 1	5.63	4.35	5.41	6.13	6.07	6.16
(9)	Living in Zone 2	5.36	4.44	5.63	6.06	6.08	6.13
<i>Consumption:</i>							
(10)	Type 1/0 Ratio of Consumption	1.77	1.51	1.65	1.82	1.81	1.82
<i>Population:</i>							
(11)	Total Low Skill	67%	67%	67%	67%	67%	67%
(12)	Living in Zone 1	64%	66%	67%	65%	64%	64%
(13)	Living in Zone 2	36%	34%	33%	35%	36%	36%
(14)	Total High Skill	33%	33%	33%	33%	33%	33%
(15)	Living in Zone 1	59%	56%	54%	58%	56%	57%
(16)	Living in Zone 2	41%	44%	46%	42%	44%	43%

Notes: 1) We parameterize the model to the pre-COVID world. 2) In columns (2)-(4), we cut \bar{A}^b by 50% to capture social distancing from the pandemic. 3) Columns (3)-(6) capture the improvement in WFH technology during the pandemic by increasing A^h to the level required to triple the share of hours worked from home for type 1 in going from columns (1) to (4). 4) We hold the supply of space fixed at the pre-COVID baseline in counterfactuals (2)-(4). In counterfactual (5), we adjust the supply of space such that rents are equal to their pre-COVID benchmark in column (1). In column (6), we keep the stock of office space at the level in column (1) but adjust the stocks of residential space such that residential rents return to the level in column (1).

Table 4: Model Predictions for Work Location, Space, and Rents

Row		Pre-COVID	COVID Scenarios		Post-COVID Scenarios		
		Baseline (1)	Start (2)	End (3)	SR (4)	LR (5)	LR Putty-Clay (6)
	<i>Hours Worked:</i>						
(17)	Type 0 Hours per Worker	0.69	0.70	0.70	0.69	0.69	0.69
(18)	Type 1 Effective Hours per Worker	0.73	0.46	0.60	0.80	0.78	0.81
(19)	Type 1 Hours Worked in CBD per Worker	0.63	0.36	0.18	0.51	0.47	0.49
(20)	Living in Zone 1	0.66	0.40	0.21	0.55	0.52	0.54
(21)	Living in Zone 2	0.59	0.30	0.15	0.45	0.41	0.43
(22)	Type 1 Hours Worked at Home per Worker	0.07	0.39	0.59	0.22	0.25	0.23
(23)	Living in Zone 1	0.06	0.35	0.56	0.18	0.21	0.19
(24)	Living in Zone 2	0.09	0.44	0.62	0.26	0.30	0.28
(25)	Ratio Hours Worked at Home to Total Hours	0.10	0.52	0.76	0.30	0.35	0.32
(26)	Living in Zone 1	0.08	0.46	0.73	0.25	0.29	0.26
(27)	Living in Zone 2	0.13	0.59	0.81	0.37	0.42	0.39
	<i>Demand for Space:</i>						
(28)	Aggregate Office Space in CBD	0.36	0.36	0.36	0.36	0.29	0.36
(29)	Aggregate Space in Zone 1	1.95	1.95	1.95	1.95	2.10	2.11
(30)	Home Office per Type 1	0.25	1.21	1.91	0.77	0.96	0.89
(31)	Per Type 1 Other Housing per Person	3.17	2.54	2.48	3.03	3.28	3.34
(32)	Per Type 0 Other Housing per Person	2.97	2.84	2.57	2.79	3.04	3.07
(33)	Aggregate Space in Zone 2	1.63	1.63	1.63	1.63	1.95	1.94
(34)	Home Office per Type 1	0.54	2.06	2.84	1.47	1.93	1.80
(35)	Per Type 1 Other Housing per Person	4.36	3.44	3.32	4.11	4.68	4.75
(36)	Per Type 0 Other Housing per Person	4.03	3.60	3.12	3.63	4.13	4.17
	<i>Rent per Unit of Space:</i>						
(37)	CBD	1.00	0.42	0.25	0.85	1.00	0.84
(38)	Zone 1	0.35	0.31	0.38	0.38	0.35	0.35
(39)	Zone 2	0.24	0.23	0.29	0.28	0.24	0.24

Notes: 1) See notes to Table 3.

Table 5: The Effect of Availability of Technology: A Hypothetical 1990 Pandemic

Row		Hypothetical 1990 Pandemic		2020 Pandemic	
		Pre-COVID (1)	COVID Start (2)	Pre-COVID (3)	COVID Start (4)
	<i>Technology:</i>				
(1)	A^b	0.94	0.47	0.94	0.46
(2)	A^h	0.11	0.11	0.37	0.37
	<i>Hours Worked:</i>				
(3)	Type 0 Hours per Worker	0.69	0.69	0.69	0.70
(4)	Type 1 Effective Hours per Worker	0.72	0.36	0.73	0.46
(5)	Type 1 Hours Worked at Home per Worker	0.00	0.01	0.07	0.39
(6)	Ratio Hours Worked at Home to Total Hours	0.00	0.01	0.10	0.52
	<i>Incomes:</i>				
(7)	Type 0 Income per Worker	3.04	2.43	3.07	2.63
(8)	Type 1 Income per worker	5.34	3.40	5.52	4.39
	<i>Demand for Space:</i>				
(9)	Aggregate Office Space in CBD	0.39	0.39	0.36	0.36
(10)	Aggregate Space in Zone 1	1.89	1.89	1.95	1.95
(11)	Aggregate Space in Zone 2	1.52	1.52	1.63	1.63
	<i>Rent per Unit of Space:</i>				
(12)	CBD	1.00	0.63	1.00	0.42
(13)	Zone 1	0.35	0.26	0.35	0.31
(14)	Zone 2	0.24	0.18	0.24	0.23

Table 6: Sensitivity of Results to EOS Between Work at Home and Office

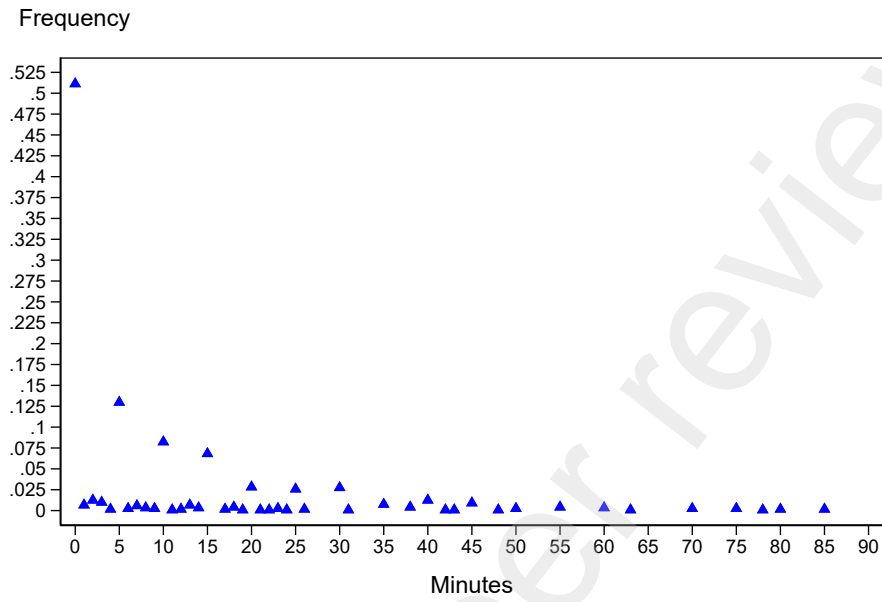
Row		Pre-COVID	COVID Scenarios		Post-COVID Scenarios		
		Baseline (1)	Start (2)	End (3)	SR (4)	LR (5)	LR Putty-Clay (6)
<i>A. Technology</i>							
				EOS = 5			
(1)	A^b	0.94	0.46	0.45	0.93	0.93	0.93
(2)	A^h	0.37	0.37	0.54	0.54	0.54	0.54
				EOS = 3			
(3)	A^b	0.94	0.47	0.46	0.93	0.93	0.93
(4)	A^h	0.21	0.21	0.42	0.42	0.42	0.42
				EOS = 7			
(5)	A^b	0.94	0.45	0.44	0.93	0.93	0.93
(6)	A^h	0.45	0.45	0.59	0.59	0.59	0.59
<i>B. Rents</i>							
				EOS = 5			
(7)	CBD	1.00	0.42	0.25	0.85	1.00	0.84
(8)	Zone 1	0.35	0.31	0.38	0.38	0.35	0.35
(9)	Zone 2	0.24	0.23	0.29	0.28	0.24	0.24
				EOS = 3			
(10)	CBD	1.00	0.56	0.42	0.88	1.00	0.87
(11)	Zone 1	0.35	0.28	0.35	0.40	0.35	0.35
(12)	Zone 2	0.24	0.20	0.26	0.28	0.24	0.24
				EOS = 7			
(13)	CBD	1.00	0.29	0.16	0.84	1.00	0.82
(14)	Zone 1	0.35	0.34	0.39	0.38	0.35	0.35
(15)	Zone 2	0.24	0.26	0.31	0.27	0.24	0.24
<i>C. Incomes</i>							
				EOS = 5			
(16)	Type 1 / 0 Income	1.80	1.67	1.92	1.92	1.93	1.94
(17)	Type 1 Income / Worker	5.52	4.39	5.51	6.10	6.07	6.15
(18)	Type 0 Income / Worker	3.07	2.63	2.88	3.17	3.15	3.18
				EOS = 3			
(19)	Type 1 / 0 Income	1.80	1.55	1.83	1.96	1.96	1.97
(20)	Type 1 Income / Worker	5.52	3.94	5.18	6.33	6.31	6.38
(21)	Type 0 Income / Worker	3.07	2.54	2.83	3.23	3.21	3.24
				EOS = 7			
(22)	Type 1 / 0 Income	1.80	1.77	1.98	1.91	1.93	1.93
(23)	Type 1 Income / Worker	5.52	4.79	5.77	6.02	6.02	6.08
(24)	Type 0 Income / Worker	3.07	2.70	2.92	3.15	3.12	3.16

Table 7: Greater Agglomeration Economies in the CBD

		Pre-COVID	COVID Scenarios		Post-COVID Scenarios		
		Baseline	Start	End	SR	LR	LR Putty-Clay
<i>A. Technology</i>							
$\delta_b = 0.04$ (benchmark)							
(1)	A^b	0.94	0.46	0.45	0.93	0.93	0.93
(2)	A^h	0.37	0.37	0.54	0.54	0.54	0.54
$\delta_b = 0.10$							
(3)	A^b	0.86	0.40	0.37	0.84	0.83	0.84
(4)	A^h	0.34	0.34	0.49	0.49	0.49	0.49
<i>B. Rents</i>							
$\delta_b = 0.04$							
(5)	CBD	1.00	0.42	0.25	0.85	1.00	0.84
(6)	Zone 1	0.35	0.31	0.38	0.38	0.35	0.35
(7)	Zone 2	0.24	0.23	0.29	0.28	0.24	0.24
$\delta_b = 0.10$							
(8)	CBD	1.00	0.39	0.21	0.84	1.00	0.83
(9)	Zone 1	0.35	0.31	0.38	0.38	0.35	0.35
(10)	Zone 2	0.24	0.23	0.29	0.27	0.24	0.24
<i>C. Incomes</i>							
$\delta_b = 0.04$							
(11)	Type 1 / 0 Income	1.80	1.67	1.92	1.92	1.93	1.94
(12)	Type 1 Income / Worker	5.52	4.39	5.51	6.10	6.07	6.15
(13)	Type 0 Income / Worker	3.07	2.63	2.88	3.17	3.15	3.18
$\delta_b = 0.10$							
(14)	Type 1 / 0 Income	1.80	1.67	1.91	1.92	1.92	1.93
(15)	Type 1 Income / Worker	5.52	4.37	5.45	6.04	6.00	6.09
(16)	Type 0 Income / Worker	3.07	2.62	2.85	3.15	3.13	3.16

Figure 1: Differences in and Levels of Reported Commute Times

(a) Absolute Value of Difference of Individual Reported Commutes



(b) Raw Distribution of Individual Reported Commutes

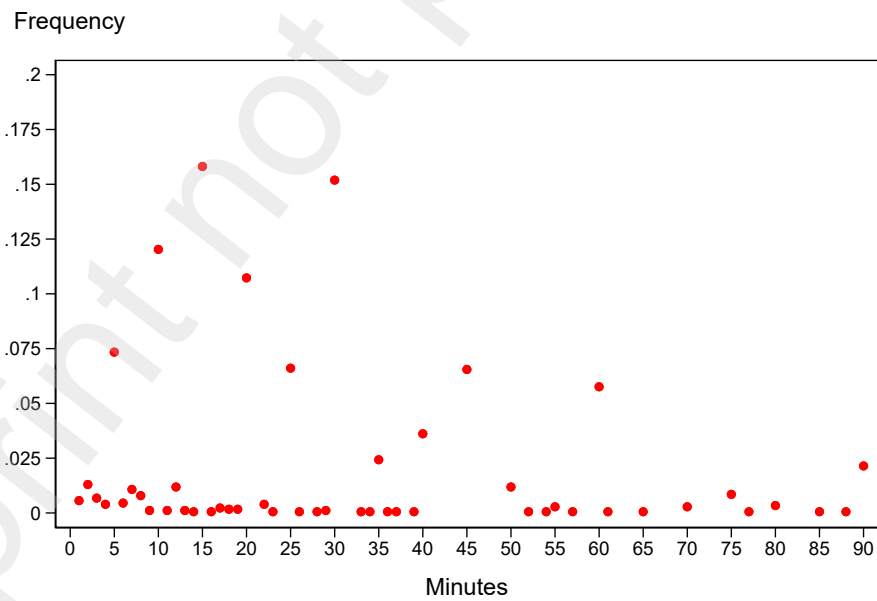
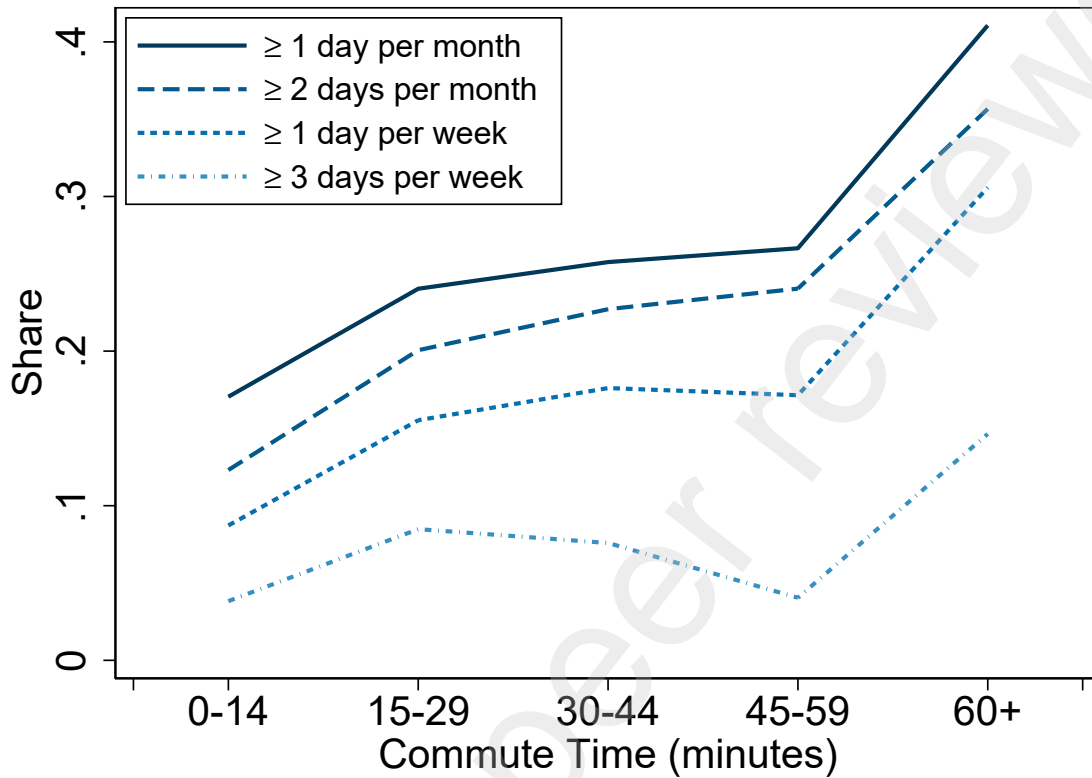


Figure 2: WFH Percentages versus Binned Commute Times



Notes: Observations are binned by average reported commute times. The x-axis is the commute-time bin and the y-axis reports the percentage of observations, conditional on the x-axis bin, sample respondents work from home at least one day per month (solid line), two days per month (dashed), one day per week (dotted), and three days per week (dash-dot). Outcomes are not mutually exclusive, for example a respondent that works from home at least three days per week also works from home at least one day per week, at least two days per month, and at least 1 day per month. Observations from the entire estimation sample are included and every share is computed using the IPWs described in the text.

A High-Skill Worker Problem

Denote consumption, housing, leisure, and amenities in location n for high-skill workers as c_n^1 , h_n^1 , ℓ_n^1 , and χ_n^1 . Utility over these variables for high-skill workers is

$$(A.1) \quad \nu^1 [\log \chi_n^1 + (1 - \alpha^1) \log c_n^1 + \alpha^1 \log h_n^1 + \psi^1 \log \ell_n^1].$$

High-skill workers maximize utility by choosing consumption, housing, leisure, hours to work in the CBD and at home, and office space to rent at the CBD and at home. Denote r^b as the rent per unit of office space in the CBD. For the time being, we suppress location subscripts (the n) and high-skill superscripts (the 1) to keep notation manageable. Thus, at any given location, high-skill workers maximize utility by solving

$$\max_{y, y^b, y^h, l^b, l^h, s^b, s^h, c, h, \ell} \nu [\log \chi + (1 - \alpha) \log c + \alpha \log h + \psi \log \ell]$$

subject to

$$\begin{aligned} 0 &= \mu_c [wy - c - r^b s^b - r (s^h + h)] \\ 0 &= \mu_y \left\{ [(y^b)^\rho + (y^h)^\rho]^{1/\rho} - y \right\} \\ 0 &= \mu_b \left[A^b (s^b)^\theta (l^b)^{1-\theta} - y^b \right] \\ 0 &= \mu_h \left[A^h (s^h)^\theta (l^h)^{1-\theta} - y^h \right] \\ 0 &= \mu_\ell [1 - (1 + t)l^b - l^h - \ell] \end{aligned}$$

where μ_c , μ_y , μ_b , μ_h , and μ_ℓ are Lagrange multipliers.

The first-order conditions are

$$\begin{aligned}
y : \quad & \mu_y = w\mu_c \\
y^b : \quad & \mu_b = \mu_y y^{1-\rho} (y^b)^{\rho-1} \\
y^h : \quad & \mu_h = \mu_y y^{1-\rho} (y^h)^{\rho-1} \\
l^b : \quad & \mu_\ell (1+t) = \mu_b (1-\theta) (y^b/l^b) \\
l^h : \quad & \mu_\ell = \mu_h (1-\theta) (y^h/l^h) \\
s^b : \quad & \mu_c r^b = \mu_b \theta (y^b/s^b) \\
s^h : \quad & \mu_c r = \mu_h \theta (y^h/s^h) \\
c : \quad & \mu_c = (1-\alpha)\nu/c \\
h : \quad & \mu_c r = \alpha\nu/h \\
\ell : \quad & \mu_\ell = \psi\nu/\ell.
\end{aligned}$$

From the FOCs for y^b and y^h we get

$$\frac{\mu_b}{\mu_h} = \left(\frac{y^b}{y^h}\right)^{\rho-1}$$

and the FOCs for s^b and s^h imply

$$(A.2) \quad \frac{s^b}{s^h} = \left(\frac{\mu_b}{\mu_h}\right) \left(\frac{y^b}{y^h}\right) \left(\frac{r^b}{r}\right)^{-1} = \left(\frac{y^b}{y^h}\right)^\rho \left(\frac{r^b}{r}\right)^{-1}.$$

Now use the production function for y^b and y^h to determine

$$\begin{aligned}
\frac{y^b}{y^h} &= \left(\frac{A^b}{A^h}\right) \left(\frac{s^b}{s^h}\right)^\theta \left(\frac{l^b}{l^h}\right)^{1-\theta} \\
&= \left(\frac{A^b}{A^h}\right) \left(\frac{y^b}{y^h}\right)^{\rho\theta} \left(\frac{r^b}{r}\right)^{-\theta} \left(\frac{l^b}{l^h}\right)^{1-\theta} \\
\left(\frac{y^b}{y^h}\right)^{1-\rho\theta} &= \left(\frac{A^b}{A^h}\right) \left(\frac{r^b}{r}\right)^{-\theta} \left(\frac{l^b}{l^h}\right)^{1-\theta} \\
(A.3) \quad \rightarrow \frac{y^b}{y^h} &= \left(\frac{A^b}{A^h}\right)^{\frac{1}{1-\rho\theta}} \left(\frac{r^b}{r}\right)^{\frac{-\theta}{1-\rho\theta}} \left(\frac{l^b}{l^h}\right)^{\frac{1-\theta}{1-\rho\theta}}.
\end{aligned}$$

Return to the FOCs for l^b and l^h

$$\begin{aligned}
\frac{l^b}{l^h} &= \left(\frac{\mu_b}{\mu_h} \right) \left(\frac{y^b}{y^h} \right) (1+t)^{-1} \\
&= \left(\frac{y^b}{y^h} \right)^\rho (1+t)^{-1} \\
&= \left(\frac{A^b}{A^h} \right)^{\frac{\rho}{1-\rho\theta}} \left(\frac{r^b}{r} \right)^{\frac{-\rho\theta}{1-\rho\theta}} \left(\frac{l^b}{l^h} \right)^{\frac{\rho(1-\theta)}{1-\rho\theta}} (1+t)^{-1} \\
\rightarrow \left(\frac{l^b}{l^h} \right)^{\frac{1-\rho}{1-\rho\theta}} &= \left(\frac{A^b}{A^h} \right)^{\frac{\rho}{1-\rho\theta}} \left(\frac{r^b}{r} \right)^{\frac{-\rho\theta}{1-\rho\theta}} (1+t)^{-1}
\end{aligned}$$

which gives us

$$(A.4) \quad \frac{l^b}{l^h} = \left(\frac{A^b}{A^h} \right)^{\frac{\rho}{1-\rho}} \left(\frac{r^b}{r} \right)^{\frac{-\rho\theta}{1-\rho}} (1+t)^{\frac{-(1-\rho\theta)}{1-\rho}}.$$

Equation (A.4) yields an expression for l^b/l^h , which we use with equation (A.3) to solve for y^b/y^h given prices r^b and r . Given y^b/y^h , r^b , and r we use equation (A.2) to solve for s^b/s^h .

Next, we combine the FOCs for l^b , l^h , and ℓ to show that leisure is a constant. Note that

$$\mu_\ell [(1+t)l^b + l^h + \ell] = \psi\nu + (1-\theta) [\mu_b y^b + \mu_h y^h].$$

Impose the time constraint and use the FOCs for y^b and y^h to get

$$\begin{aligned}
\mu_\ell &= \psi\nu + (1-\theta) \mu_y y^{1-\rho} [(y^b)^\rho + (y^h)^\rho] \\
&= \psi\nu + (1-\theta) \mu_y y^{1-\rho} [y^\rho] \\
&= \psi\nu + (1-\theta) \mu_y y \\
&= \psi\nu + (1-\theta) \mu_c w y.
\end{aligned}$$

Now consider the FOCs for c , h , s^h and s^b

$$\mu_c [c + r(s^h + h) + r^b s^b] = (1-\alpha)\nu + \alpha\nu + \theta [\mu_b y^b + \mu_h y^h].$$

Impose the budget constraint to get

$$\begin{aligned}
 \mu_c w y &= \nu + \theta [\mu_b y^b + \mu_h y^h] \\
 &= \nu + \theta \mu_c w y \\
 \text{(A.5)} \quad \rightarrow \mu_c w y &= \frac{\nu}{1 - \theta}
 \end{aligned}$$

which implies $\mu_\ell = \nu(1 + \psi)$. Insert this into the first order condition for ℓ to uncover

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

yielding that leisure is constant and independent of n . Given a value of the parameter ψ , equation (A.4) completely characterizes how the household uses time not spent enjoying leisure.

The expression for $\mu_c w y$ in equation (A.5) allows us to directly solve for consumption, housing, and spending on office space in the CBD and at home as a function of labor income (from the first-order conditions):

$$\begin{aligned}
 c &= (1 - \theta)(1 - \alpha) w y \\
 r h &= (1 - \theta) \alpha w y \\
 \text{(A.6)} \quad r^b s^b + r s^h &= \theta w y.
 \end{aligned}$$

Given a solution for s^b/s^h , and given solutions for l^b and l^h , equation (A.6) enables us to solve for s^b and s^h separately. Rewrite (A.6) as

$$s^h \left[r^b \left(\frac{s^b}{s^h} \right) + r \right] = \theta w y.$$

From the production function(s), we can then write

$$\theta w y = \theta w (s^h)^\theta \left[\left(A^b \left(\frac{s^b}{s^h} \right)^\theta (l^b)^{1-\theta} \right)^\rho + \left(A^h (l^h)^{1-\theta} \right)^\rho \right]^{1/\rho}.$$

Combining these last two equations gives an expression for s^h that is a function of all

terms that are known,

$$s^h = \left\{ \frac{\theta w \left[\left(A^b \left(\frac{s^b}{s^h} \right)^\theta (l^b)^{1-\theta} \right)^\rho + \left(A^h (l^h)^{1-\theta} \right)^\rho \right]^{1/\rho}}{\left[r^b \left(\frac{s^b}{s^h} \right) + r \right]} \right\}^{\frac{1}{1-\theta}}.$$

Once we know s^h , we also know s^b . Given knowledge of l^b , s^b , l^h , and s^h , we therefore know income wy and the entire allocation and utility for high-skill workers at any location n .

B Using Commute Times to Estimate the EOS between Work from Home and the Office

B.1 Constructing \bar{C}_i

A set of questions in the LJF allows us to determine the fraction of time each month that a respondent spends working at home. The first relevant question in the LJF is, “Are there days when you work only at home?” If the answer to this question is “no,” then we set the temporary variable $\tau_i = 0.0$. If the answer is “yes,” then respondents are asked the follow up question of “How often do you work only at home?” Rather than give a continuous number, possible responses are listed below along with our coding of τ_i :

Response	τ_i	calculation
5 or more days a week	21.25	5.0*4.25
3 to 4 days a week	14.875	3.5*4.25
1 to 2 days a week	6.375	1.5*4.25
at least once a week	4.25	1.0*4.25
once ever two weeks	2.125	0.5*4.25
once a month	1.0	
less than once a month	0.5	

We set \bar{C}_i , the fraction of time spent at the office, equal to $\frac{21.25 - \tau_i}{21.25}$.

B.2 The Linear Approximation of the Logistic Function

Define the logistic function in x as

$$f(x) = \frac{e^{a+bx}}{1 + e^{a+bx}}$$

A first order approximation to $f(x)$ around \bar{x} is

$$\begin{aligned} f(x) &\approx f(\bar{x}) + f'(\bar{x})(x - \bar{x}) \\ (A.7) \quad &= f(\bar{x}) + f(\bar{x})[1 - f(\bar{x})]b(x - \bar{x}) \\ &= \tilde{a} + f(\bar{x})[1 - f(\bar{x})]bx \end{aligned}$$

where $\tilde{a} = f(\bar{x}) \{1 - [1 - f(\bar{x})]b\bar{x}\}$.

In Table 1, we estimate the parameters of $f(x)$ for $x = \ln(1+t)$ using GMM and observed data on the fraction of days individuals work at home. We can thus map the approximation in Equation (A.7) to our strategy for estimating Ψ . We set $b = -3.0$ which is approximately equal to the estimate of Ψ in columns 1 and 2 of Table 1, $\bar{x} = 0.10$ (its sample average), and $a = 2.5$ which yields $f(\bar{x}) = 0.9$, roughly the sample average of $f(x)$ in our data.

Figure A.1 graphs $f(x)$ and its linear approximation for this parameterization. The figure shows $f(x)$ and its approximation for all commutes in the data; the vertical red lines bracket the middle 95 percent of commutes. The figure shows that for all commutes, but especially the 95 percent of commutes between the vertical lines, the linear approximation yields very close values to the actual function.

In the event that x is not measured with error, the near linearity of $f(x)$ for actual commute times and fraction of days worked shown in Figure A.1 suggests that if we were to run a linear regression of y on x , the regression coefficient would be approximately equal to

$$(A.8) \quad \hat{\gamma}^{OLS} \approx bf(\bar{x})[1 - f(\bar{x})].$$

This near linearity also implies that an unbiased estimate of b from GMM, \hat{b}^{GMM} , has the property

$$(A.9) \quad \hat{b}^{GMM} \approx \frac{\hat{\gamma}^{OLS}}{f(\bar{x})[1 - f(\bar{x})]}.$$

We believe that x is measured with error, such that when y is regressed on measured x , the regression coefficient from OLS will be equal to the estimate in equation (A.8) times ζ , where ζ is the attenuation bias due to the presence of measurement error. In the next section, we derive ζ^{-1} , the exact correction for attenuation bias in the case of OLS. Equations (A.8) and (A.9) suggest this correction will also work for our GMM estimate. The next section verifies this conjecture using a Monte Carlo simulation.

B.3 Monte Carlo Simulation of Analytical Bias Correction

B.3.1 Commute Time Data Generating Process

We conduct Monte Carlo simulation experiments to assess the performance of our proposed bias correction. The data generating process that we consider is,

$$\begin{aligned}
 i &= 1, \dots, N \\
 x_i^* &\sim N(\mu_{x^*}, \sigma_{x^*}^2) \\
 y_{it} &= \begin{cases} 1 & \text{with probability} = \Lambda(a + bx_i^*) \\ 0 & \text{with probability} = 1 - \Lambda(a + bx_i^*) \end{cases}, \text{ for } t = 1, \dots, T \\
 \bar{y}_i &= \frac{1}{T} \sum_{t=1}^T y_{it}
 \end{aligned}$$

There are N individuals. Each individual draws x_i^* from a normal distribution. The variable has a causal effect (logit parameter b) on the probability that a binary outcome y equals one. Each individual realizes $T = 5$ Bernoulli draws y_{it} , the average of which is \bar{y}_{it} .

The econometrician does not observe x_i^* , but does observe two measures

$$\begin{aligned}
 x_{i1} &= x_i^* + e_1 \\
 x_{i2} &= x_i^* + e_2
 \end{aligned}$$

$$\begin{bmatrix} e_{i1} \\ e_{i2} \end{bmatrix} \sim N \left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_e^2 & \rho_e \sigma_e^2 \\ \rho_e \sigma_e^2 & \sigma_e^2 \end{bmatrix} \right)$$

The measurement errors e_{i1} and e_{i2} are uncorrelated with x_i^* but are potentially correlated with one another (correlation ρ_e).

Our experiments involve simulating $R = 1,000$ datasets from this process for each of value of $\rho_e = 0.0, 0.1, 0.2, 0.3, 0.4, 0.5$. In each dataset, we compute the naive (ignoring measurement error) logit GMM estimator \hat{b}^{GMM} using the mis-measured variable x_1 as the only right-hand side regressor, and our proposed bias-corrected estimator \hat{b}^{BC} . The naive GMM estimator solves,

$$(\hat{a}^{GMM}, \hat{b}^{GMM}) = \arg \min_{(a,b)} \hat{m}'(a,b) \mathcal{W} \hat{m}(a,b)$$

where

$$\begin{aligned} \epsilon_i(a,b) &= \bar{y}_i - \Lambda(a + bx_{i1}) \\ \hat{m}_0(a,b) &= \sum_i \epsilon_i(a,b) \\ \hat{m}_1(a,b) &= \sum_i x_{i1} \epsilon_i(a,b) \\ \hat{m}(a,b) &= \begin{bmatrix} \hat{m}_0(a,b) \\ \hat{m}_1(a,b) \end{bmatrix} \end{aligned}$$

and \mathcal{W} is an optimal weighting matrix. As described in the text, the bias-corrected estimator is computed using

$$\begin{aligned} \hat{b}^{BC} &= \hat{b}^{GMM} \left(\frac{\widehat{var}(x_1)}{\widehat{var}(x^*)} \right) \\ &= \hat{b}^{GMM} \left(\frac{\widehat{var}(x_1)}{\widehat{var}(x_1) - \widehat{var}(e)} \right) \\ \text{(A.10)} \quad &= \hat{b}^{GMM} \left(\frac{\widehat{var}(x_1)}{\widehat{var}(x_1) - \left(\frac{\widehat{var}(x_1) - \widehat{cov}(x_1, x_2)}{1 - \rho_e} \right)} \right) \end{aligned}$$

where ρ_e is an assumed value, and $\widehat{var}(x_1)$, $\widehat{cov}(x_1, x_2)$ are computed in the (simulated) data.

B.3.2 Parameter Values for Simulations

For each simulated dataset, we set $N = 1700$. We do separate experiments for each value of ρ_e for $\rho_e = 0.0, 0.1, 0.2, 0.3, 0.4$ and 0.5 . At each assumed ρ_e , we choose values for the other parameters of the data generating process to match three moments from the actual commute data.

- Data moment $\text{var}(\ln(1 + t_{i1})) = .0707^2 = .005$ to set $\text{var}(x_1) = .005$
- Data moment $\text{cov}(\ln(1 + t_{i1}), \ln(1 + t_{i2})) = .00348$ to set $\text{cov}(x_1, x_2) = .00348$
- Naive estimator $\hat{\Psi}^{GMM} \approx -3$ to set b (by targeting the attenuated \hat{b}^{GMM})

To find the values of $\sigma_{x^*}^2$ and σ_e^2 that are consistent with these moments, we note that

$$\begin{aligned}\text{var}(x_1) &= \sigma_{x^*}^2 + \sigma_e^2 \\ \text{cov}(x_1, x_2) &= \sigma_{x^*}^2 + \rho_e \sigma_e^2\end{aligned}$$

which imply

$$\begin{aligned}\sigma_e^2 &= \frac{\text{var}(x_1) - \text{cov}(x_1, x_2)}{1 - \rho_e} = \frac{.005 - .00348}{1 - \rho_e} \\ \sigma_{x^*}^2 &= \text{var}(x_1) - \sigma_e^2 = .005 - \sigma_e^2\end{aligned}$$

Beginning with equation (A.10), we set

$$\begin{aligned}b &= \hat{b}^{GMM} \times \left(\frac{\text{var}(x_1)}{\text{var}(x_1) - \left(\frac{\text{var}(x_1) - \text{cov}(x_1, x_2)}{1 - \rho_e} \right)} \right) \\ &= -3 \times \left(\frac{.005}{.005 - \left(\frac{.005 - .00348}{1 - \rho_e} \right)} \right)\end{aligned}$$

We choose $\mu_{x^*} = 0.1$ and thus set $a = 1.7$ to approximately match the unconditional fraction of days spent working in the office.

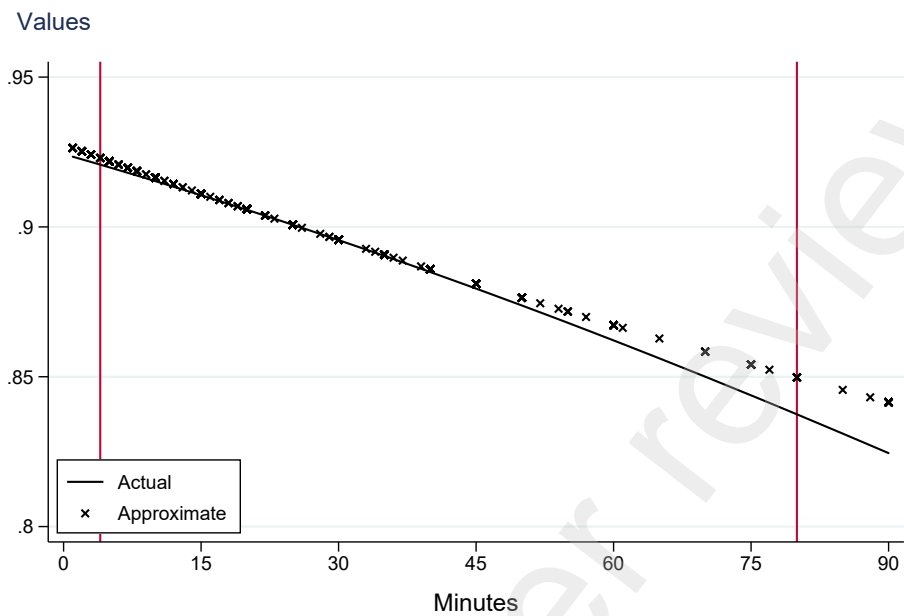
B.3.3 Results

In each simulated dataset, we compute the naive GMM estimator \hat{b}^{GMM} and compute the corresponding bias corrected estimator using equation (A.10). Table A.1 summarizing the results. For each value of ρ_e , the bias corrected estimator has a sampling mean that is close to the assumed value of b , which occurs because the naive GMM estimator has a sampling mean that is close to -3, suggesting that, under a correct assumptions of ρ_e , the bias-corrected GMM estimator provides unbiased estimates of b with measurement error in x_1 and x_2 that mimics the properties of the measurement error in our commute data.

Table A.1: Monte Carlo Simulation Results

ρ_e	Assumed b	\hat{b}^{BC}	\hat{b}^{GMM}
0.0	-4.31	-4.30	-2.99
0.1	-4.53	-4.51	-2.98
0.2	-4.84	-4.85	-3.00
0.3	-5.30	-5.26	-2.98
0.4	-6.08	-6.05	-2.98
0.5	-7.65	-7.56	-2.96

Figure A.1: Logistic Function and First-Order Approximation



Notes: 1) Recall that $t = 2 * \text{minutes} / (8 * 60)$, where minutes refers to the time required for a one-way commute to work.