Measuring the Productivity of Working from Home

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Abstract

We document a doubling of hours worked at home in the US from 2003 to 2019. We propose a model where workers choose optimally where (at home, at the office, or both) and how many hours to supply at each location. These choices depend on the availability of work-from-home technology, the relative productivity of working from home, worker preferences across locations, and commute times. We estimate the model, allowing each of these factors to vary over time and decompose the rise in remote hours. We find that changes in technology and productivity account for approximately 62% of the increase, while rising commute times and changes in preferences account for a further 30%.

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1 Introduction

Are we more productive working from home than at the office? This question has never been more salient than now. Since the start of the pandemic researchers have tried to understand how a sudden shift in working from home has affected individuals' productivity and preference for working there. In this paper, we estimate the productivity and preferences for working from home prior to the pandemic, and document how these have changed over time, across demographic groups, and across occupations. Finally, we quantify to what extent changes in preferences, productivity, and the composition of the workforce have contributed to the rise of working from home.

Using the American Time Use Survey (ATUS) from 2003 to 2019, we document three facts that together motivate our modeling choices. First, the propensity and intensity of working from home vary substantially across occupations and have garnered increased attention due to the COVID-19 pandemic, [Dingel and Neiman, 2020, Hensvik et al., 2020, Adams-Prassl et al., 2022, Bick et al., 2023]. This heterogeneity points to something occupation-specific, such as the nature of tasks performed, as a primary determinant of the productivity of home-based work. Second, average weekly hours worked at home nearly doubled between 2003 and 2019. We show that this increase is driven by increases along two distinct margins: the number of workers who primarily work from home, similar to Mateyka et al. [2012], and the number of people who split their workday across the workplace and home.[1] These two margins have evolved differently. The intensive margin among splitters remains broadly flat while hours among full-day home workers have risen. This suggests the mechanisms driving participation and intensity are distinct and calls for a model that separates them. Third, average commute times rose over the same period, increasing the time cost of attending the workplace independently of any change in preferences or productivity.

To decompose the rise in work from home, we build a model in which workers optimally choose both how many hours to work and where to work, at home, at the workplace, or both, taking as given

[1] Also see Mas and Pallais [2020] for a nice review of the trends in alternative work arrangements in the US.

their preferences, their commute time, and the productivity of home-based work in their occupation. The model distinguishes three channels through which the rise in remote hours can occur. The first is a technology channel: not all jobs offer a work-from-home option, and an increase in the fraction that do, reflecting improvements in firm-level infrastructure for remote work, raises the share of workers with any home hours. The second is a productivity channel: conditional on having the option to work from home, a worker's allocation of hours across locations depends on how productive an hour at home is relative to an hour at the office, which varies by occupation. Here, we allow the model to distinguish between workers who split their day and teleworkers by including a productivity shock, which allows workers to work the full day at home. An increase in this shock can reflect changes in the task composition of occupations over time. The third is a preference channel: workers differ in their relative disutility for working at home, which varies across demographic groups. Commute times, which vary across workers, enter the model directly as a time cost of attending the workplace: longer commutes push workers toward working from home independently of any change in preferences or productivity.

We model the disutility of working as CES between hours at the office and hours at home, with a common substitution parameter that governs the curvature of the tradeoff between the two locations. Because this substitution parameter cannot be separately identified from the relative disutility of work from home within the model, we estimate it in a first stage using the ATUS Job Flexibility and Leave Module. We exploit variation in whether workers are paid for the work they do at home as a proxy for the relative productivity of home hours to estimate the elasticity of substitution. The first-stage estimates imply that home and office hours are substitutes in the disutility of work, with an elasticity of substitution of 2.6, which is considerably lower than the value used by Kaplan et al. [2020]. Taking this first-stage estimate as given, we then estimate the remaining parameters by simulated method of moments, matching moments of the distribution of hours worked at home and at the workplace by occupation and demographic group separately for 2003-2010 and 2011-2019.

From the estimated model, we find that on the preference side, the relative disutility of working from home has fallen for most demographic groups between the two periods, with the largest declines among low-education workers. On the productivity and technology side, we find that the estimated relative productivity of home hours is low on average, around 0.11 across occupations, consistent with the interpretation that splitters bring home marginal tasks rather than full workdays. The probability of receiving a teleworking shock, has increased in most occupations. The fraction of firms offering a work-from-home option averages around 21% in the first period, rising modestly to 23%, with the largest increases in management and arts occupations.

To quantify the contribution of each channel to the observed rise in home hours, we construct four counterfactuals, each holding one group of parameters fixed at its first-period values. Holding the fraction of WFH-offering firms fixed (the technology channel), weekly home hours would have risen by only about 30 minutes rather than the observed hour, implying technology accounts for approximately 50% of the rise. Holding productivity parameters fixed accounts for a further 12%, and holding preferences fixed accounts for approximately 28%. Rising commute times account for less than 1% of the observed increase. Together, technology and productivity account for roughly 62% of the rise, while preferences and commutes account for a further 30%, with the remainder reflecting changes in the occupational and demographic composition of employment. The finding that productivity and technology has played a larger role is similar to Bick et al. [2023] who find that the widespread adoption of working from home due to the pandemic accounts for its persistence after reopening, rather than preferences to work from home.

Prior to the COVID-19 pandemic, there were few studies trying to estimate the productivity of working from home, notably Bloom et al. [2015] run an experiment at a call center in China and find that productivity, measured as calls per minute, increased by about 4% for workers allowed to work from home. Similarly, Emanuel and Harrington [2024] find that the productivity of call center workers rose another 7.6% when forced to work from home due to COVID-19. However, Monteiro et al. [2019], using evidence from policy changes in Portuguese firms find that WFH has negative effects on productivity but differs largely across firm types. Post-pandemic research on the productivity of WFH relies largely on worker or firm surveys and also varies in results. In a survey of workers and firms in Japan, Morikawa [2022] finds productivity from home is about 60%-70% lower than at the workplace. On the other hand, Barrero et al. [2021], using a survey of workers in the US, show that many workers report being more productive from home. Etheridge et al. [2020] show evidence from a survey of workers in the UK, that self-reported productivity during the pandemic differs for workers who had experience working from home prior to the lockdowns.

Overall, the literature on the relative productivity of working from home is in its infancy, and the results are mixed so far. In this paper, we contribute to this literature by providing evidence of the relative productivity of working from home prior to the pandemic and across different occupations. Similar to the studies using worker surveys, we find that worker characteristics, such as gender and education, play an important role in the decision to work from home or the workplace, see Bick et al. [2023], Etheridge et al. [2020], Pabilonia and Vernon [2022]. We differ from these previous studies by estimating productivity from workers' optimal hours choices rather than self-reported productivity. While both approaches have their benefits, we believe that one advantage of our approach is that productivity is defined clearly by the model, and its definition does not differ across workers in the model, in contrast to self-reported productivity where differences in reported productivity can stem from disparities in the understanding of what productivity is.

Two closely related papers study the rise in working from home using structural spatial equilibrium models but take opposing positions on its underlying driver. Davis et al. [2024] argue that the pandemic induced a large and permanent increase in the productivity of working from home relative to the office, and that this productivity shift is the primary engine behind the rise in remote work. In their model, workers freely allocate time between home and office, and the observed increase in WFH is rationalized by a large change in relative total factor productivity. Delventhal and Parkhomenko [2025], by contrast, attribute the post-pandemic rise in remote work primarily to a decline in workers' aversion to working from home, rather than a change in productivity. In their model, pre-pandemic workers exhibit substantial disutility from telecommuting, and the pandemic caused a large reduction in this aversion while the productivity of remote work changed only modestly. Our paper contributes to this debate by estimating both channels simultaneously from pre-pandemic data, allowing the data to determine their relative importance, rather than assuming one channel drives the rise. We find that both matter, though technology and productivity together account for a larger share of the pre-pandemic trend than preferences.

2 Data

The main source of data is the 2003–2019 releases of the American Time Use Survey (ATUS), which, on top of a host of individual characteristics, contains information on where, how, and with whom Americans spend their time. The ATUS contains a random sample of individuals who, within the last 2 to 5 months, have completed their final interview for the Current Population Survey (CPS). A respondent is asked to recount what activities they engaged in, when and where these activities took place, and with whom, if others were present, on a single interview ("diary") day. All of the activities in the diary day are then coded into one of over 400 categories.

We restrict our sample to people between the ages of 25 and 64, who were interviewed on a weekday. We drop self-employed and those working without pay. Table 1 contains summary statistics for demographic characteristics and job characteristics. Within our sample 79% of respondents worked at their place of work on the interview day and 85% spent some time working on the interview day.

There are two measures of work that are of primary interest. First, if the respondent went to work on the diary day, we construct *total time working at the workplace* by summing the duration of all work-related activities done at the workplace. About 43% of the sample spends some time not working while at work (on average 43 minutes) and this time is not included in our measure of working at work. This

Table 1: Demographic Summary Statistics: ATUS 2003-2019

Characteristic	Sample Mean	Characteristic	Sample Mean
Female	0.48	College	0.26
Married	0.63	Black	0.11
Age	42.73	White	0.82
Child	0.45	Other	0.07
Less than HS	0.06	Full Time	0.87
High School	0.27	At Work Place	0.79
Some College	0.26	Worked	0.87
Advanced Degree	0.15		
Total number of Observations			45,543

Note: ATUS weights used in all calculations, the weights adjusted so that each day is $1/5^{th}$ of our subsample. For more on the importance of these weights, see Frazis and Stewart [2014]. The variable "At Work Place" summarizes the number of respondents that reported working at their place of work during the interview day. The variable "Worked" summarizes the number of people that reported spending some time working on the interview day.

time is mostly spent eating but also includes other activities. The distinction between work and non-work activities in the ATUS comes from the purpose of the activity. For example, if the interviewee states that they used a computer for 40 minutes at the workplace, the activity is recorded as work if the computer was used for work purposes.[2] Otherwise, if the computer was used for non-work purposes (for example reading the news) the activity is recorded as computer used for "Socializing, Relaxing, and Leisure."[3] Similar structures are used for other activities that could be done for multiple purposes. Second, we measure total *work from home (WFH)* as the duration of work, either for the main job or any other jobs, done at the respondent's home.

We document three features of the data that motivate our model. First, the propensity and intensity of working from home varies considerably across occupations, suggesting that something occupation-specific, such as the nature of the tasks workers perform, shapes the productivity of home-based work. Second, average weekly hours worked at home have increased substantially since 2003, driven by both

[2] ATUS activity code 50101.
[3] ATUS activity code 120308.

more workers doing any work from home and more workers working exclusively from home. Third, average commute times have risen over the same period, increasing the time cost of attending the workplace and making the option to work from home more valuable. Together these facts point toward a model in which occupation-specific productivity of home-based work, worker preferences for working from home, and commute times jointly determine where and how much workers choose to work.

2.1 Fact 1: Large Cross-Occupation Differences in Work from Home

Table 2 contains summary statistics about time at work. Panel (a) summarizes all work (work at the workplace and work at home): 85% of the sample participated in any work on the interview day. The average time spent working is about 7 hours and, conditional on participating in some work, the average hours worked on the interview day is 8.15. Panel (b) summarizes time spent working at the workplace, which 79% of the respondents did on the interview day. Among the entire sample, the average time spent working at the workplace is 6.5 hours, and conditional on working at the workplace, respondents spent 8.19 hours working. Finally, panel (c) summarizes working from home. 15% of the sample participated in some work from home. This is similar to Brynjolfsson et al. [2020], who find in a survey conducted April 2020 that 15% of workers say they used to work from home before the start of the pandemic. Unconditionally, the average time working at home is about 25 minutes, and conditional on working from home the average time spent doing so is 2.86 hours.

These aggregate statistics, however, mask substantial differences across occupations. Figure 1 plots participation in WFH and average minutes of WFH by occupation. Education, training, and library occupations have the highest probability of observing a person working from home (0.31) while production occupations have the lowest (0.04). The differences in minutes are similarly large: computer and mathematical science occupations worked on average an hour and 15 minutes at home, whereas production and food preparation and serving-related occupations spent about 5 minutes working at home on average. The ranking is similar when looking at conditional minutes. The magnitude of these

Table 2: Hours Worked Summary Statistics: ATUS 2003-2019

	Sample Mean
Panel (a): All Work	
Participation	0.87
Hours per worker	7.19
Hours per participating worker	8.26
Panel (b): Work at Workplace	
Participation	0.79
Hours per worker	6.52
Hours per participating worker	8.21
Panel (c): Work at Home	
Participation	0.15
Hours per worker	0.44
Hours per participating worker	2.85
Total number of Observations	45,543

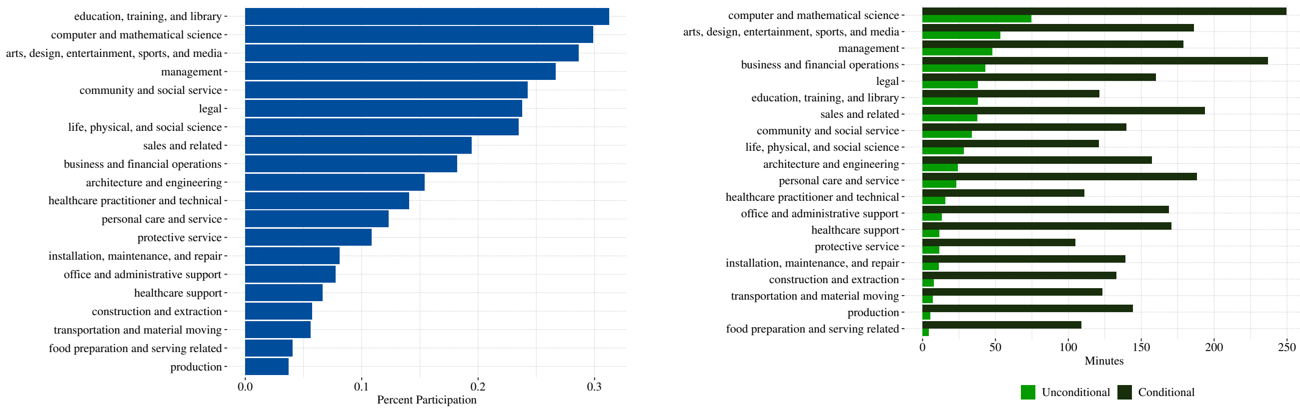
Note: ATUS weights used in all calculations. The weights are adjusted so that each day is $1/5^{th}$ of our subsample. For each category of work, participation summarizes the number of respondents that participated in the activity, unconditional hours summarize the average hours spent in the activity across all respondents, and conditional hours summarize the hours spent in the activity across all respondents that participated.

differences suggests that occupation plays a central role in determining the productivity of home-based work, an hour at home is simply more feasible in some occupations than others. This motivates our approach of allowing the productivity of home-based work to vary across occupations.

2.2 Fact 2: Hours Worked at Home Have Increased on Both Margins

Panel (a) of Figure 2 plots average weekly hours worked at home per worker from 2003 to 2019. Hours worked at home nearly double over the period, rising from around 2 hours per week in 2003 to close to 4 hours per week by the end of 2019. Total hours worked per worker were broadly stable over the same period, implying that the rise in home hours represents a genuine substitution of home for office time

Figure 1: Participation and Minutes of WFH



(a) Participation Percentage

(b) Minutes

Note: ATUS weights used in all calculations. The weights are adjusted so that each day is $1/5^{th}$ *of our subsample. Panel (a) plots the average participation rate of work from home in each occupation over the sample period. Panel (b) plots the average hours worked from home in each occupation, unconditional on participation and conditional on participation over the sample period.*

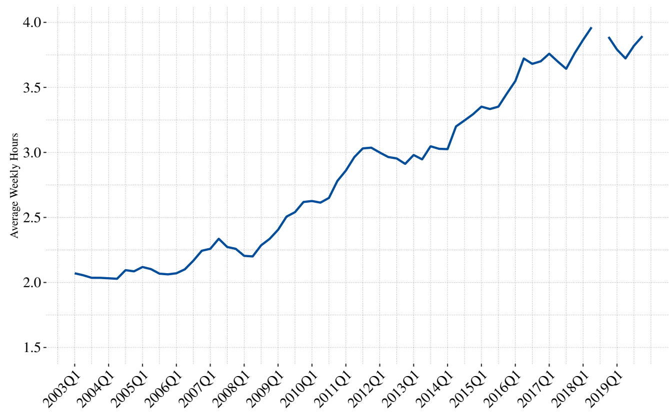
rather than an overall increase in work effort.

One potential concern is that this increase reflects workers answering emails or finishing tasks in the evening after a full day at the office, rather than genuine substitution of home for office hours during the working day. Figure 3 addresses this directly by decomposing total hours worked at home into those worked during standard working hours (9am–5pm) and those worked outside of standard hours. The majority of the increase is concentrated during the standard working day, confirming that the rise in home hours reflects real substitution between locations rather than a secular increase in after-hours work.

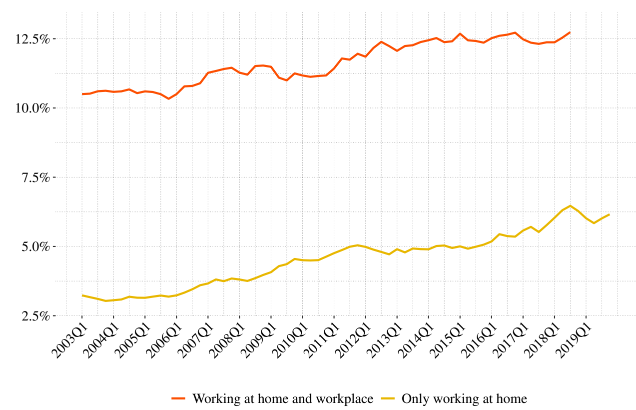
The rise in average hours worked at home is driven by changes along two distinct margins, shown in panel (b) of Figure 2. Both the share of workers splitting their workday between home and the office and the share working exclusively from home (teleworkers) have increased over the sample period: the fraction of teleworkers rose from around 3.8% in 2003 to nearly 7% in 2019, while the fraction of workers splitting their workday increased from 10% to 12.5%.[4]

[4] This is similar to what others have found. Pabilonia and Vernon [2022] find the fraction of workers working exclusively from home is 2.8% in the Job Leave and Flexibility Module of the ATUS, Mateyka et al. [2012] find 6.6% in the Survey of Income and Program Participation in 2010 and 12% in 2017 using the National Household Travel Survey.

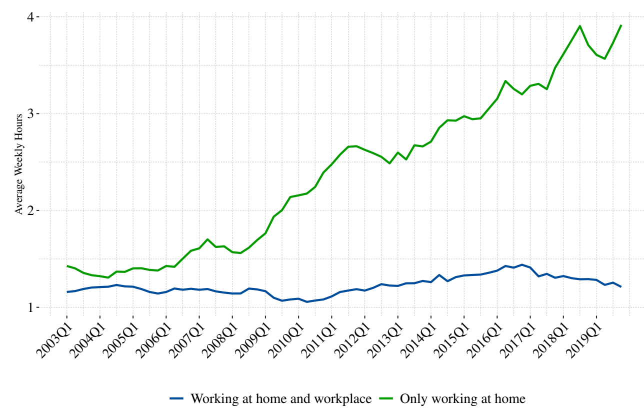
Figure 2: Trends in Hours Worked at Home



(a) Average Weekly Hours Worked at Home



(b) Fraction Who Participated in WFH

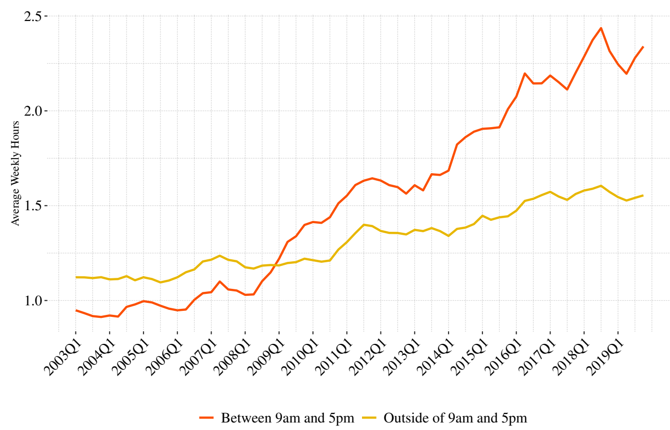


(c) Average Weekly Hours of WFH by Group

Note: ATUS weights used in all calculations. The weights are adjusted so that each day is $1/5^{th}$ *of our subsample. Panel (a) plots average weekly hours worked at home per worker. Panel (b) plots the fraction of workers who worked from home and the workplace and the fraction who worked only from home on the diary day. Panel (c) plots average weekly hours worked at home separately for workers who split their time between home and the workplace and workers who worked only from home. See Appendix A.1 for details about how these series are constructed.*

The two margins tell different stories, as shown in panel (c) of Figure 2. Among workers who split their time between home and the office, the average hours devoted to home has remained broadly stable over the period, suggesting that the relative attractiveness of home versus office work has not changed much for this group. In contrast, among workers who work exclusively from home, average hours at home have increased substantially. The aggregate rise in WFH hours therefore reflects two distinct forces: an increase in the fraction of workers doing any work from home, and an increase in hours among those who work exclusively at home. Understanding what drives each of these margins

Figure 3: Work From Home during Standard Work Hours



Note: ATUS weights used in all calculations. The weights are adjusted so that each day is $1/5^{th}$ *of our subsample. The figure decomposes total hours worked at home into those worked during standard working hours (9am–5pm) and those worked outside of standard working hours.*

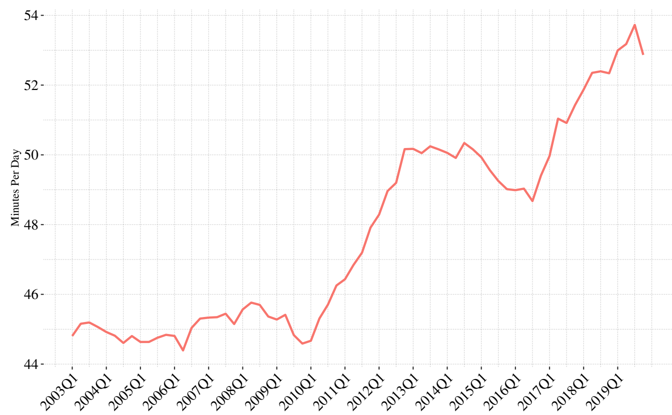
separately, whether it is the availability of work-from-home jobs, the productivity of home-based work, or worker preferences, requires a model that distinguishes between them, which we develop in the next section.

2.3 Fact 3: Commute Times Have Increased

Figure 4 plots average commute times over the sample period.[5] Average commute times have increased over the period, meaning that the time cost of attending the workplace has grown. This matters for the decision of where to work in two ways. First, a longer commute reduces the time available for work, pushing more workers toward the time constraint and making the option to work from home more valuable. Second, conditional on being time-constrained, a longer commute makes working exclusively from home more attractive relative to commuting to the office. Together, these forces imply that rising commute times can independently generate an increase in hours worked at home, even holding fixed the productivity of home-based work and worker preferences. Accounting for changes in commute times is therefore important for correctly attributing the rise in WFH to its underlying causes.

[5]We measure commute time as the total duration of travel to and from the workplace on the diary day, constructed by summing work-related travel activities in the ATUS. This concept corresponds directly to the commute time that enters the model.

Figure 4: Average Commute Time per Worker



Note: ATUS weights used in all calculations. The weights adjusted so that each day is $1/5^{th}$ *of our subsample. Commute time is measured as total travel time to and from the workplace on the diary day.*

2.4 Summary

Together, these three facts point toward a model with three key ingredients. The cross-occupation heterogeneity in WFH intensity calls for occupation-specific productivity of home-based work. The two-margin rise in WFH hours calls for both a model of which jobs offer a work-from-home option and a model of how workers who have that option optimally allocate their time across locations, allowing for heterogeneous worker preferences. The rise in commute times calls for a role for the time cost of attending the workplace as a driver of the WFH decision. In the next section we develop a model that incorporates each of these features, and in the estimation section we use the variation documented here to separately identify the contribution of each channel to the rise in hours worked at home.

3 Model

In this section, we build a model of working from home in which firms demand units of labor input and workers can produce units of labor input using hours worked, either at the workplace or at home. The relative productivity of working from home, as well as preferences for working from home determine how workers choose to divide their time between the workplace and home. We abstract from occupational choice and do not allow for shirking at the workplace or at home. The model is static; each day of length T hours, workers choose how many hours to work at home and at the workplace, given their preferences, the productivity of working from home, and their commute time.

Workers are heterogeneous with respect to a set of observable characteristics. For the purposes of estimation, workers are indexed by d, denoting one of eight mutually exclusive demographic groups defined by sex, parental status, and education. Each demographic group is characterized by one preference parameter that determines the relative attractiveness of working from home χ_d. Within each demographic group, workers remain heterogeneous with respect to their total disutility of work, $\eta \sim G_\eta(k_d^\eta, \theta_d^\eta)$, and their commute time, $m \sim G_m(k_d^m, \theta_d^m)$, both of which are drawn from distributions whose parameters are common within the demographic group but whose realized values differ across workers.

Jobs are heterogeneous with respect to occupation, indexed by o. Within each occupation, a fraction ϕ_o of jobs allow workers to choose between working at the workplace or at home, while the remaining $1-\phi_o$ jobs require workers to work exclusively at the workplace. For jobs that offer a work-from-home option, two parameters characterize the productivity of working from home. First, with probability ψ_o the worker receives a teleworking shock and works the full day at home. We interpret this shock as the probability that the worker is assigned tasks that can be done fully remotely. Second, if the worker does not receive a teleworking shock, the relative productivity of working from home, γ_o, is common across all jobs within the same occupation. In this case, the worker can choose to transfer some of their hours worked at the workplace to home at a rate γ_o. For the purposes of estimation, o indexes one of 17 two-digit occupations, within which jobs are assumed to share common productivity parameters γ_o, ψ_o, and ϕ_o.

3.1 Workers at jobs without work-from-home option

A worker in demographic group d employed at a job without a work from home option, who draws total disutility $\eta \sim G_\eta(k_d^\eta, \theta_d^\eta)$ and commute time $m \sim G_m(k_d^m, \theta_d^m)$, maximizes:

$$\max_{c,h^w} \log(c) - \eta h^w$$

$$\text{s.t. } c = wh^w$$

$$h^w + m \leq T.$$

The optimal hours worked for a worker without a work-from-home option depends on their disutility of work, η, and their commute time

$$h^w = \begin{cases} \frac{1}{\eta} & \frac{1}{\eta} - m \leq T \\ T - m & \frac{1}{\eta} - m > T \end{cases} \tag{1}$$

$$h^h = 0. \tag{2}$$

Workers with a sufficiently short commute or low disutility of work are unconstrained and work $\frac{1}{\eta}$ hours, while workers with a long commute relative to their desired hours hit the time constraint and work $T - m$ hours instead. Equation (1) shows that hours worked at jobs without a work-from-home option vary both within and across demographic groups. Within a demographic group, heterogeneity in hours worked arises from dispersion in the draws of η and m, whose distributions are characterized by group-specific shape and scale parameters $(k_d^\eta, \theta_d^\eta)$ and (k_d^m, θ_d^m), respectively. Across demographic groups, differences in the mean and variance of hours worked reflect differences in these distribution parameters.

3.2 Jobs with work-from-home option

For jobs that offer a work-from-home option, the labor input of a worker in occupation o is the sum of hours worked at the workplace and hours worked at home, weighted by the relative productivity of working from home, $\gamma_o \geq 0$, that is $\ell = h^w + \gamma_o h^h$. Workers are paid w per unit of labor input, so their budget constraint reflects the total labor input they deliver across both locations. A worker in demographic group d employed at a job with the option of working from home, who draws total disutility $\eta \sim G_\eta(k_d^\eta, \theta_d^\eta)$ and commute time $m \sim G_m(k_d^m, \theta_d^m)$, and does not receive a teleworking shock (probability $1 - \psi_o$), maximizes utility subject to their budget constraint and commute time:

$$\max_{\{c,h^h,h^w\}} \log(c) - \eta[(\chi_d h^h)^\rho + (h^w)^\rho]^{\frac{1}{\rho}}$$

$$\text{s.t. } c = w(h^w + \gamma_o h^h)$$

$$h^w + h^h + m \leq T.$$

The first-order conditions for hours worked at an interior solution are

$$\frac{1}{h^w + \gamma_o h^h} - \eta[(\chi_d h^h)^\rho + (h^w)^\rho]^{\frac{1}{\rho}-1}(h^w)^{\rho-1} = 0$$

$$\frac{\gamma_o}{h^w + \gamma_o h^h} - \eta[(\chi_d h^h)^\rho + (h^w)^\rho]^{\frac{1}{\rho}-1}(h^h)^{\rho-1}\chi_d^\rho = 0.$$

Dividing the two first-order conditions, the ratio of optimal hours worked at home to hours worked at the workplace is given by

$$\frac{h^h}{h^w} = \left(\frac{\gamma_o}{\chi_d^\rho}\right)^{\frac{1}{\rho-1}}. \tag{3}$$

Equation 3 shows that the hours ratio depends only on the relative productivity of working from home, γ_o, and the relative disutility of working from home, χ_d, and is common to all workers within the same demographic group d employed in the same occupation o. Total hours at home and at the workplace for an unconstrained worker are

$$h^h = \frac{\chi_d^{\frac{\rho}{1-\rho}} \gamma_o^{\frac{1}{\rho-1}}}{\eta \left[1 + \chi_d^{\frac{\rho}{1-\rho}} \gamma_o^{\frac{\rho}{\rho-1}}\right]^{\frac{1}{\rho}}} \tag{4}$$

$$h^w = \frac{1}{\eta \left[1 + \chi_d^{\frac{\rho}{1-\rho}} \gamma_o^{\frac{\rho}{\rho-1}}\right]^{\frac{1}{\rho}}}. \tag{5}$$

Equations (4) and (5) show that while the hours ratio is common within demographic group and occupation, the levels of hours worked at home and at the workplace vary across workers within a group through heterogeneity in the draw of total disutility η. Workers with higher disutility of work supply fewer hours at both locations, but in the same ratio. Across demographic groups, differences in χ_d shift the hours ratio and therefore the allocation of hours between home and the workplace, while differences in the distribution of η generate differences in the level of total hours worked.

A worker is constrained if their desired total hours exceed the available time net of commuting, that is,

$$m + \frac{\chi_d^{\frac{\rho}{1-\rho}} \gamma_o^{\frac{1}{\rho-1}} + 1}{\eta \left[1 + \chi_d^{\frac{\rho}{1-\rho}} \gamma_o^{\frac{\rho}{\rho-1}}\right]^{\frac{1}{\rho}}} > T. \tag{6}$$

In this case, the time constraint binds, and the worker chooses between three options: splitting their time between the workplace and home, working only at the workplace, or working only at home. If the worker splits the day between the workplace and home, they allocate the available time $T - m$ across the two locations in the same ratio as the unconstrained solution:

$$h^{w,S} = \frac{T - m}{\left[1 + \chi_d^{\frac{\rho}{1-\rho}} \gamma_o^{\frac{1}{\rho-1}}\right]}$$

$$h^{h,S} = \frac{(T - m)\chi_d^{\frac{\rho}{1-\rho}} \gamma_o^{\frac{1}{\rho-1}}}{\left[1 + \chi_d^{\frac{\rho}{1-\rho}} \gamma_o^{\frac{1}{\rho-1}}\right]}.$$

If instead the worker chooses to work only at the workplace or only at home, their optimal hours are

$$h^{w,C} = \begin{cases} \frac{1}{\eta} & \frac{1}{\eta} - m \leq T \\ T - m & \frac{1}{\eta} - m > T \end{cases} \qquad h^{h,C} = \begin{cases} \frac{1}{\eta} & \frac{1}{\eta} \leq T \\ T & \frac{1}{\eta} > T. \end{cases}$$

The constrained worker chooses whichever option delivers the highest utility, where the consumption values associated with each option are $c^S = w(h^{w,S} + \gamma_o h^{h,S})$, $c^{C_w} = wh^{w,C}$, and $c^{C_h} = w\gamma_o h^{h,C}$ respectively. Whether a worker is constrained and which option they choose depends on their draws of η and m, generating further dispersion in hours worked within demographic groups and occupations beyond that arising from the unconstrained solution.

The final case is when the worker receives a teleworking shock, which occurs with probability ψ_o. In this case the worker maximizes

$$\max_{\{c,h^h\}} \log(c) - \eta\chi_d h^h$$
$$\text{s.t. } c = w\gamma_o h^h.$$

The optimal hours worked for a worker with a preference shock to work the full day at home are

$$h^h = \frac{1}{\eta\chi_d} \tag{7}$$
$$h^w = 0. \tag{8}$$

Hours worked at home for these workers depend on the draw of η and the group-specific relative disutility χ_d, and are independent of the relative productivity γ_o and commute time m.

3.3 Model Summary

The model delivers a set of observable hours worked at home and at the workplace, and the parameters governing preferences and productivity map distinctly onto three observable margins of working from home. We group the parameters into four categories that will form the basis of the counterfactual analysis in section 5. The relative disutility of working from home, χ_d, captures worker *preferences* for home-based work. The relative productivity of working from home, γ_o, and the occupation-specific teleworking shock, ψ_o, together capture the *productivity* of home-based work. The fraction of firms offering a work-from-home option, ϕ_o, captures the *technology* and organizational infrastructure that makes remote work feasible. Finally, the parameters of the commute time distribution, k_d^m and θ_d^m, capture the *commute* costs of attending the workplace.

Workers with no hours at home. Observing a worker with $h^h = 0$ can arise through two channels. First, the worker may be employed in a job that does not offer a work-from-home option, which occurs with probability $1 - \phi_o$ and depends on the occupation o in which the worker is employed. Second, the worker may be employed at a WFH-offering firm but have a commute time large enough that their time constraint binds. In this case, the worker works only at the workplace if the relative productivity of working from home, γ_o, is sufficiently low that the utility from working exclusively at the workplace exceeds that from splitting time or working fully at home. Therefore, an increase in the fraction of workers with positive home hours can be generated either by an increase in ϕ_o, more jobs offering a work-from-home option, or by an increase in γ_o, making home hours sufficiently productive that constrained workers prefer to split their time rather than work exclusively at the workplace.

Workers with no hours at the workplace. Observing a worker with $h^w = 0$ occurs through two distinct channels. First, a worker at a WFH-offering firm with a binding time constraint will work exclusively at home if γ_o is large enough that the utility from working only at home exceeds that from splitting time or working only at the workplace. Second, a worker may receive a teleworking shock, which occurs with probability ψ_o and is independent of the commute time. Therefore, an increase in the fraction of workers working exclusively from home can be generated by an increase in γ_o or an increase in ψ_o.

Workers who split their time. For workers observed with positive hours at both locations, the extensive margin (the fraction of workers splitting their time) is determined primarily by ϕ_o, since a worker at a WFH-offering firm who is unconstrained will always optimally choose positive hours at both locations. The intensive margin (the ratio of hours at home to hours at the workplace) is determined by γ_o and χ_d alone, as shown in Equation 3. An increase in γ_o or a decrease in χ_d both shift the hours ratio toward more time at home relative to the workplace.

Identification. The three margins map cleanly onto the model parameters. Variation across occupations in the fraction of workers with any home hours identifies ϕ_o. Variation across occupations in the fraction of workers with no workplace hours identifies ψ_o. Variation in the hours worked at home from teleworkers across demographic groups identifies χ_d. Finally, variation across occupations in the hours worked at home from workers who split their day identifies γ_o. In what follows, we use data from the ATUS on both the intensive and extensive margins of working from home to estimate these parameters by method of simulated moments, and use the estimated model to decompose the rise in hours worked at home into changes in productivity and preferences. A detailed description of which moments identify which parameters is given in Section 4.2.

4 Estimation

To understand changes in hours worked at home from the model we need to estimate a set of relative productivities, γ, the probability the worker receives a teleworking shock ψ, and worker preferences, which consist of the total disutility of work, η, the relative disutility of working from home, χ, and the substitution parameter ρ.

To identify each of these parameters, we use variation in the hours worked at home and at the workplace from the ATUS. From Equation 3 it is clear that given an estimate of ρ, we can identify the relative productivity of working from home from variation in the hours worked across occupations and relative disutility of working from home from variation in the hours worked across individuals. Therefore our estimation strategy consists of two steps. First, we identify ρ externally using the American Time Use Survey Leave and Job Flexibility Module (LJF). Second, using our estimate of ρ we estimate a set of relative productivities and disutilities by matching a set of moments of observed hours worked at home and the workplace in the main ATUS sample.

4.1 Elasticity of Substitution of Hours Worked

The starting point for the estimation of the substitution parameter in hours, ρ, is the hours worked at home ratio from the model. Taking logs of Equation 3 gives

$$\ln \frac{h^h}{h^w} = \frac{1}{\rho - 1} \ln \gamma_o + \frac{\rho}{1-\rho} \ln \chi_d. \tag{9}$$

If we could observe either the relative productivity of working from home or the relative disutility of working from home, we could estimate ρ using simple OLS.

We use data from the ATUS Job Flexibility and Leave Module (JFL), which contains a proxy for the relative productivity of working from home, to estimate ρ. The data module was run from January 2017 to December 2018 and asked respondents about their job flexibility and paid/unpaid leave. Importantly, within the scope of job flexibility, respondents are asked about how many days they work at home and if they are paid for the work they do at home, which we use to get an estimate of ρ.

To construct a proxy for the relative productivity of working from home, we use information about whether workers are paid for the work they do at home. Specifically, workers are asked *"Are you paid for the hours that you work at home, or do you just take work home from the job?"* and responses are binned into categories: paid, take work home or both. In the model, workers are paid per unit of labor input, $\ell = h^w + \gamma_o h^h$, therefore, observing a worker paid for the work they do at home and a worker who is not paid for the work they do at home is a proxy for observing a change in γ. We construct our proxy for γ as a dummy variable that takes on the value 1 if the worker is paid for any work they do at home (i.e. responses "paid" and "both") and zero otherwise in our main specification.

To estimate the elasticity of substitution, we run the following regression

$$\ln \frac{h_i^h}{h_i^w} = \beta_1 paid_i + \beta_2 X_i^1 + \beta_3 X_i^2 + \delta_{o(i)} + \delta_{k(i)} + \varepsilon_i \tag{10}$$

where $paid_i$ is a dummy that takes on the value 1 if the worker is paid for their work at home, X_i^1 is a vector of observable demographic characteristics (sex, race, age, full/part-time, education, marital status, children), X_i^2 is a set of observable job characteristics[6], and $\delta_{o(i)}$ and $\delta_{k(i)}$ are occupation and industry fixed effects. The estimate $\hat{\beta}_1$ gives us an estimate of the elasticity of substitution and $\hat{\rho} = 1/\hat{\beta}_1 + 1$. A full description of the JFL sample used for the estimation can be found in Appendix A.2.

A potential concern with the estimation of equation (10) is that the sample of workers with an observed hours ratio is selected; that is, only workers employed at firms offering a work-from-home option and who chose to work from home on the interview day are included in the estimation. If workers with stronger preferences for working from home sort into WFH-offering firms, the error term in equation (10) may be correlated with the regressors, biasing our estimate of $\hat{\beta}_1$. The first-order concern for sorting is that workers with stronger preferences for working from home select into occupations where WFH is prevalent, rather than sorting across firms within occupations.[7] The occupation fixed effects $\delta_{o(i)}$ absorb this primary margin of selection. The demographic controls in equation (10) therefore absorb the component of within-occupation sorting that operates through observable worker charac-

[6]The job characteristics include how ofter per week the worker works the full day from home and if they job offers flexible hours.

[7]Regressing a dummy variable of whether a firm offers work from home on occupational fixed effects produces an R-squared of 0.27, adding our demographic controls $X_{1,i}$ increases the R-squared to 0.3. That is, occupation fixed effects alone explain about 27% of the variation in WFH firm status, and adding the full set of demographic controls only raises that to 30%, demonstrating that demographics contribute very little incremental explanatory power beyond what occupation already captures. This suggests that occupation is the dominant sorting margin, and within-occupation sorting through observable demographic characteristics is small.

teristics. While some residual sorting across firms within occupations, driven by unobservables, is likely, it would need to be the case that the most WFH-preferring workers end up specifically at the paying firms rather than the non-paying firms within an occupation. This requires either that workers can observe and sort on this specific compensation policy, or that firms that pay for home hours actively recruit workers with stronger WFH preferences within the same occupation. Since WFH was not very prevalent during the time period of our estimation, we would argue that this channel of sorting is weaker than sorting into occupations.

Table 3: Elasticity of Substitution Estimates

	All		Paid vs Unpaid	
	(1)	(2)	(3)	(4)
paidhome	0.756***	0.465***	0.840***	0.569***
	(0.149)	(0.156)	(0.150)	(0.159)
ρ	2.323	3.150	2.191	2.759
SE	(0.261)	(0.719)	(0.213)	(0.493)
Occupation & Industry FE	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes
WFH Variables	No	Yes	No	Yes
Observations	887	887	772	772

*Notes: Robust standard errors in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard Errors for ρ are calculated using the delta method. Column (1) reports the estimate using the full sample of workers where $paid_i$ is one for workers reporting that they are "paid" or "both" for their work at home and includes occupation and industry fixed effects and demographic variables, column (2) added job characteristics. Column (3) reports the estimate for workers that report either being "paid" or "take work home" where $paid_i$ is one for workers that report they are "paid" and includes occupation and industry fixed effects, demographics, and job characteristics, column (4) adds job characteristics.*

Table 3 reports the estimated coefficient on $paid_i$ and the resulting estimated value for ρ. The first column is our main specification as described above, excluding job characteristics; the estimated value of the coefficient on the paid variable is 0.756, implying an estimated substitution parameter equal to 2.3. Since workers receive disutility from hours worked, a value of ρ greater than one implies indifference curves that are concave to the origin. Column (2) include job characteristics which decrease the estimate of the elasticity of substitution to 0.465 and increase the value of ρ to 3.1. Column (3) excludes workers who report being "both" paid and unpaid for the work from home from the estimation. The resulting estimated elasticity of substitution is 0.84 and the value of ρ is 2.19. Column (4) controls for job characteristics in the restricted sample and the estimated value of ρ increases to 2.76. In what follows we use $\hat{\rho} = 2.52$ and conduct a sensitivity analysis of our second stage estimates to the value of ρ.

4.2 Relative Productivity and Disutility of Work From Home

We estimate the remaining parameters of the model by method of simulated moments (MSM) for two periods: $t \in \{2003 - 2010, 2011 - 2019\}$. We set $T = 24$ since the data show a maximum of 22 hours per day. The relative disutility of working from home χ_d varies by worker characteristics by binning workers into 8 mutually exclusive types determined by their sex, whether or not they have a child, and two education levels (some college or less and college or advanced degree). Similarly, the relative productivity of work from home, γ_o, the fraction of firms that allow work from home, ϕ_o, and the teleworking shock ψ_o vary by occupation. We allow these parameters to vary by the 17 2-digit occupations.[8] For each worker in group d a commute time is drawn from a Gamma distribution with shape parameter k_d^m and scale parameter θ_d^m. For each type d, the disutility of total work (η) is drawn from a log-normal distribution with mean μ_d^η and standard deviation σ_d^η. In total, we have 91 parameters to estimate in each time period.

To estimate the parameters, we simulate the model and match a total of 91 moments separately for each time period. To identify the shape and scale parameters of the disutility of work $(k_d^\eta, \theta_d^\eta)$ for each demographic group, we match the mean and variance of hours worked for individuals who we observe only working at their workplace for each demographic group (16 moments). Equation 1 shows

[8] We drop 5 occupations due to a small number of workers reporting work from home. The occupations we drop are: farming, fishing, and forestry, building and grounds cleaning and maintenance, construction and extraction, and food preparation and serving related occupations, and personal care and service occupations

that these hours worked are only determined by the disutility of work and therefore identify the shape and scale parameters. Similarly, we match the mean and variance of the observed commute times by demographic group to identify the shape and scale parameters of the commute distributions k_d^m and θ_d^m (16 moments).

Equation 7 shows that, given the identification of η, hours worked at home for workers who only work at home identify the relative disutility of work from home. Therefore, we match the hours worked at home for workers who do not work at their workplace by demographic group to get an estimate of χ_d (8 moments). Given the identification of the total disutility and relative disutility parameters, the relative productivity of working from home (γ_o) is identified by matching the average hours worked at home in each occupation (17 moments). Finally, the fraction of firms that allow work from home (ϕ_o) are identified by matching the fraction of workers that work any hours from home in each occupation (17 moments) and the probability a worker works the full day from home (ψ_o) is identified by matching the fraction of workers who work no hours at their workplace in each occupations (17 moments).

We estimate the model for each time period separately by pooling the ATUS data across years in each time period. Before estimating the model we residualize the observed hours worked by all other observable characteristics other than occupation and our demographic groups. This reduces the variation in observed hours worked from factors that are external to the model, allowing for better estimates of the model parameters. subsection A.3 describes this process in detail.

4.3 Model Fit

Overall, the model fits the data well across both time periods. The model and data moments of the 91 matched moments can be found in Appendix section A.4. Table 4 reports the average weekly hours worked at home and at the workplace, the proportion of workers who work any hours from home, and the proportion who work exclusively from home, for both the data and the estimated model. The aggregated moments reported in the table are not directly targeted in estimation; rather, the model is estimated on

Table 4: Model Fit

	Data	Model
Hours at Home		
2003-2010	2.69	2.69
2011-2019	3.73	3.74
Hours at Workplace		
2003-2010	41.05	42.59
2011-2019	40.56	42.36
Proportion WFH		
2003-2010	0.188	0.190
2011-2019	0.222	0.226
Proportion Only WFH		
2003-2010	0.036	0.035
2011-2019	0.052	0.053

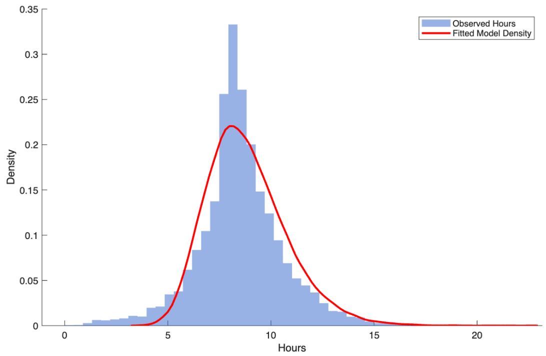
Notes: The column labeled "Data" reports the average hours worked at home and at the workplace per week in the residualized data used to estimate the model. The column labeled "Model" reports the resulting hours worked at home and the workplace per week in the estimated model.

disaggregated moments at the occupation and demographic group level. The model reproduces the level of weekly hours worked at home in both periods nearly perfectly. The model slightly overpredicts hours at the workplace in both periods. This is driven by the concentration of workers at exactly 8 hours in the data, a feature the model cannot reproduce, given that the hours choice is continuous. The extensive margin moments are matched closely: the model reproduces the fraction of workers who work any hours from home (0.190 versus 0.188 in the first period; 0.226 versus 0.222 in the second) and the fraction who work exclusively from home (0.036 in both the data and 0.035 the model in the first period; 0.052 in the data and 0.053 in the model in the second period).

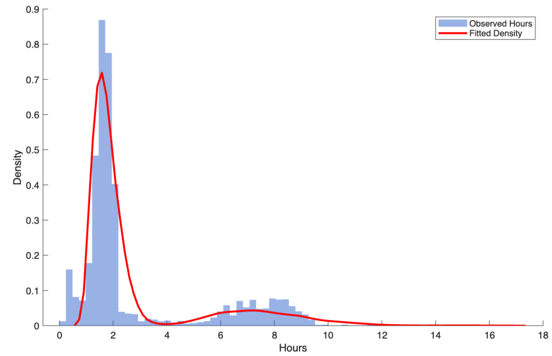
Figure 5 provides a more demanding check on model fit by comparing the full distribution of hours worked at home and at the workplace implied by the estimated model against the empirical distribution for each time period. Importantly, the distributions themselves are not directly matched in estimation;

Figure 5: Hours Worked: Data and Model

2003-2010

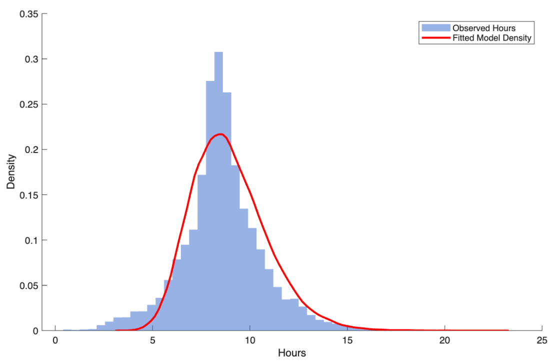


(a) Hours Worked at the Workplace

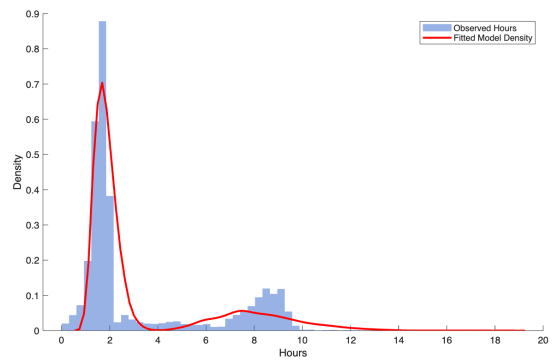


(b) Hours Worked at Home

2011-2019



(c) Hours Worked at the Workplace



(d) Hours Worked at Home

Note: Panel (a) and (c) plot the histogram of hours worked at the workplace and the fitted model density of hours worked at the workplace. Panel (b) and (d) plot the histogram of hours worked at home and the fitted model density of hours at the workplace.

only the mean and variance of hours at the workplace and the mean of hours at home are targeted as moments. For hours worked at the workplace (panels a and c), the model reproduces the overall shape and spread of the empirical distribution well in both periods. The model does not fully capture the sharp spike at 8 hours in the data. This is unsurprising, as the concentration of workers at exactly 8 hours likely reflects social norms around the standard workday and institutional constraints such as fixed-hours contracts, neither of which are features of the model. For hours worked at home (panels b and d), the empirical distribution exhibits a bimodal pattern, with one mass of workers reporting a relatively small number of hours at home and a second at longer durations, reflecting the distinction between workers who bring some work home and those who work primarily from home. The model captures this bimodal structure well in both time periods.

The model's ability to reproduce the broader shape of the empirical distributions therefore provides evidence of fit beyond the targeted moments. The dispersion in hours at the workplace and at home is generated entirely by heterogeneity in the total disutility of work, η, while the relative productivity of working from home, γ_o, varies only across occupations, and the relative disutility of home hours, χ_d, varies only across demographic groups. This suggests that, conditional on these two sources of heterogeneity, variation in the overall disutility of work is sufficient to account for most of the dispersion in hours choices.

Table 5: Unmatched Moments: $P(h^w = 0)$ by Demographic Group

	2003-2010		2011-2019	
	Data	Model	Data	Model
Man, No Child, Low Educ	0.024	0.030	0.019	0.041
Woman, No Child, Low Educ	0.026	0.031	0.037	0.046
Man, Child, Low Educ	0.030	0.033	0.029	0.045
Woman, Child, Low Educ	0.032	0.029	0.043	0.043
Man, No Child, High Educ	0.047	0.048	0.079	0.075
Woman, No Child, High Educ	0.035	0.035	0.065	0.060
Man, Child, High Educ	0.052	0.046	0.074	0.058
Woman, Child, High Educ	0.052	0.037	0.084	0.051

Notes: The table reports the fraction of workers working the full day at home in the data and the estimated model by 8 demographic groups. The moments are not matched during the estimation process.

Finally, Table 5 reports the fraction of teleworkers by demographic group that is not matched during estimation. Rather than matching this moment directly, the model targets the fraction of teleworkers by occupation, so the demographic-level telework rates are implied by the occupation distribution of each demographic group. The model fits the fraction of teleworkers by demographic group well, undershooting the fraction slightly for workers with both a high education level and children in both periods. In the second period, the model slightly overpredicts the fraction of teleworkers with low education. The fact that the model fits demographic telework rates closely without targeting them suggests that occupation-level heterogeneity in ψ_o captures the relevant variation in telework propensity.[9]

4.4 Estimation Results

Estimates of the total difficulty of working from home and commute times can be found in Table A.9. Figure 6 plots the estimated relative disutility of work from home χ_d (panel a), probability of teleworking ψ_o (panel b), relative productivity γ_o (panel c), and the fraction of firms offering work from home ϕ_o (panel d). Point estimates for these parameters can be found in Table A.10 and Table A.11.

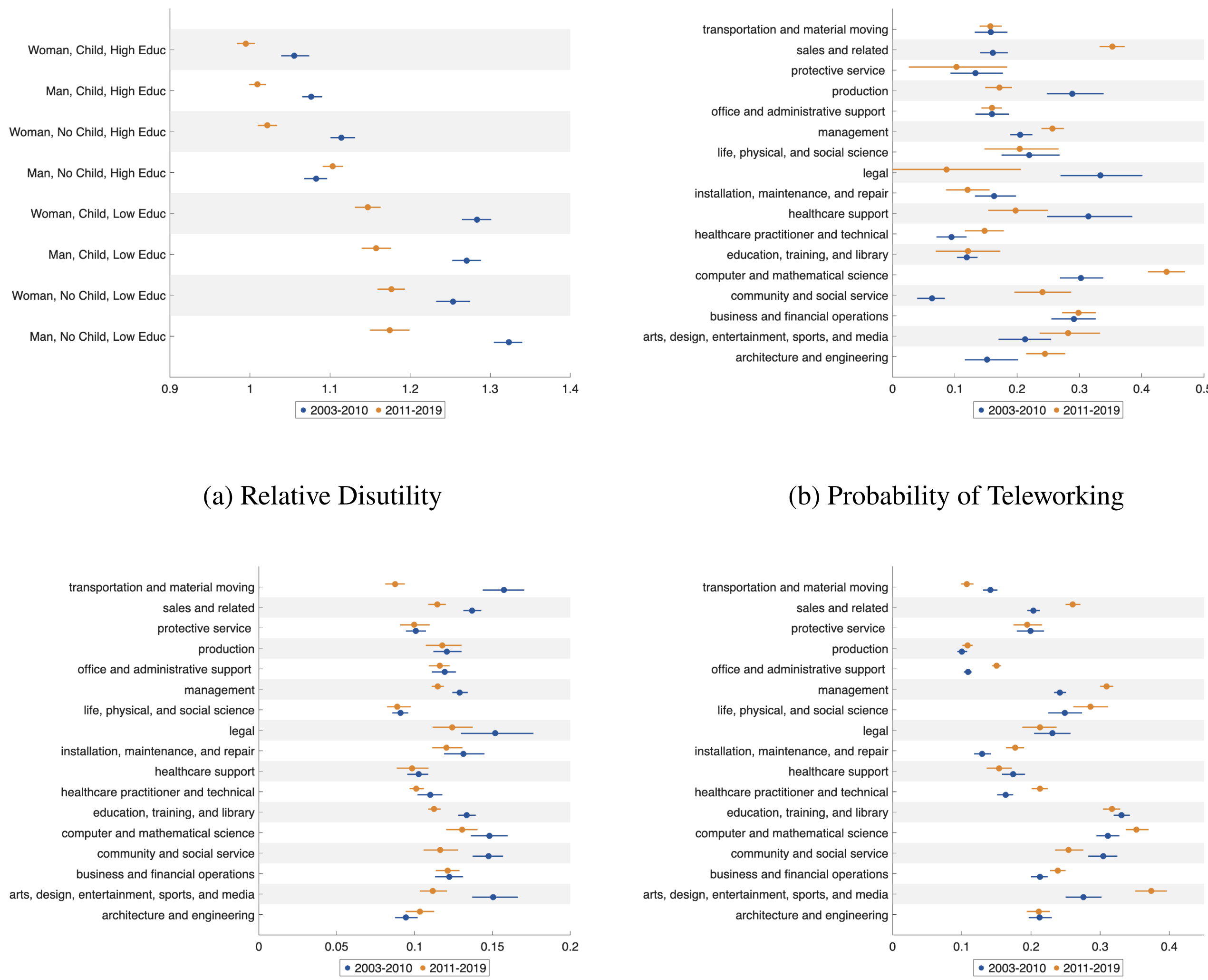
Panel (a) of Figure 6 shows that the relative disutility of work from home has decreased for most of the demographic groups. In 2003-2010, the estimated parameters are all above 1, implying that all workers disliked working one hour at home more than one hour at the workplace. In the second period, 2011-2019, the relative disutility of working from home for highly educated workers with children is all close to 1, implying equal disutility from hours at home compared to the workplace. Panel (b) shows that the probability of teleworking has increased in 7 occupations, with sales and related occupations experiencing the largest increase.

Panel (c) plots the relative productivity of working from home by occupation. The estimated relative productivity of working from home is low on average, with a mean of around 0.11 across occupations. This is consistent with the interpretation of γ_o as the productivity of home hours for workers who split their workday between home and the workplace. These workers are not full-time remote workers but rather bring a subset of tasks home, tasks that are likely to be among the least collaborative and least equipment-dependent, but also not necessarily the most productive. For example, these tasks might

[9] Adding a separate demographic-specific telework shock would contribute little additional explanatory power and cannot be identified cleanly. Identification would require either a normalization in each period, making comparisons across periods difficult, or would rely on a functional form assumption for how the two shocks combine.

include things like writing emails, drafting meeting notes, or grading assignments. The low estimates, therefore, reflect the productivity of marginal home hours, rather than the productivity of a full workday at home.

Figure 6: Estimated Parameters



(a) Relative Disutility

(b) Probability of Teleworking

(c) Relative Productivity

(d) Fraction of Firms offering WFH

Notes: The figure plots the estimated model coefficients for each period, along with the 5th–95th percentile from 500 bootstrapped estimates. Details of the bootstrapped estimate can be found in appendix section A.5. Panel (a) plots the estimated relative disutilities by demographic group χ_d, panels (b-d) plot the estimated probability of teleworking (ψ_o), relative productivity (γ_o), and fraction of firms offering WFH (ϕ_o) by occupation, respectively.

Finally, panel (d) plots the estimated fraction of firms offering a work-from-home option by occupation. There is substantial variation across occupations, ranging from less than 10% in hands-on occupations such as production and installation to nearly 40% in occupations such as computer and mathematical science and education. On average across occupations, 21% of firms offered work from home in the first period, rising modestly to 23% in the second period. Management occupations and art, design, entertainment, sports, and media occupations experienced the largest increase in the fraction of firms that allow work from home.

5 Counterfactual

To understand the effect of changing preferences, productivity, technology, and commute times on weekly hours worked at home, we construct four counterfactual series for hours worked at home. In each counterfactual, we hold one group of parameters fixed at their first-period estimated values while allowing all other parameters to take their second-period estimated values. We simulate the model and construct the implied counterfactual hours worked at home.

The four counterfactuals correspond to the four parameter groups. The preference counterfactual holds χ_d fixed, isolating the contribution of changes in the relative disutility of working from home across demographic groups. The productivity counterfactual holds γ_o and ψ_o fixed, isolating the contribution of changes in the occupation-level productivity of home-based work and the propensity for teleworking. The technology counterfactual holds ϕ_o fixed, isolating the contribution of changes in the availability of work-from-home jobs across occupations. Finally, the commute counterfactual holds k_d^m and θ_d^m fixed, isolating the contribution of rising commute times to the increase in hours worked at home.

Table 6 reports the results of the counterfactual exercises. The first and second columns report the average weekly hours worked at home, matched by the estimated model in the first and second periods. The total increase in weekly hours worked at home is 1 hour and 3 minutes. Column 3 reports the counterfactual hours worked at home if the fraction of firms offering WFH had not increased, that is, if the availability of WFH jobs had remained at its first-period levels. In this case, the weekly hours worked at home would have increased by about 30 minutes rather than an hour, implying that the technology increase accounts for about 50% of the observed rise in weekly hours worked at home.

Table 6: Counterfactual Hours Worked

	2003-2010	2011-2019				
	Model	Model	Fixed Technology	Fixed Productivity	Fixed Preferences	Fixed Commute
Level	2.69	3.74	3.22	3.61	3.44	3.73
	(2.60,2.77)	(3.61,3.84)	(3.11,3.30)	(3.52,3.69)	(3.32,3.53)	(3.61,3.83)
Change		1.05	0.52	0.92	0.75	1.04
		(0.90,1.19)	(0.42,0.62)	(0.84,0.99)	(0.60,0.89)	(0.90,1.19)
% Accounted			50.12	12.32	28.39	0.64
			(44.84,54.98)	(1.73,20.37)	(24.42,33.62)	(-2.02,2.11)

Notes: Column (1) and (2) report the average weekly hours worked at home, predicted by the estimated model in each period. Columns (3)-(6) report the results from the four counterfactual exercises. The first row reports the level of average weekly hours worked at home, the second row reports the level difference from the model-predicted hours in 2003-2010, and the final row reports the difference between the model-predicted hours in the second period and the counterfactual hours, expressed as a fraction of the total rise in home hours between the two periods. The 5th and 95th percentiles of 500 bootstrapped estimates are reported in parentheses; see appendix section A.5 for details.

Columns 4 and 5 report the counterfactual hours worked at home if productivity and preferences were held fixed at their period one levels, respectively. If the productivity of WFH (γ and ψ) had not increased, hours worked at home would have risen to 3.61 hours per week, an increase of about 55 minutes, implying productivity changes account for roughly 12% of the observed rise. On the other hand, if the relative disutility of working from home (χ) had not decreased, the average weekly hours of work from home would have increased by about 45 minutes, accounting for nearly 30% of the observed rise in hours at home. Finally, column 6 shows that the increase in commute times has little effect on hours worked at home, accounting for less than 1% of the observed increase. The remaining observed increase in hours at home is accounted for by changes in the occupational and demographic employment distributions.

5.1 Robustness: Alternative ρ

Since ρ is estimated in a first stage using the JFL module rather than jointly with the remaining parameters, one may be concerned that uncertainty in $\hat{\rho}$ feeds into the second-stage estimates and counterfactual results. To assess this, we re-estimate the model at several alternative values of ρ and recompute the counterfactual hours series for each.

From our estimates in section 4.1, $\rho = 2$ serves as a lower bound on the robustness range. Davis et al. [2024] do not have a substitution parameter on the labor supply side of hours; however, they estimate production-side elasticities between home and office work that play the same role as ρ in determining the degree to which workers substitute between home and office hours. Davis et al. [2024] estimate an elasticity of substitution between days worked at home and at the office of approximately 3.6. Similarly, Delventhal and Parkhomenko [2025] calibrate the corresponding elasticity to between 3.78 and 6.27, depending on worker education and industry. Delventhal and Parkhomenko [2025] calibrate the parameter used to capture the disutility of commuting to 3. Together, these estimates suggest that values in the range of our estimate and somewhat above it are empirically plausible; therefore, we re-estimate the model for $\rho = \{2, 3, 4\}$.

Across all three values of ρ, the estimates of χ, η, ϕ, and ψ are virtually unchanged, while the estimates of γ vary with the choice of curvature parameter. The intuition for why only $\hat{\gamma}$ responds to the choice of ρ follows directly from the identification discussion in section 4.2. From Equation 3, the log ratio of home to workplace hours for workers splitting time between the two locations depends on ρ, γ, and χ. Since χ is identified from the mean hours worked at home by workers who work only at home (a moment that does not involve ρ), it is estimated independently of the curvature parameter. Similarly, none of the moments identifying other parameters depend on ρ. With χ pinned down independently, variation in ρ is absorbed entirely by $\hat{\gamma}$, which adjusts to match the conditional mean home hours among splitters for any given value of the curvature parameter. Figure A.7 plots the estimates of γ for the different values of ρ.

Table 7: Robustness to alternative ρ

	Fixed Technology	Fixed Productivity	Fixed Preferences	Fixed Commute
ρ = 2.52 (Baseline)	50.12	12.32	28.39	0.64
ρ = 2	50.65	2.74	35.95	0.35
ρ = 3	50.71	12.77	24.95	-0.01
ρ = 4	52.03	17.40	26.33	0.89

Notes: The table reports the percent of the rise in hours worked at home accounted for by holding fixed the technology parameters (ϕ_o), the productivity parameters (γ_o, ψ_o), the preference parameters (χ_d), and the commute parameters (k_d^m,θ_d^m).

Table 7 reports the percent of the increase in hours worked at home accounted for by our four counterfactuals. For each alternative value of ρ, the percent accounted for by each counterfactual falls into the 90% confidence interval of the baseline estimation. Since γ is the parameter most affected by the choice of ρ, the counterfactual that exhibits the greatest sensitivity to ρ is the one in which the productivity parameters are held fixed. Even so, the variation across values of ρ for this counterfactual remains within the confidence interval of the baseline.

6 Conclusion

In this paper, we have documented a significant rise in the share of hours worked at home and differences in the uptake of working from home and the length of time working at home across occupations. We show that since 2003 the average weekly hours of work from home per worker have nearly doubled, using data from the American Time Use Survey. We estimate a model in which workers optimally choose how much and where to work depending on the relative productivity of working from home, preference for working from home, and their commute time. We estimate the model using variation in hours worked at home and the workplace across occupations and demographic groups. Using the estimated model, we show that changes in technology and productivity account for nearly 62% of the observed increase in hours worked at home, whereas commute times and preferences account for about 30%.

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A Appendix

A.1 ATUS time series aggregation

To construct total hours worked at the workplace in our sample we sum the product of individual hours worked at the workplace (h_{it}^w where i indexes the individual) and the ATUS sample weight (wgt_{it}) for each quarter t:[10]

$$H_t^w = \sum_i h_{it}^w \times wgt_{it}. \tag{A.11}$$

The resulting values are total quarterly hours worked at the workplace, H_t^w. To construct average weekly hours at the workplace per person per quarter ($\bar{H}^w$), we divide aggregate hours by 13 weeks per quarter and the total number of employed per quarter. We use bars to represent average weekly per-worker values.

$$\bar{H}_t^w = \frac{H_t^w}{13 \times E_t}, \tag{A.12}$$

where E_t is the total number of employed in our sample, constructed by summing the ATUS weight across people each quarter:

$$E_t = \sum_i \frac{wgt_{it}}{92}. \tag{A.13}$$

Summing just the sample weight give the total number of workers times days per quarter, therefore we divide by 92 (the average number of days per quarter) to recover total employment.

Similarly, we construct average weekly hours worked from home per person ($\bar{H}^h$) and average

[10]We adjust the ATUS sample weight such that each day of the week is 1/5th in our final sample of workers. The sampling weights in the ATUS are constructed such that each day of the week is equally represented and their sum is equal to person-days per quarter. The sample weights are representative at some but not all levels of disaggregation. For our final sample, we rescale the weights such that each day of the week is equally represented within each quarter.

weekly total hours worked per worker ($\bar{H}$) as:

$$\bar{H}_t^h = \frac{\sum_i h_{it}^h \times wgt_{it}}{13 \times E_t} \tag{A.14}$$

$$\bar{H}^h = \frac{\sum_i (h_{it}^w + h_{it}^h) \times wgt_{it}}{13 \times E_t}, \tag{A.15}$$

where h_{it}^h is individual i's hours worked at home. All resulting series are smoothed using a 12-quarter simple moving average.

A.2 Job Flexibility and Leave Module

The Job Flexibility and Leave Module was conducted from January 2017 to December 2018, all respondents from the ATUS who are employed and completed a 24 hour diary are selected to be in the module. We apply the same selection criteria to the JFL data as we do to the time diary data; we restrict the sample to workers between the ages of 25 and 64. Table A.8 reports the summary statistics of the demographic characteristics of the sample. The demographic composition is similar to our main ATUS sample, although slightly more educated.

Table A.8: Job Flexibility and Leave Module Summary Statistics

	Mean		Mean
Female	0.46	Advanced Degree	0.35
Married	0.67	White	0.84
Age	42.45	Black	0.08
Child	0.45	Other	0.09
Less than HS	0.00	Full Time	0.93
High School	0.06	Paid work at home	0.75
Some College	0.14	Take work home	0.12
College	0.44	Both paid at and take work home	0.12
Observations			1,363

A.3 Data Residualization

First, the sampling weights in the ATUS are constructed such that each day of the week is equally represented and their sum is equal to person-days per quarter. The sample weights are representative at some but not all levels of disaggregation. For our final sample, we rescale the weights such that each day of the week is equally represented within each quarter.

Next, to remove some of the variation in observed hours worked that arises from factors that are excluded from the model, we residualize the data. We do this in two steps. First, for each sub period $t \in T = \{2003 - 2010, 2011 - 2019, 2022 - 2024\}$ we run a tobit model on hours worked at home and hours worked at the workplace. Define the latent variable of hours worked at the workplace as

$$h_{it}^{w} = \beta_1 ft_{it} + \beta_2 h_{it}^{h} + \beta_3 ft_{it} \cdot h_{it}^{h} + \beta_4 X_{it}^{1} + \beta_5 X_{it}^{2} + \delta_t + \delta_{i(j)} + \delta_{t(m)} + \delta_{t(d)} + \varepsilon_{it}^{w} \tag{A.16}$$

where ft_{it} is a dummy variable that takes on the value 1 if the worker is full time, X_{it}^{1} is the set of observables that are used to create the demographic groups in the model (sex, child, education), X_{it}^{2} are the remaining demographic observables (age, married, race, a dummy for being paid hourly), δ_t is a year fixed effect, $\delta_{t(m)}$ is a calendar month fixed effect, $\delta_{t(d)}$ is a calendar day fixed effect, and $\delta_{i(j)}$ is an occupation fixed effect. ε_{it}^{w} is a normally distributed error term with mean 0 and standard deviation σ^{w}. Similarly, for hours worked at home, we define the latent variable as

$$h_{it}^{h} = \beta_1 ft_{it} + \beta_2 \mathbb{I}\{h_{it}^{w} > 0\} + \beta_3 ft_{it} \cdot \mathbb{I}\{h_{it}^{w} > 0\} + \beta_4 X_{it}^{1} + \beta_5 X_{it}^{2} + \delta_t + \delta_{i(j)} + \delta_{t(m)} + \delta_{t(d)} + \varepsilon_{it}^{h} \tag{A.17}$$

where $\mathcal{I}\{h_{it}^{w} > 0\}$ is an indicator for whether the worker has positive hours worked at the workplace and ε_{it}^{h} is a normally distributed error term with mean 0 and standard deviation σ^{h}.

Next, we construct the predicted conditional hours worked as

$$\hat{h}^w_{it} = \hat{\beta}^w X_{it} + \hat{\sigma}^w \left[\frac{\phi(\hat{\beta}^w X_{it}/\hat{\sigma}^w)}{\Phi(\hat{\beta}^w X_{it}/\hat{\sigma}^w)} \right] \tag{A.18}$$

$$\hat{h}^h_{it} = \hat{\beta}^h X_{it} + \hat{\sigma}^h \left[\frac{\phi(\hat{\beta}^h X_{it}/\hat{\sigma}^h)}{\Phi(\hat{\beta}^h X_{it}/\hat{\sigma}^h)} \right] \tag{A.19}$$

where $\hat{\beta}^w X_{it}$ and $\hat{\beta}^h X_{it}$ are the predicted values from Equation A.16 and Equation A.17, respectively. We define the conditional error term as

$$\epsilon^w_{it} = \mathbb{I}\{h^w_{it} > 0\}[u^w_{it} > \Phi(\hat{\beta}^w X_{it}/\hat{\sigma}^w)](h^w_{it} - \hat{h}^w_{it}) \tag{A.20}$$

$$\epsilon^h_{it} = \mathbb{I}\{h^h_{it} > 0\}[u^h_{it} > \Phi(\hat{\beta}^h X_{it}/\hat{\sigma}^h)](h^h_{it} - \hat{h}^h_{it}) \tag{A.21}$$

where u^w_{it} and u^h_{it} are draws from correlated uniform random variables, where the correlation is the empirical correlation between $h^h > 0$ and $h^w > 0$ for each of the 8 demographic groups used in the model estimation. The conditional error is the difference between the predicted conditional hours worked and the observed hours worked for individuals who have positive hours worked and a random draw above the probability that their hours worked are positive.

Finally to construct the residualized hours worked by first predicting the latent hours worked (Equation A.16 and Equation A.17) keeping the workers covariates which are used in the model estimation X^1_{it} at their original values and fixing the other covariates such that all workers are full time, married, white, not paid hourly, and observed in March. Occupation is kept at the observed occupation, and the year variable is fixed at 2006 in the first period, 2015 for the second period, and 2023 for the third period. For the prediction of latent hours worked at home we replace the dummy variable for if the worker worked at the workplace with an indicator created from the draw of the uniform random variable used to create the conditional error term, that is $\hat{\mathbb{I}}\{h^w_{it} > 0\} = \mathbb{I}\{u^w_{it} > \Phi(\hat{\beta}^w X_{it}/\hat{\sigma}^w)\}$. The predicted conditional hours worked at home are

$$\tilde{h}_{it}^{h} = \hat{\beta}^{h}\tilde{X}_{it} + \hat{\sigma}^{h}\left[\frac{\phi(\hat{\beta}^{h}\tilde{X}_{it}/\hat{\sigma}^{h})}{\Phi(\hat{\beta}^{h}\tilde{X}_{it}/\hat{\sigma}^{h})}\right] + \epsilon_{it}^{h} \tag{A.22}$$

where $\tilde{X}_{it}$ are the alternative covariates described above. To predict the latent hours worked at the workplace we replace the hours worked at home with $\tilde{h}_{it}^{h} - \epsilon_{it}^{h}$ and predict the conditional hours worked at the workplace as

$$\tilde{h}_{it}^{w} = \hat{\beta}^{w}\tilde{X}_{it} + \hat{\sigma}^{w}\left[\frac{\phi(\hat{\beta}^{w}\tilde{X}_{it}/\hat{\sigma}^{w})}{\Phi(\hat{\beta}^{w}\tilde{X}_{it}/\hat{\sigma}^{w})}\right] + \epsilon_{it}^{w}. \tag{A.23}$$

We predict conditional hours worked at the workplace and at home from each individual for Monday through Friday and average across the 5 values for the final data used in the model estimation.

A.4 Estimated Parameters

Table A.9 reports the estimated parameters for the distribution of total disutility of work and commute times by demographic group for both time periods. Table A.10 reports the estimated relative productivity of work from home (γ), the probability of working a full day from home (ψ), and the probability of working for a firm that offers work from home (ϕ), by occupation. Table A.11 reports the estimated relative disutility of working from home (χ) by demographic group. Standard errors reported in each table are calculated as the standard deviation of parameter estimates from 500 bootstraps and reported in parentheses.

Table A.12 reports the model and data moments by demographic group. The moments matched by demographic group are the first and second uncentered moments of hours worked at the workplace. Both moments fit the data well for all demographic groups. Similarly, the first and second uncentered moments of commute times are matched by demographic group and fit well in both time periods. Finally, the average hours worked at home for workers who do not work at the workplace align well across all demographic groups and time periods. Table A.13 reports the model and data moments by

Table A.9: Estimates: Total Disutility of Work and Commute Times

	Total Disutility of Work (η)				Commute Times (m)			
	2003-20110		2011-2019		2003-20110		2011-2019	
	μ_η	σ_η	μ_η	σ_η	k_m	θ_m	k_m	θ_m
Man, No Child, Low Educ	-2.173	0.227	-2.194	0.216	1.017	0.913	0.413	2.702
	(0.003)	(0.003)	0.003	0.003	(0.122)	(0.119)	(0.037)	(0.286)
Woman, No Child, Low Educ	-2.143	0.187	-2.152	0.200	1.434	0.544	1.597	0.504
	(0.002)	(0.003)	0.003	0.003	(0.147)	(0.059)	(0.372)	(0.094)
Man, Child, Low Educ	-2.206	0.219	-2.213	0.224	1.222	0.812	0.413	2.468
	(0.003)	(0.004)	0.003	0.004	(0.186)	(0.131)	(0.070)	(0.464)
Woman, Child, Low Educ	-2.114	0.203	-2.132	0.211	1.501	0.504	1.096	0.712
	(0.003)	(0.003)	0.003	0.005	(0.111)	(0.041)	(0.176)	(0.115)
Man, No Child, High Educ	-2.181	0.222	-2.196	0.209	1.181	0.791	0.993	1.097
	(0.004)	(0.003)	0.003	0.003	(0.223)	(0.158)	(0.101)	(0.123)
Woman, No Child, High Educ	-2.165	0.213	-2.152	0.206	1.260	0.686	1.794	0.521
	(0.003)	(0.003)	0.003	0.003	(0.245)	(0.140)	(0.125)	(0.039)
Man, Child, High Educ	-2.154	0.221	-2.180	0.208	1.066	0.975	0.786	1.413
	(0.004)	(0.004)	0.004	0.004	(0.158)	(0.157)	(0.135)	(0.254)
Woman, Child, High Educ	-2.105	0.216	-2.127	0.216	1.315	0.633	1.000	0.907
	(0.004)	(0.004)	0.004	0.004	(0.301)	(0.153)	(0.139)	(0.149)

Note: The table reports parameter estimates for the distribution of total disutility of working and the distribution of commute times. Standard errors are calculated as the standard deviation of 500 bootstrap estimates; see subsection A.5 for details. ATUS sample weights used. The weights are adjusted so that each day is $1/5^{th}$ of our subsample.

occupation. The moment model fits all moments, hours at home by workers who split their day, the probability of working any time at home, and the probability of working the full day at home, well, for all occupations in both time periods.

A.5 Standard Errors

We construct standard errors for the MSM estimates using a linearized bootstrap. Rather than re-estimating the model for each bootstrap draw, we exploit the asymptotic linearity of the MSM estimator to approximate the sampling distribution of $\hat{\theta}$ using only the Jacobian of the simulated moments evaluated at the point estimate.

Linearized Bootstrap

Let m_{data} denote the 82×1 vector of empirical moments and $m_{sim}(\theta)$ the corresponding vector of simulated moments. The MSM estimator solves

$$\hat{\theta} = \arg\min_{\theta} \left[m_{data} - m_{sim}(\theta)\right]' W \left[m_{data} - m_{sim}(\theta)\right] \tag{A.24}$$

where W is the weighting matrix used in estimation. By the asymptotic linearity of the estimator, a first-order approximation around $\hat{\theta}$ gives

$$\hat{\theta}^b \approx \hat{\theta} + (G'WG)^{-1}G'W\left(m^b_{data} - m_{data}\right) \tag{A.25}$$

where $G = \frac{\partial m_{sim}(\theta)}{\partial \theta}\Big|_{\hat{\theta}}$ is the 91×91 Jacobian of the simulated moments evaluated at the point estimate, and m^b_{data} are the empirical moments recomputed on the b-th bootstrap resample of the data. For each bootstrap draw $b = 1, \ldots, 500$, we resample the data with replacement, recompute m^b_{data}, and update the parameter vector using Equation A.25. Standard errors are then computed as the standard deviation of $\{\hat{\theta}^b\}_{b=1}^{500}$ across bootstrap draws. Confidence intervals for the counterfactual exercises and aggregated moments are computed as the 5th and 95th percentiles of the distribution of counterfactual outcomes and aggregate moments evaluated at each $\hat{\theta}^b$.

Jacobian Estimation

The Jacobian G is estimated numerically using forward finite differences. For the majority of parameters, the finite difference approximation performs well. However, for the 17 occupation-specific firm WFH offer probabilities ϕ_o and the 17 occupation-specific shock probabilities ψ_o, the finite difference approximation yields near-zero derivatives. This occurs because the moments identifying these parameters (the fraction of workers working any hours from home by occupation and the fraction working exclusively from home by occupation) are discrete outcomes that do not respond smoothly to small perturbations of ϕ_o and ψ_o in a finite simulation. For these 34 parameters, we replace the finite difference columns of G with analytical derivatives computed directly from the simulated data at $\hat{\theta}$.

For ϕ_o, the identifying moment is the fraction of workers in occupation o who work any positive hours from home. In the model, this equals

$$m_o(\phi_o) = \phi_o \cdot P\left(h^h > 0 \mid \text{WFH job, occupation } o\right). \tag{A.26}$$

The derivative with respect to ϕ_o is therefore $P(h^h > 0 \mid \text{WFH job, occupation } o)$, which we estimate as the fraction of simulated workers in occupation o who are assigned to a WFH firm and choose positive home hours.

For ψ_o, the identifying moment is the fraction of workers in occupation o who work no hours at the workplace. In the model, this equals

$$m_o(\psi_o) = \phi_o \left[\psi_o + (1 - \psi_o) \cdot P\left(h^w = 0 \mid \text{no shock, WFH job, occupation } o\right)\right] \tag{A.27}$$

The derivative with respect to ψ_o is

$$\frac{\partial m_o}{\partial \psi_o} = \phi_o \left[1 - P\left(h^w = 0 \mid \text{no shock, WFH job, occupation } o\right)\right]. \tag{A.28}$$

Both ϕ_o and the conditional probability are estimated directly from the simulated data at $\hat{\theta}$. The corresponding columns of G are set to zero everywhere except the row of the identifying moment, where the analytical derivative is inserted.

A.6 Robustness: Alternative ρ

To understand the effect of the uncertainty about ρ on our estimated parameters, we re-estimate the model for different values of ρ. Specifically, we re-estimate for $\rho \in \{2, 3, 4\}$. As discussed in subsection 4.1, the parameters that are affected most by changes in ρ are the relative productivity of work from home.

Figure A.7 plots the estimated relative productivity parameters by occupations for different values of ρ. The figure shows that as ρ increases, the estimated relative productivity increases. However, the relative ranking across occupations is preserved. The rescaling of γ across values of ρ has little consequence for the counterfactual decomposition because relative productivity governs only the intensive margin of home hours among workers who already split time between home and the workplace. Since the rise in hours worked at home over our sample period was driven primarily by growth at the extensive margin, i.e., an increasing fraction of workers doing any work from home, changes in the estimated relative productivities have little effect on the counterfactual.

Figure A.7: Relative Productivity Estimates: Robustness

(a) 2003-2010

(b) 2011-2019

Note: The figure plots the estimated relative productivity parameters for different values of ρ.

Table A.10: Estimates: Occupational Parameters

	Relative Prod. (γ)		Prob. Full day Home (ψ)		Prob. WFH Firm (ϕ)	
	2003-2010	2011-2019	2003-2010	2011-2019	2003-2010	2011-2019
architecture and engineering	0.094	0.104	0.152	0.245	0.213	0.211
	(0.004)	(0.006)	(0.025)	(0.019)	(0.011)	(0.011)
arts, design, entertainment, sports, and media	0.150	0.112	0.213	0.282	0.276	0.374
	(0.009)	(0.005)	(0.026)	(0.029)	(0.016)	(0.015)
business and financial operations	0.122	0.121	0.291	0.298	0.213	0.239
	(0.005)	(0.005)	(0.022)	(0.016)	(0.007)	(0.007)
community and social service	0.148	0.116	0.063	0.241	0.304	0.254
	(0.006)	(0.007)	(0.014)	(0.028)	(0.013)	(0.013)
computer and mathematical science	0.148	0.130	0.302	0.440	0.311	0.352
	(0.007)	(0.006)	(0.021)	(0.017)	(0.010)	(0.010)
education, training, and library	0.133	0.113	0.119	0.121	0.331	0.317
	(0.003)	(0.002)	(0.010)	(0.030)	(0.007)	(0.008)
healthcare practitioner and technical	0.110	0.101	0.094	0.148	0.163	0.213
	(0.005)	(0.003)	(0.015)	(0.020)	(0.007)	(0.007)
healthcare support	0.103	0.099	0.315	0.198	0.174	0.154
	(0.004)	(0.006)	(0.042)	(0.029)	(0.010)	(0.011)
installation, maintenance, and repair	0.131	0.120	0.163	0.120	0.130	0.177
	(0.008)	(0.006)	(0.020)	(0.021)	(0.007)	(0.008)
legal	0.152	0.124	0.333	0.087	0.231	0.213
	(0.014)	(0.008)	(0.040)	(0.074)	(0.016)	(0.015)
life, physical, and social science	0.091	0.089	0.219	0.204	0.249	0.286
	(0.003)	(0.005)	(0.029)	(0.037)	(0.015)	(0.015)
management	0.129	0.115	0.205	0.257	0.242	0.310
	(0.003)	(0.002)	(0.011)	(0.011)	(0.005)	(0.006)
office and administrative support	0.119	0.116	0.160	0.160	0.109	0.150
	(0.004)	(0.004)	(0.017)	(0.010)	(0.003)	(0.004)
production	0.121	0.118	0.289	0.172	0.100	0.108
	(0.006)	(0.007)	(0.029)	(0.013)	(0.004)	(0.005)
protective service	0.101	0.100	0.133	0.103	0.199	0.194
	(0.004)	(0.006)	(0.026)	(0.048)	(0.012)	(0.012)
sales and related	0.137	0.115	0.161	0.353	0.203	0.260
	(0.004)	(0.003)	(0.013)	(0.012)	(0.006)	(0.007)
transportation and material moving	0.157	0.088	0.158	0.157	0.141	0.107
	(0.008)	(0.004)	(0.017)	(0.011)	(0.006)	(0.005)

Note: The table reports parameter estimates for the relative productivity of work from home, the probability of working a full day at home, and the probability of working for a firm that offers work from home. Standard errors are calculated as the standard deviation of 500 bootstrap estimates; see subsection A.5 for details. ATUS sample weights used. The weights are adjusted so that each day is $1/5^{th}$ *of our subsample.*

Table A.11: Estimates: Demographic Parameters

	Relative disutility (χ)	
	2003-2010	2011-2019
Man, No Child, Low Educ	1.323	1.175
	(0.011)	(0.015)
Woman, No Child, Low Educ	1.253	1.177
	(0.013)	(0.011)
Man, Child, Low Educ	1.271	1.158
	(0.010)	(0.011)
Woman, Child, Low Educ	1.283	1.147
	(0.011)	(0.009)
Man, No Child, High Educ	1.083	1.103
	(0.009)	(0.008)
Woman, No Child, High Educ	1.114	1.022
	(0.010)	(0.008)
Man, Child, High Educ	1.076	1.009
	(0.008)	(0.006)
Woman, Child, High Educ	1.055	0.995
	(0.011)	(0.007)

Note: The table reports parameter estimates for the relative disutility of working from home. Standard errors are calculated as the standard deviation of 500 bootstrap estimates; see subsection A.5 for details. ATUS sample weights used. The weights are adjusted so that each day is $1/5^{th}$ *of our subsample.*

Table A.12: Moments Demographic Groups

	2003-2010									
	Hours at Workplace		Hours at Workplace Sqr.		Hours at Home | Hw=0		Commute Time		Commute Time Sqr.	
	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model
Man, No Child, Low Educ	9.11	9.01	4.43	4.50	7.02	6.85	0.89	0.94	1.81	1.77
Woman, No Child, Low Educ	8.58	8.71	2.79	2.70	6.82	6.88	0.76	0.78	1.05	1.02
Man, Child, Low Educ	9.21	9.31	4.43	4.44	7.26	7.28	0.92	1.01	1.97	1.87
Woman, Child, Low Educ	8.40	8.44	3.01	3.03	6.64	6.73	0.71	0.74	0.91	0.89
Man, No Child, High Educ	8.95	9.07	4.22	4.18	8.45	8.50	0.91	0.94	1.71	1.64
Woman, No Child, High Educ	8.77	8.89	3.71	3.58	7.98	8.05	0.83	0.87	1.40	1.36
Man, Child, High Educ	8.93	8.81	4.05	4.02	8.37	8.34	1.00	1.06	2.29	2.21
Woman, Child, High Educ	8.43	8.37	3.39	3.36	7.91	7.93	0.79	0.82	1.23	1.19
	2011-2019									
	Hours at Workplace		Hours at Workplace Sqr.		Hours at Home | Hw=0		Commute Time		Commute Time Sqr.	
	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model
Man, No Child, Low Educ	9.21	9.17	3.98	4.05	7.97	7.86	1.08	1.08	4.16	4.00
Woman, No Child, Low Educ	8.69	8.78	3.11	3.15	7.39	7.34	0.81	0.82	1.06	1.07
Man, Child, Low Educ	9.34	9.40	4.52	4.56	8.02	8.06	1.01	1.03	3.76	3.57
Woman, Child, Low Educ	8.62	8.65	3.51	3.39	7.53	7.57	0.79	0.79	1.21	1.19
Man, No Child, High Educ	9.16	9.17	3.75	3.72	8.43	8.31	1.03	1.05	2.33	2.22
Woman, No Child, High Educ	8.81	8.82	3.31	3.33	8.51	8.68	0.90	0.93	1.35	1.34
Man, Child, High Educ	9.01	9.01	3.65	3.55	8.84	8.96	1.09	1.13	3.13	2.96
Woman, Child, High Educ	8.59	8.57	3.56	3.54	8.66	8.62	0.90	0.93	1.79	1.76

Table A.13: Moments Occupations

	2003-2010					
	hh of splitters		Prob(hh>0)		Prob(hw=0)	
	Data	Model	Data	Model	Data	Model
architecture and engineering	1.53	1.58	0.212	0.213	0.041	0.041
arts, design, entertainment, sports, and media	2.00	2.03	0.295	0.271	0.049	0.049
business and financial operations	1.78	1.75	0.193	0.197	0.054	0.054
community and social service	2.04	1.99	0.326	0.327	0.023	0.023
computer and mathematical science	2.01	1.94	0.289	0.291	0.092	0.091
education, training, and library	1.93	1.94	0.302	0.314	0.043	0.042
healthcare practitioner and technical	1.59	1.61	0.169	0.170	0.016	0.016
healthcare support	1.29	1.31	0.139	0.142	0.044	0.043
installation, maintenance, and repair	1.56	1.59	0.125	0.125	0.017	0.016
legal	2.01	1.98	0.237	0.237	0.050	0.050
life, physical, and social science	1.55	1.50	0.237	0.238	0.039	0.039
management	1.81	1.79	0.239	0.243	0.053	0.053
office and administrative support	1.49	1.48	0.110	0.111	0.021	0.021
production	1.48	1.47	0.089	0.091	0.023	0.023
protective service	1.53	1.57	0.164	0.173	0.026	0.026
sales and related	1.70	1.74	0.209	0.212	0.034	0.034
transportation and material moving	1.77	1.78	0.139	0.140	0.017	0.017
	2011-2019					
	hh of splitters		Prob(hh>0)		Prob(hw=0)	
	Data	Model	Data	Model	Data	Model
architecture and engineering	1.76	1.76	0.213	0.214	0.035	0.035
arts, design, entertainment, sports, and media	1.87	1.86	0.363	0.365	0.090	0.089
business and financial operations	1.96	1.96	0.242	0.242	0.085	0.084
community and social service	1.95	1.98	0.261	0.261	0.060	0.059
computer and mathematical science	2.09	2.06	0.342	0.344	0.160	0.160
education, training, and library	1.93	1.91	0.320	0.320	0.050	0.049
healthcare practitioner and technical	1.72	1.72	0.224	0.224	0.031	0.031
healthcare support	1.55	1.52	0.169	0.164	0.038	0.039
installation, maintenance, and repair	1.77	1.79	0.157	0.157	0.014	0.014
legal	1.97	2.03	0.221	0.221	0.031	0.029
life, physical, and social science	1.68	1.68	0.256	0.262	0.037	0.036
management	1.90	1.89	0.308	0.309	0.075	0.075
office and administrative support	1.76	1.73	0.143	0.143	0.023	0.023
production	1.70	1.71	0.088	0.088	0.019	0.020
protective service	1.62	1.65	0.185	0.185	0.025	0.025
sales and related	1.81	1.80	0.261	0.266	0.089	0.088
transportation and material moving	1.43	1.46	0.106	0.111	0.009	0.009