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 or at the office) and how much time to work at the chosen location. The place and time depend on worker preferences across locations and the relative productivity of working from home. We estimate the model allowing for both preferences and productivity to change over time and decompose the rise in hours worked. Changes in preferences and the demographic composition of the workforce played little role in the rise of working from home. Instead, increases in the relative productivity of working from home and employment shifts toward occupations with higher relative productivity can account for most of the observed increase in hours worked at home.

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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.

We document a considerable rise in weekly hours worked from home using data from the American Time Use Survey (ATUS) from 2003 to 2019. The ATUS contains detailed accounts of where and how Americans spend their time. We construct data on how long people worked at their workplace and how long they worked at home. In 2003 the average worker in our sample spent 47.5 hours per week working at their workplace and 2 hours per week working from home. By the end of 2019, the average hours at the workplace decreased to 45 hours per week and hours worked from home had nearly doubled to 4 hours per week. We show that this trend is driven by both the number of workers who primarily work from home, similar to Mateyka et al. [2012], but also an increase in the number of people that split their workday across the workplace and home.[1] We also document large differences in the propensity and duration of work from home across occupations which have garnered increased attention due to the COVID-19 pandemic, [Dingel and Neiman, 2020, Hensvik et al., 2020, Adams-Prassl et al., 2020, Bick et al., 2020].

To decompose the rise in work from home, we build a model in which firms demand labor units and workers optimally choose the total number of hours worked and the location of that work, home or the workplace. Hours in each location are perfect substitutes in the production of a labor unit, but the productivity of an hour worked from home, relative to an hour at the workplace differs across occupations. Similarly, the disutility of an hour worked from home, relative to an hour at the office differs across types of workers. The model produces a ratio of hours worked from home to the workplace which is a function of worker preferences and the relative productivity of work. Using individual-level data from the ATUS we estimate the parameters of the model by maximizing the likelihood of

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

observing workers' hours ratios.

The estimation delivers a series for the relative productivity of working from home for each 2-digit occupation. Occupations differ considerably in their average relative productivity of working from home, for example, on average, an hour worked from home in computer and mathematical occupations is about 55% as productive as an hour at the workplace, whereas an hour from home for production occupations is about 16% as productive as an hour at the workplace. We also show that some occupations have seen a substantial increase in the relative productivity of working from home (computer and mathematical science occupations increased from 34% to nearly 76%) whereas others saw no increase since 2003. Overall, the aggregate relative productivity of WFH has increased by 40%, from 27% as productive at the workplace in 2003 to 39% as productive in 2019.

Prior to the COVID-19 pandemic, there were few studies trying to estimate the productivity of working from home, notably Bloom et al. [2014] 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, Harrington and Emanuel [2022] 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 WHF 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. Morikawa [2021] on a survey of workers and firms in Japan finds productivity from home is about 60%-70% than that at the workplace, however, Barrero et al. [2020] 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 that 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 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., 2020, 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. A disadvantage of treating productivity generally is that we cannot account for why productivity has changed, i.e. have firms allowed more work from home because of better monitoring technology, or has better technology increased the number of tasks workers can productively do from home? To understand why productivity has changed we would need more detailed data on what exactly workers are doing from home which unfortunately is not included in the ATUS.

Our estimation also delivers a series of estimates of worker preferences for working from home. We model the disutility of working as CES between working at the office and working from home and estimate both the relative disutility of working from home for different demographic groups and a common substitution parameter. We estimate the substitution parameter from the ATUS Leave and Job Flexibility Module using variation in whether or not a worker gets paid for the work they do from home. We find work from home and at the office are substitutes in the disutility of work with an elasticity of 2.6, which is significantly lower than what Kaplan et al. [2020]. We find that the relative disutility of working from home is increasing in education and higher for men with children than women with children. The estimation also reveals that the disutility of working from home has decreased for some demographic groups, specifically low-educated groups.

Further our approach allows us to decompose the rise in work from home into changes in the composition of the workforce, productivity, and preferences. To do so we construct two counterfactual hours worked series using the model where, first, we hold the relative disutility of work for each demographic group fixed at the estimated 2003 levels, and second, we hold the relative productivity of working from home fixed for each occupation fixed at the estimate 2003 level. In doing so, we find that within occupation increases in the relative productivity of working from home can account for nearly the entire increase in hours worked from home, whereas changes in preferences account for little. This finding is similar to Bick et al. [2020] 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. Finally, we construct two counterfactual work-from-home series where we allow disutility and productivity to change as estimated but fix the demographic and occupational composition of the workforce fixed at their 2003 values. The exercise reveals that demographic changes in the workforce played little role in the rise of working from home. Instead, changes in the occupational employment composition of the workforce account for 60% of the observed increase in hours worked from home since 2003 and can account for increases after 2017.

In the next section, we outline aggregate trends in hours worked at the workplace vs from home and document considerable differences in the update and intensity of work from home across occupations. In section 3 we present a model of how workers choose the location of where to work and in section 4 we estimate the model. Section 5 presents the decomposition exercise for the aggregate relative productivity of working from home and aggregate weekly hours worked from home and section 6 concludes.

2 Data

The main source of data comes from 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% spend 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 time is mostly spent eating but also includes other activities. The distinction between work and non-work activities in the ATUS

Table 1: Demographic Summary Statistics: ATUS 2003-2019

Characteristic	Sample Mean	Characteristic	Sample Mean
Female	0.47	Less than HS	0.07
Married	0.63	Black	0.12
Age	42.79	Other	0.07
Child	0.45	White	0.82
Advanced Degree	0.14	Full Time	0.86
College	0.25	At Work Place	0.79
High School	0.28	Worked	0.85
Some College	0.26		
Total number of Observations			47,792

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 [2004]. The variable "At Work Place" summarized 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.

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.

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

[2]ATUS activity code 50101.

[3]ATUS activity code 120308.

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

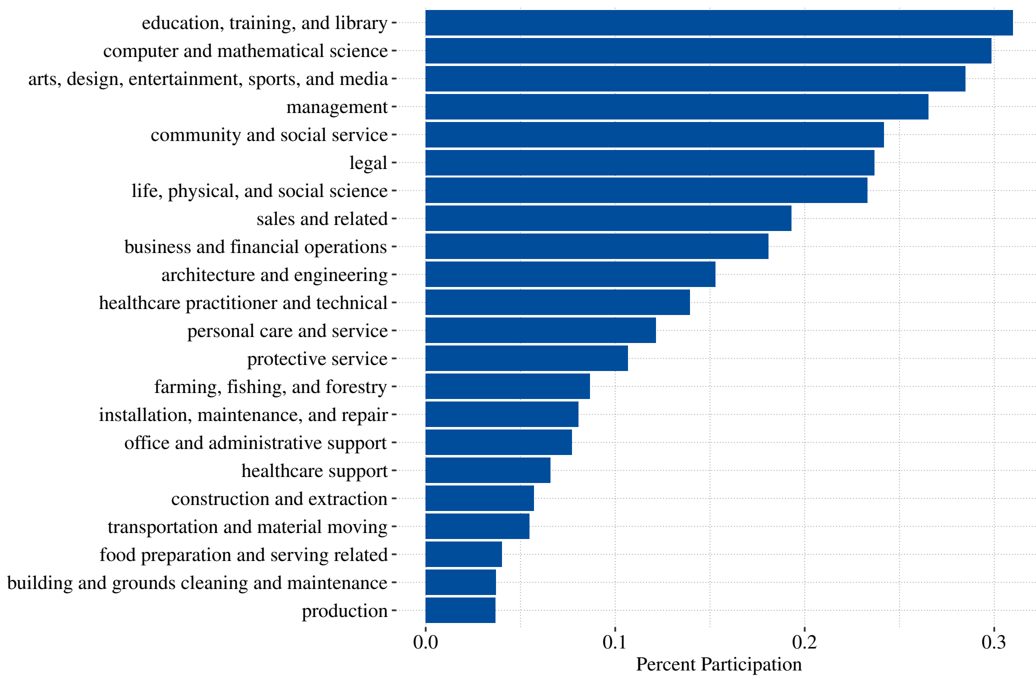
	Sample Mean
Panel (a): All Work	
Participation	0.85
Unconditional Hours	6.92
Conditional Hours	8.15
Panel (b): Work at Workplace	
Participation	0.79
Unconditional Hours	6.50
Conditional Hours	8.19
Panel (c): Work at Home	
Participation	0.15
Unconditional Hours	0.42
Conditional Hours	2.86
Total number of Observations	47,792

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.

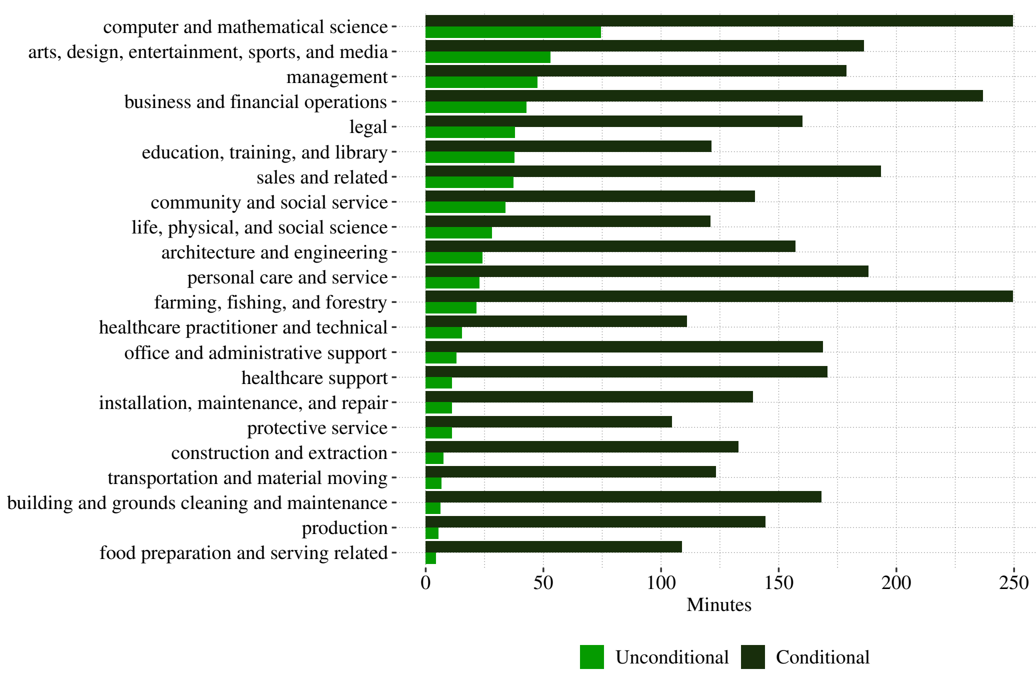
8.19 hours working. Finally, panel (c) summarizes working from home. 15% of the sample participated in some work from home. This is similar to Brynjolfsson et al. [2020], who find in a survey conducted April 2020 that 15% of workers say they used to work from home before the start of the pandemic. Unconditionally, 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.

Work from home varies markedly, both in participation and minutes, across occupations. Panel (a) of Figure 1 plots the participation probabilities of WFH across occupations. Education, training, and library occupations have the highest probability of observing a person working from home (0.31) and production occupations have the lowest (0.04).

Figure 1: Participation and Minutes of WFH



(a) Participation Percentage



(b) Minutes

Note: ATUS weights used in all calculations. The weights adjusted so that each day is $1/5^{th}$ *of our subsample.*

Panel (b) plots the unconditional average minutes of WFH by occupation. Again we see substantial differences across occupations. For example, computer and mathematical science occupations work on average an hour and 15 minutes at home whereas production and food preparation and serving related occupations spend about 5 minutes working at home on average. The ranking is similar when looking at conditional minutes.

2.1 Trends in Hours Worked

Using our measures of hours worked at the individual level, we aggregate to a measure of average weekly hours per worker per quarter. In the ATUS the sample weights aggregate measures of daily time spent in each activity to total quarterly time spent. 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}) and the ATUS sample weight (wgt_{it}) for each quarter t:[4]

$$H_t^w = \sum_i h_{it}^w \times wgt_{it}. \tag{1}$$

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.

$$\bar{H}_t^w = \frac{H_t^w}{13 \times E_t}, \tag{2}$$

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

$$E_t = \sum_i \frac{wgt_{it}}{92}. \tag{3}$$

The sample weight is divided by the average days per quarter to get the total employed.

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

[4]We adjust the ATUS sample weight such that each day of the week is 1/5th in our final sample of workers. More information can be found in Appendix A.4

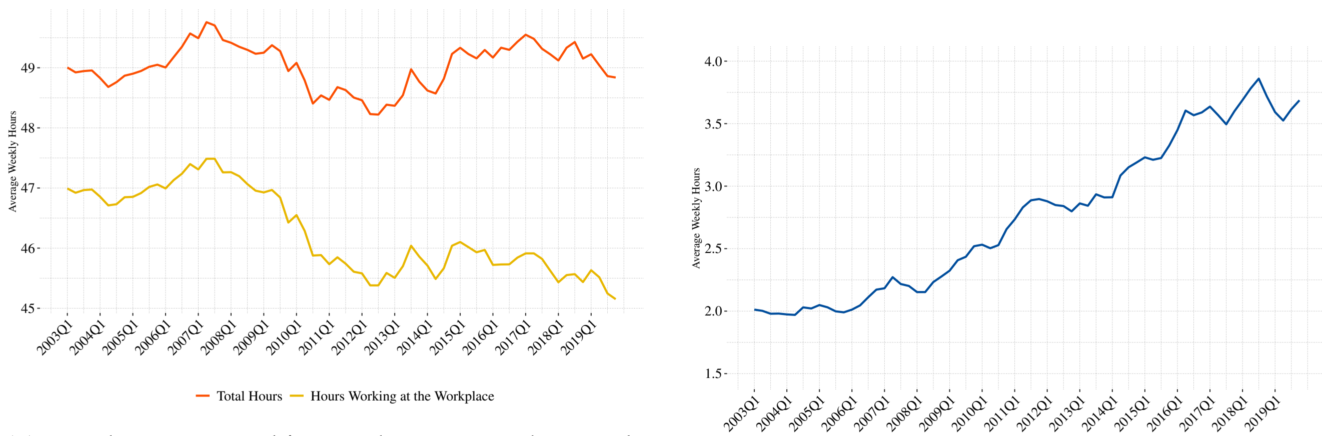
average weekly total hours worked per worker ($\bar{H}$) as:

$$\bar{H}_t^h = \frac{\sum_i h_{it}^h \times wgt_{it}}{13 \times E_t} \tag{4}$$

$$\bar{H}_t^h = \frac{\sum_i (h_{it}^w + h_{it}^h) \times wgt_{it}}{13 \times E_t}, \tag{5}$$

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

Figure 2: Average Weekly Hours per Worker



(a) Total Hours Working and Hours at the Workplace

(b) Work from Home

Note: ATUS weights used in all calculations. The weights adjusted so that each day is $1/5^{th}$ of our subsample.

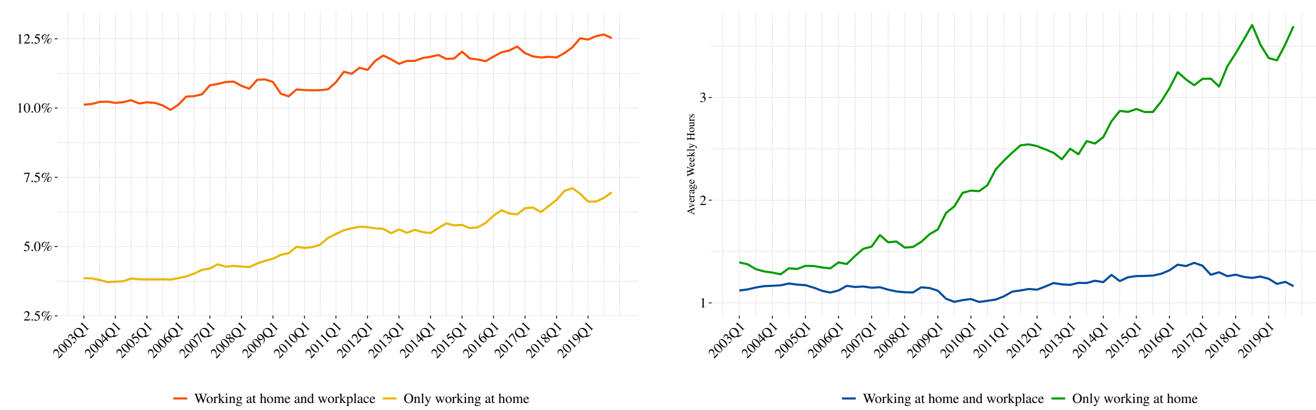
Panel (a) of Figure 2 plots the average weekly total hours worked per worker and the average weekly hours worked at the workplace per worker. The two series are similar until the start of 2008, after which they diverge. The difference between the two series is the amount of time workers spent working at home, plotted in panel (b). The average weekly hours worked at home nearly doubles from 2 hours to 4 hours per week by the end of 2019.

The rise in average weekly hours worked at home is due to both an increase in teleworkers, that is, workers who work exclusively from home, and an increase in workers that choose to work both at home and at the workplace. Panel (a) of Figure 3 plots the fraction of workers who work solely from home; the fraction of teleworkers has increased from about 3.8% in 2003 to nearly 7% in 2019.[5] Panel (a) also plots the fraction of workers who worked from

[5] This is similar to what others have found. Pabilonia and Vernon [2022] find the fraction of workers working exclusively

home among workers that also worked at the workplace on the diary day, that is, those that split their workday across home and the office. The fraction of people splitting their workday has also increased over the sample, from 10% in 2003 to 12.5% in 2019. Panel (b) plots the average weekly hours of work from home by both groups. The average hours of workers who split their time across the workplace and home has stayed relatively stable over the sample, while the average weekly time working at home by teleworkers has increased from an hour and 25 minutes to three hours and 40 minutes. Overall, the figure shows that both an increase in the intensive and extensive margins of working from home have occurred since 2003.

Figure 3: Work From Home Participation and Average Hours



(a) Fraction Who Participated in WFH

(b) Average Weekly Hours of WFH

Note: ATUS weights used in all calculations. The weights adjusted so that each day is $1/5^{th}$ *of our subsample. Panel (a) plots the fraction of people who worked from home and the workplace and the fraction of people that worked only from home on the diary day. Panel (b) plots the average weekly hours worked at home among those that worked at home and the workplace and those that worked only at home.*

In this section, we have documented two features of working from home. First, the propensity of working from home and the time spent working from home varies widely across occupations. Second, there has been a substantial rise in hours worked at home, arising from both the number of teleworkers and workers splitting their time between the workplace and home. In the next section, we develop and estimate a model with occupational-specific relative productivity of working from home and decompose the rise in working from home into changes in occupational composition and within occupation increases in the relative productivity of working from home.

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.

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 determines how workers choose to divide their time between the workplace and home. This lets us abstract from the firm's decision to allow workers to work from home. We also abstract from occupational choice and do not allow for shirking at the workplace or at home. When taking the model to the data, our estimate of the relative productivity of working from home will, as other estimates of productivity such as TFP, be a residual, unexplained by the model.

3.1 Production

Aggregate production is Cobb-Douglas in capital K_t and labor input L_t with aggregate productivity A_t and capital share α:

$$Y_t = A_t K_t^{\alpha} L_t^{1-\alpha}.$$

Labor input is aggregated across occupations using a CES aggregator function with substitution parameter ω. Within occupations, labor input from individuals are perfect substitutes with marginal productivity θ_i:

$$L_t = \Big(\sum_j L_{jt}^{\omega} \Big)^{\frac{1}{\omega}}$$
$$L_{jt} = \sum_i \theta_i \ell_{ijt}$$

where L_{jt} is total labor input of occupation j in year t and ℓ_{ijt} is individual i's labor input in occupation j in year t.

The labor input of worker i is the sum of hours worked at home (h^h) and at the workplace (h^w), that is

$$\ell_{ijt} = h_{ijt}^{w} + \gamma_{ijt} h_{ijt}^{h}$$

where $\gamma_{ijt} \geq 0$ is the relative productivity of hours worked at home. For each worker, the relative productivity is a draw from an occupation-specific distribution with a time-varying mean, $\gamma \sim F_{jt}(\gamma)$ where F_{jt} is the CDF of the relative productivity distribution for occupation j at time t.

Markets are perfectly competitive and workers get paid for their marginal product. Worker i in occupation j and year t gets paid:

$$w_{ijt} = (1-\alpha)A_t K_t^{\alpha} L_t^{1-\alpha-\omega} L_{jt}^{\omega-1}\theta_i \tag{6}$$

In the model, firms do not choose whether to allow work from home, rather all firms allow work from home and let workers optimally allocate time working at home and at the office. Through the lens of our model, changes in the availability of working from home, ie more firms offering flexible work schedules, should be interpreted as an increase in the relative productivity of working from home. We believe this interpretation is reasonable in the sense that profit-maximizing firms would only allow work from home if it was productive, and therefore, an increase in the relative productivity of working from home would induce more firms to allow splitting their time.

3.2 Workers

Workers have utility over consumption and hours worked at the workplace and hours worked at home:

$$u(c_{it}, h_{ijt}^h, h_{ijt}^w) = log(c_{it}) - \eta_i[(\chi_{it} h_{ijt}^h)^\rho + (h_{ijt}^w)^\rho]^{\frac{1}{\rho}}$$

where h_{ijt}^h is the hours worked at home and h_{ijt}^w is the hours worked at the workplace by individual i in occupation j in year t. Workers get aggregate disutility of working by aggregating time at home and at the workplace with substitution parameters ρ, common to all workers. The utility of working is decreasing in both hours at home and hours at the workplace and we restrict $\rho \geq 1$ such that the indifference curves are concave to the origin. Workers are heterogeneous in their disutility of working, η_i, and relative disutility of working from home, χ_{it}.

Workers cannot save and receive a wage w_{ijt} for each unit of labor input they deliver. Hours worked at home and at the workplace are perfect substitutes in producing a unit of labor input with relative productivity of working from home γ_{ijt}. That is, a worker i's labor input in occupation j and year t is $\ell_{ijt} = h_{ijt}^w + \gamma_{ijt} h_{ijt}^h$.

Workers maximize utility subject to their budget constraint,

$$\max_{\{c_{it},h^h_{ijt},h^w_{ijt}\}} log(c_{it}) - \eta_i[(\chi_{it}h^h_{ijt})^\rho + (h^w_{ijt})^\rho]^{\frac{1}{\rho}}$$
$$\text{s.t. } c_{it} = w_{ijt}(h^w_{ijt} + \gamma_{ijt}h^h_{ijt}).$$

The first-order conditions for hours worked are

$$\frac{1}{h^w_{ijt} + \gamma_{ijt}h^h_{ijt}} - \eta_i[(\chi_{it}h^h_{ijt})^\rho + (h^w_{ijt})^\rho]^{\frac{1}{\rho}-1}(h^w_{ijt})^{\rho-1} = 0$$
$$\frac{\gamma_{ijt}}{h^w_{ijt} + \gamma_{ijt}h^h_{ijt}} - \eta_i[(\chi_{it}h^h_{ijt})^\rho + (h^w_{ijt})^\rho]^{\frac{1}{\rho}-1}(h^h_{ijt})^{\rho-1}\chi^\rho_{it} = 0$$

and the ratio of optimal hours worked at home to hours worked in the workplace is given by

$$\frac{h^h_{ijt}}{h^w_{ijt}} = \left(\frac{\gamma_{ijt}}{\chi^\rho_{it}}\right)^{\frac{1}{\rho-1}}. \tag{7}$$

Total hours at home and at the workplace are

$$h^h_{ijt} = \frac{\chi_{it}^{\frac{\rho}{1-\rho}}\gamma_{ijt}^{\frac{1}{\rho-1}}}{\eta_i\left[1+\chi_{it}^{\frac{\rho}{1-\rho}}\gamma_{ijt}^{\frac{\rho}{\rho-1}}\right]^{\frac{1}{\rho}}} \tag{8}$$
$$h^w_{ijt} = \frac{1}{\eta_i\left[1+\chi_{it}^{\frac{\rho}{1-\rho}}\gamma_{ijt}^{\frac{\rho}{\rho-1}}\right]^{\frac{1}{\rho}}} \tag{9}$$

Equation 7 shows that the ratio of hours at home to the workplace is determined by the relative productivity of WFH and workers' preferences. Intuitively, looking at the hours choices of similar workers employed across different industries should give us some information about the relative productivity of WFH. In what follows we allow worker preferences to vary by all observable characteristics and our estimates of the relative productivity of WFH is identified as the residual needed to match the hours ratio, conditional on worker preferences.

Our model abstracts from commuting time. Although we do think that this is an important component of working from home, it should be modeled in a general equilibrium framework, together with housing location and job location as in Davis et al. [2021]. Burd et al. [2021] show that average commuting time in the US has increased from about 25 minutes per day to just over 28 minutes per day, through the lens of our model these changes should be reflected in changes in the relative disutility of working from home.[6]

4 Estimation

To understand changes in hours worked at home from the model we need to estimate a set of relative productivities, γ, and worker preferences which consist of the relative 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 ratio from the ATUS. From Equation 7 it is clear that given an estimate of ρ, we can identify the relative productivity of working from home from variation in the hours ratio across occupations and relative disutility of working from home from variation in the hours ratio 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 maximizing the likelihood of the observed hours ratio in the main ATUS sample.

4.1 Estimating ρ

The starting point for our estimation of the substitution parameters is the hours worked at home ratio from the model. Taking logs of Equation 7 gives

$$\ln \frac{h_{ijt}^h}{h_{ijt}^w} = \frac{1}{\rho - 1} \ln \gamma_{ijt} + \frac{\rho}{1-\rho} \ln \chi_{it}. \tag{10}$$

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 asks respondents about their job flexibility and paid/unpaid leave. Importantly within the scope of job flexibility, respondents are asked

[6]Since the ATUS interviews workers about only one day of the week if the worker worked strictly from home we do not observe their commute time.

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.

The JFL does not contain information on hours worked at home or the workplace so instead, we use a proxy for the hours ratio constructed using information on full days worked at home. Respondents are asked *"How often do you work only at home?"* and responses are binned into categories, 5 or more days per week, 3 to 4 days per week, 1 to 2 days per week, at least once per week, once every 2 weeks, once per month or less than once per month. We use this question to construct a measure of the ratio of days per week at home to days per week at the workplace, d^h/d^w[7]. The ratio of days at home will be used as a proxy for the hours ratio in Equation 10.

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, $\ell_{ijt} = h^w_{ijt} + \gamma_{ijt} h^h_{ijt}$, therefore observing a worker paid for the work they do at home and a worker that is not paid for the work they do at home is a proxy from 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 but do robustness to other definitions.

To estimate the elasticity of substitution we run the following regression

$$\ln \frac{d^h_{ij}}{d^w_{ij}} = \beta_1 paid_{ij} + \beta_2 X_{ij} + \delta_j + \varepsilon_{ij} \tag{11}$$

where $\frac{d^h_{ij}}{d^w_{ij}}$ is the ratio of full days worked at home to full days worked at the workplace by worker i in occupation j, $paid_i$ is a dummy that takes on the value 1 if the worker is paid for their work at home, X_i is the vector of observable characteristics (sex, race, age, full/part-time, education, marital status, children), and δ_j are occupation fixed effects. The estimate $\hat{\beta}_1$ gives us an estimate of the elasticity of substitution, $\hat{\rho} = 1/\hat{\beta}_1 + 1$. A full description of the JFL sample used for the estimation can be found in Appendix A.1.

Table 3 reports the estimated coefficient on $paid_{ij}$ and the resulting estimated value for

[7]A description of how this variable is coded can be found in Appendix A.1

Table 3: Elasticity of Substitution Estimates

	(1)	(2)	(3)
paid	0.601^{***}	0.424^{**}	0.625^{***}
	(0.150)	(0.180)	(0.151)
ρ	2.665	3.358	2.601
	(0.415)	(1.001)	(0.388)
Occupation FE	Yes	Yes	Yes
Observations	1363	1174	1198

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Robust standard errors in parentheses. Standard Errors for ρ are calculated using the delta method. Column (1) reports the estimate using the full sample of workers where $paid_{ij}$ is one for workers reporting that they are "paid" or "both" for their work at home. Column (2) reports the estimate for workers that report being "paid" or "both" for their work at home and $paid_{ij}$ is one only for workers that report "paid." Column (3) reports the estimate for workers that report either being "paid" or "take work home" where $paid_{ij}$ is one for workers that report they are "paid." A table with all regression coefficients can be found in Appendix

ρ. The first column is our main specification as described above; the estimated value of the coefficient on the paid variable is 0.6, implying an estimated substitution parameter equal to 2.7. Since workers receive disutility from hours worked, a value of ρ greater than one implies indifference curves that are concave to the origin.

Columns (2) and (3) report the estimate for alternative estimations. In column (2) we estimate the same equation but drop all workers that report "taking work home" and redefine $paid_{ij}$ to be 1 only for workers that report being paid and 0 otherwise. For this sample, the estimated coefficient decreases to 0.4, and the resulting estimate substation parameter increase to 3.4, but is not statistically different from our main specification. Finally, in column (3) we drop workers that report "both." The resulting coefficient estimate is 0.63 and the substitution parameter is 2.6. We take this as evidence that our estimate is robust to different samples and definitions of our proxy. In what follows we use $\hat{\rho} = 2.665$ as estimated using the full sample.

4.2 Estimating the Relative Productivity and Disutility of Work From Home

We estimate the remaining parameters of the model by maximizing the likelihood of observing the worker's ratio of hours worked at home to hours worked at the workplace. We allow worker preferences to vary with observable characteristics and over time and relative productivity to vary across occupations and over time.

Time spent working is reported in minutes and some workers report zero time working at home or at the workplace. Given the CES structure of workers' preferences between work at home and the workplace, the model does not produce corner solutions. Instead, workers reporting zeros hours worked at home are mapped to the model as having optimal hours at home less than one minute. Using Equation 8 and solving for the relative productivity of work from home such that $h^h_{ijt} < 1/60$ gives

$$\gamma_{ijt} < \chi_{it}\left[\left(\frac{60\chi_{it}}{\eta_i}\right)^{\rho} - 1\right]^{\frac{1-\rho}{\rho}} \equiv \underline{\gamma}_{it}, \tag{12}$$

where $\underline{\gamma}_{it}$ is the lower bound on the relative productivity of work from home, below which worker i reports zero time spent working from home. Similarly, workers reporting zero hours worked at the workplace are mapped to the model as having optimal hours at the workplace less than one minute. Using Equation 9, and solving for the relative productivity of work from home such that $h^w_{ijt} < 1/60$ gives

$$\gamma_{ijt} > \chi_{it}\left[\left(\frac{60}{\eta_i}\right)^{\rho} - 1\right]^{\frac{\rho-1}{\rho}} \equiv \bar{\gamma}_{it}, \tag{13}$$

where $\bar{\gamma}_{it}$ is the upper bound on the relative productivity of hours worked from home, above which worker i reports zero time working at the workplace.

We allow the relative disutility of working from home χ to differ by observable characteristics and over time. We bin workers into 24 mutually exclusive types determined by their sex, marital status, whether or not they have a child, and three education levels (high school or less, some college or college, and advanced degree). Within each type we allow the relative disutility to change over. Our final specification is $\chi_{it} = \chi^0_i + \delta^\chi_i t$ where t is a yearly time trend and we estimate a set of 24 initial relative disabilities $\{\chi^0_i\}$ and trends $\{\delta^\chi_i\}$.

The preference parameters are identified by variation of the hours ratio across demographic types and changes over time within each demographic type.

Although we do not match levels in the estimation, η_i determines the probability of observing a worker reporting either no time worked at home or at the workplace, Equation 12 and Equation 13. Therefore, we allow η_i to vary by observables Z_i, which includes an indicator if the worker is full-time, day of the week indicators for the diary day, sex, marital status, whether or not the worker has a child, five education levels, and four age categories.[8] To ensure that the estimate of the utility of work remains negative we specify the parameter as $\eta_i = exp(\beta Z_i)$, where Z_i is the set of observables, and estimate the vector β.

We specify the distribution of relative productivity of work from home as Gamma. We allow the distribution of relative productivities to vary by occupation and the scale parameter to vary over time, that is, $\gamma \sim Gamma(k_j, \theta_{jt})$. We estimate a time-varying scale parameter for each occupation using a linear trend, $\theta_{jt} = \theta_j^0 + \delta_j^\theta t$ where t is a yearly trend. The shape and scale parameters are identified by variation in the hours ratio across occupations and the change in the scale parameter is identified by changes in the hours ratio within occupations over time.

Observing a worker in occupation j in year t who chooses not to work from home is equal to the probability that the draw from the relative productivity distribution is less than $\underline{\gamma}_{it}$, that is,

$$\begin{aligned} P(h^h_{ijt}/h^w_{ijt} = 0|X_i, Z_i) &= P(\gamma_{ijt} < \underline{\gamma}_{it}|X_i, Z_i) \\ &= F(\underline{\gamma}_{it}; k_j, \theta_{jt}), \end{aligned} \tag{14}$$

where F is the CDF of the Gamma distribution and X_i is an indicator for which demographic type worker i is. Similarly, observing a worker in occupation j in year t choosing to work no time at the workplace is equal to

$$\begin{aligned} P(h^h_{ijt}/h^w_{ijt} = \infty|X_i, Z_i) &= P(\gamma_{ijt} > \bar{\gamma}_{it}|X_i, Z_i) \\ &= 1 - F(\bar{\gamma}_{it}; k_j, \theta_{jt}). \end{aligned} \tag{15}$$

[8]The educational categories are, less than high school, high school, some college, college, and advanced degree. The age categories are 24-34,35-44,45-54, and 55-65.

The probability of observing a worker that chooses an hours ratio equal to $\tilde{h}_{ijt}$ is

$$P(h^h_{ijt}/h^w_{ijt} = \tilde{h}_{ijt}|X_i, Z_i) = \frac{d}{d\,\tilde{h}_{ijt}} P\left(\left(\frac{\gamma_{ijt}}{\chi^\rho_{it}}\right)^{\frac{1}{\rho-1}} < \tilde{h}\middle| X_i, Z_i\right) \tag{16}$$

$$= P(\gamma_{ijt} = \chi^\rho_{it}\tilde{h}^{\rho-1}_{ijt}|X_i, Z_i)(\rho-1)\tilde{h}^{\rho-2}_{ijt}\chi^\rho_{it} \tag{17}$$

$$= (\rho-1)\tilde{h}^{\rho-2}_{ijt}\chi^\rho_{it} \times f(\chi^\rho_{it}\tilde{h}^{\rho-1}_{ijt}; k_j, \theta_{jt}), \tag{18}$$

where f is the PDF of the Gamma distribution.

An individual's contribution to the likelihood function is given by

$$P(h^h_{ijt}/h^w_{ijt}|X_i, Z_i) = [P(\gamma_{ijt} < \underline{\gamma}_{it}|X_i, Z_i)]^{\mathbb{1}(h^h_{ijt}=0)} \times [P(\gamma_{ijt} > \bar{\gamma}_{it}|X_i, Z_i)]^{\mathbb{1}(h^w_{ijt}=0)}$$
$$\times [\{P(\gamma_{ijt} < \bar{\gamma}_{it}|X_i, Z_i) - P(\gamma_{ijt} < \underline{\gamma}_{it}|X_i, Z_i)\}P(h^h_{ijt}/h^w_{ijt} = \tilde{h}_{ijt}|X_i, Z_i)]^{\mathbb{1}(h^w_{ijt}>0, h^h_{ijt}>0)} \tag{19}$$

and the log-likelihood function is

$$\mathcal{L}(\beta, \{k\}_j, \{\theta^0\}_j, \{\delta^\theta\}_j, \{\chi^0\}_i, \{\delta^\chi\}_j; X_i, Z_i, h^h_{ijt}, h^w_{ijt}, \hat{\rho}) = \sum_{i=1}^{N} \ln P(h^h_{ijt}/h^w_{ijt}|X_i, Z_i). \tag{20}$$

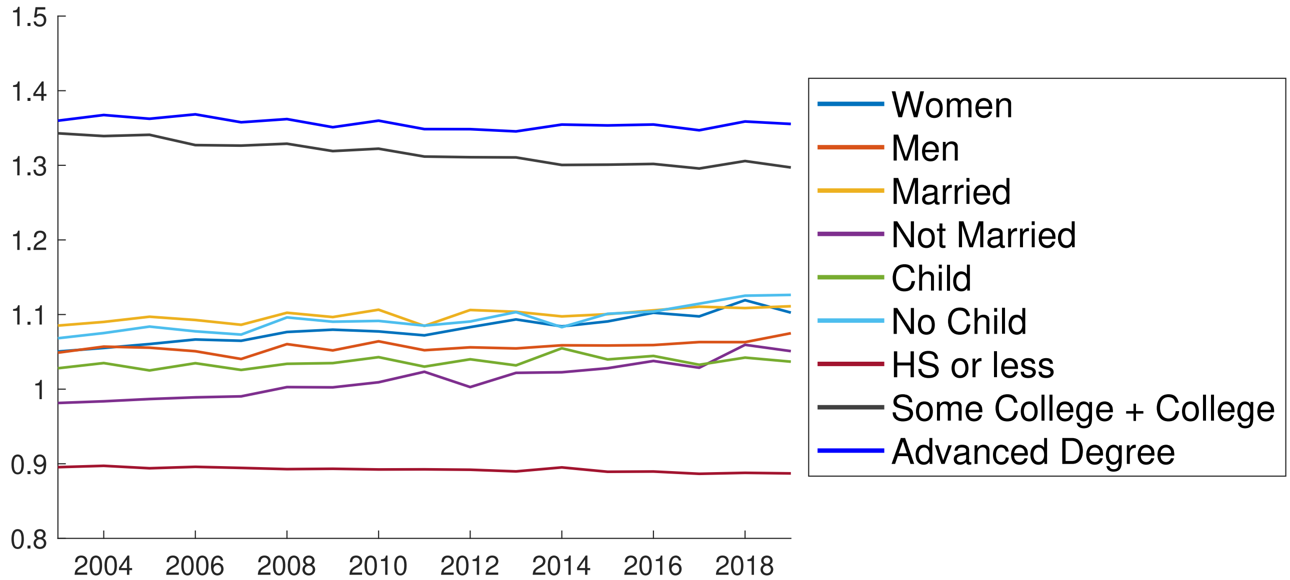
Maximizing Equation 20 gives estimates of the effect of the worker characteristics the relative disutility of work (β), the time-varying scale parameter of the relative productivity distribution for each occupation (θ^0_j and δ^θ_j), the shape parameter of the relative productivity distribution for each occupation (k_j), and time-varying relative disutility of working from home (χ^0_i and δ^χ_i).

4.3 Estimation Results

Table A.9 in Appendix A.2 reports the estimated relative disutility of working from home. In general, for both men and women the relative disutility of working from home is higher for married people, people with children, and increasing in education. Comparing married women and men with children, women have a lower relative disutility of working from home regardless of education level. Over time, many of the demographic groups' relative disutility is decreasing, for example, the disutility for married and unmarried men with children and an advanced degree is decreasing by 0.023 (2.5% of the 2003 estimated value) and 0.036

(1.4% of the 2033 estimate value) per year, respectively. However for unmarried women without children and an advanced degree the disutility has increased over time. Figure A.10 in Appendix A.2 plots the estimate relative disutility over time for each demographic group, $\hat{\chi}_{it} = \hat{\chi}_i^0 + \hat{\delta}_i t$.

Figure 4: Relative Disutility in Sample

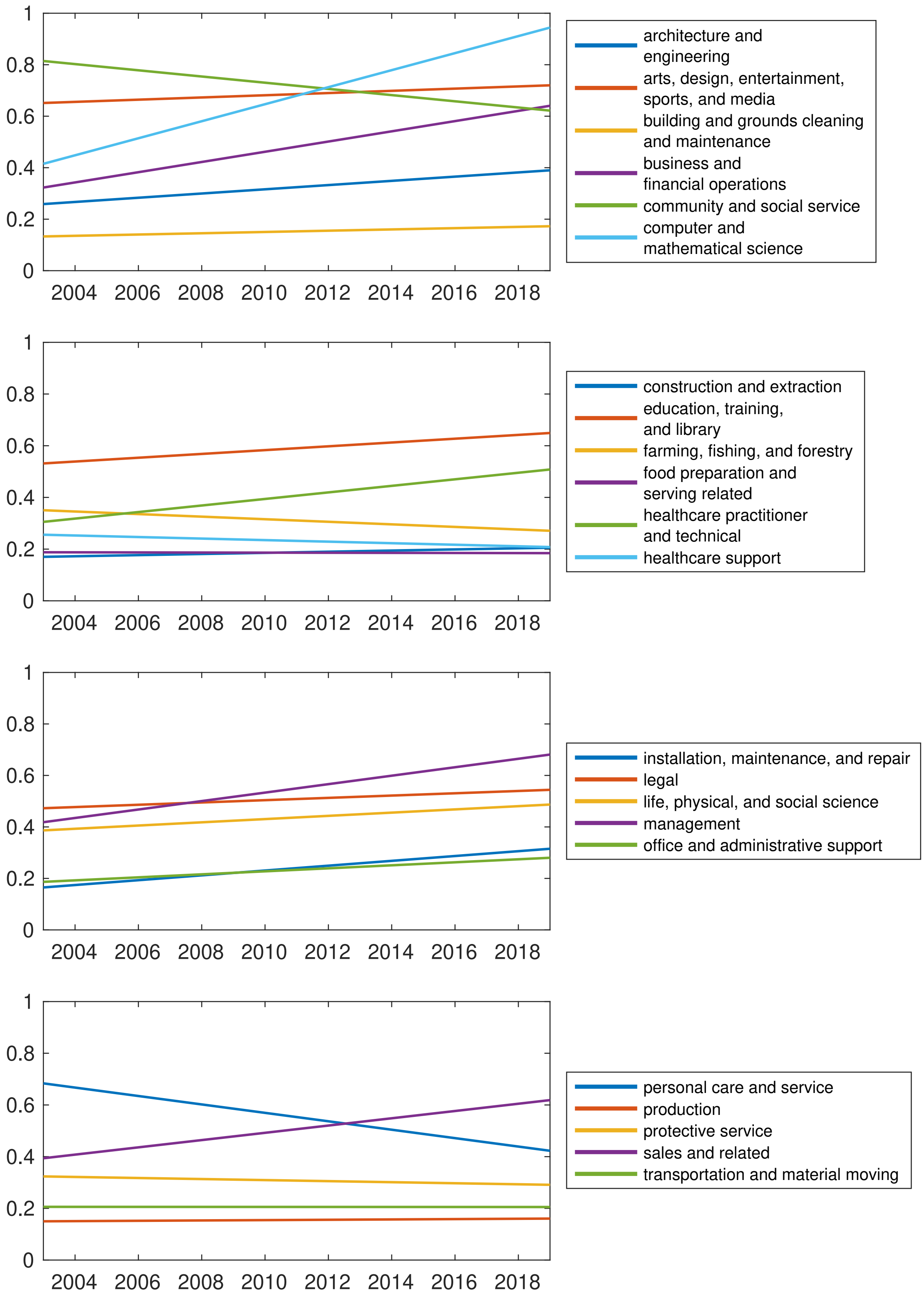


Note: The figure plots the average relative disutility of working from home within the subgroup. That is for an "Advanced Degree" the relative disutility of working from home is calculated as the weighted average of all individuals with an advanced degree.

Figure 4 plots the average relative disutility of working from home within each subgroup. For example, the line labeled “Advanced Degree" is the weighted average relative disutility of all workers with an advanced degree. Changes in the relative disutility plotted by subgroup can be driven by both compositional changes and changes in preferences. The relative disutility of working from home has decreased when looking at the average worker by education but has increased when looking at the average woman and the average worker with children. Overall, the average preferences among subgroups have not changed much since 2003, and this alludes to our findings in the next section, that changes in preferences can not account for the rise in hours worked at home.

Table A.8 in Appendix A.2 reports the estimated parameters of the relative productivity distribution for each occupation. The shape parameters (k) are similar across occupations, implying similarly shaped distributions and $k < 1$ for all occupations, implying that the mode for each occupation is 0. The scale parameter varies substantially more across occupations and therefore determines why occupations ultimately have different mean rel-

Figure 5: Relative Productivity of WFH by Occupation



Note: The figure plots the estimated mean relative productivity of working from home, calculated using Equation 21.

ative productivities. The majority of occupations have increasing relative productivity of working from home, with computer and mathematical science, business and financial operations, and management occupations increasing the fastest. Community and social services occupations have seen decreases in the relative productivity of working from home.

Figure 5 plots the estimated mean relative productivity of working from home over time for each occupation. The mean productivity for each occupation is computed as the mean of the Gamma distribution, that is

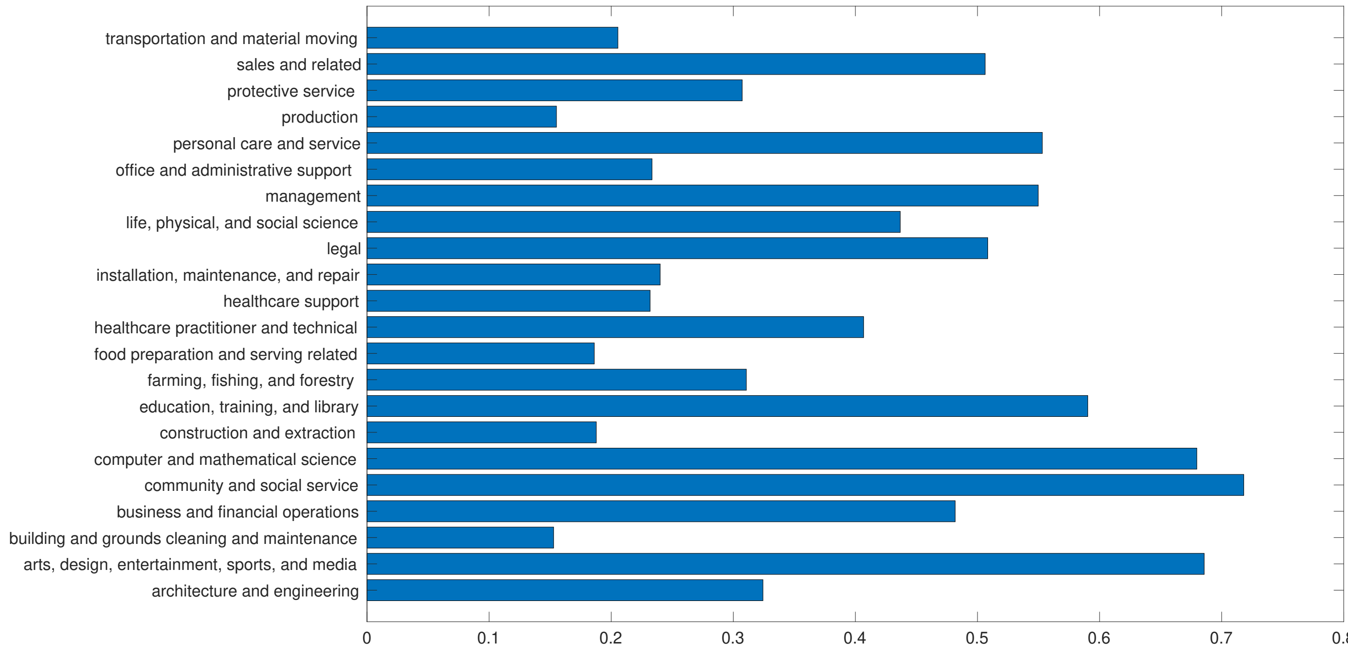
$$E[\gamma_{jt}] = \hat{k}_j \times (\hat{\theta}_j^k + \hat{\delta}_j^k t). \tag{21}$$

The figure compares both the levels and the increases in the relative productivity of WFH across occupations. Overall, the mean relative productivity is below 1 for all occupations. In 2003 all occupations except community and social services and arts, design, entertainment, sports and media, and personal care and services had relative productivity between 0.2 and 0.5, implying that the average home hour worked at home was as productive as 12 to 30 minutes worked in the office. Although some occupations have seen substantial increases in relative productivity, for example, computer and mathematical occupations' relative productivity more than doubled since 2003, many occupations have not experienced any increases, for example, food preparation and production.

Figure 6 plots the average relative productivity for each occupation from 2003 to 2019. As expected, occupations that tend to be more "hands-on" have a lower overall relative productivity. For example, the construction and extraction occupations, food preparation and serving-related occupations, and production occupations have relative productivity below 0.2, implying that an hour at home is less productive than 12 minutes at the workplace for these occupations. The occupations with low relative productivity coincide with those that have seen little growth.

Overall preferences and productivity have changed differentially by demographic group and occupation and looking at the estimates alone do not paint a clear picture of why hours worked at home have doubled since 2003. In section 5 we use the estimated parameters to decompose the increase in hours worked into changes in preferences, productivity, and compositional changed in the workforce across demographic groups and occupations.

Figure 6: Average Relative Productivity of WFH by Occupation



Note: The figure plots the average expected relative productivity (Equation 21) of working from home for each occupation from 2003 to 2019.

4.4 Model Fit

Although maximum likelihood matched the full distribution of the data, it is useful to see how well the model fits the hours ratio, the probability of observing no hours worked at home or at the workplace and the change in aggregate hours worked at home over the sample.

The predicted hours ratio for each individual is

$$\widehat{\frac{h^h_{ijt}}{h^w_{ijt}}} = \int_0^\infty \left(\frac{\gamma}{\hat{\chi}^{\hat{\rho}}}\right)^{\frac{1}{\hat{\rho}-1}} d\hat{F}_{jt}(\gamma), \tag{22}$$

where $\hat{F}_{jt}$ is the estimated CDF of the relative productivity of working from home in occupation j in year t. The predicted probability that a worker report a positive number of hours worked at home and at the workplace is,

$$\hat{P}^{int}_{ijt} = \hat{F}_{jt}(\hat{\bar{\gamma}}_{it}) - \hat{F}_{jt}(\hat{\underline{\gamma}}_{it}), \tag{23}$$

the predicted probability a worker reports no hours worked at home is,

$$\hat{P}^{h^h=0}_{ijt} = \hat{F}_{jt}(\hat{\underline{\gamma}}_{it}), \tag{24}$$

Table 4: Model and Data Moments

	Data	Model
Hours ratio	0.383	0.370
$\text{P}(h^h > 0 \ \& \ h^w > 0)$	0.107	0.103
$\text{P}(h^h = 0)$	0.828	0.830
$\text{P}(h^w = 0)$	0.065	0.067

and the predicted probability a worker reports no hours worked at the workplace is,

$$\hat{P}_{ijt}^{h^w=0} = 1 - \hat{F}_{jt}(\hat{\bar{\gamma}}_{it}), \tag{25}$$

where $\hat{\bar{\gamma}}_{it}$ and $\hat{\underline{\gamma}}_{it}$ are the estimated upper and lower bounds of reporting positive hours worked at home and the workplace, Equation 12 and Equation 13. Table 4 reports the average sample and model predicted hours ratio and probabilities. Overall the fit of the model's key moments is good; the model under-predicts the average hours ratio by about 4%, over-predicts the probability that a worker reports working no hours at home by 0.2 percentage points, and under-predicts that a worker reports working both at home and at the workplace by about 0.5 percentage point.

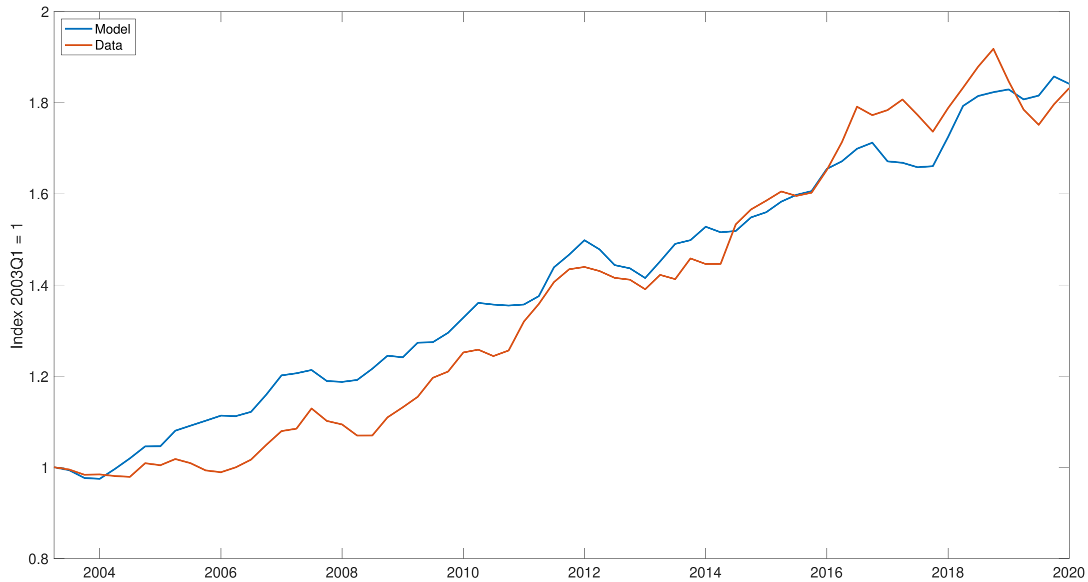
We construct predicted hours of work from home for each worker ($\widehat{h_{ijt}^h}$) using Equation 8 and the estimated model parameters. Then aggregate to predicted weekly hours worked at home are constructed as follows

$$\widehat{\bar{H}^h}_t = \sum_{i,j}(1 - P^{\hat{h^h}=0}{}_{ijt}) \times \widehat{h_{ijt}^h} \times wgt_{ijt}, \tag{26}$$

where wgt_{ijt} is the workers ATUS sampling weight.

Figure 7 plots the resulting predicted and observed average weekly hours worked at home per person. Since we do not match the level of hours worked and we are ultimately interested in decomposing the rise we index each series to 1 in 2003. The predicted hours worked at home follow the trend of observed hours worked at home closely.

Figure 7: Average Weekly Hours Worked From



Note: The figure plots in orange weekly hours worked at home per worker constructed using Equation 2 and indexed to 1 in 2003 and in blue the model predicted weekly hours worked at home constructed using Equation 26 and indexed to 1 in 2003.

5 Counterfactuals

Using the parameter estimate of the model we run two counterfactual exercises. First, we analyze the effect of changes in the relative productivity of working from home and changes in the relative disutility of working from home on hours worked at home. Second, we decompose the effect of the changing composition of the workforce into changes across demographic groups and changes across occupations.

5.1 Preferences vs Productivity

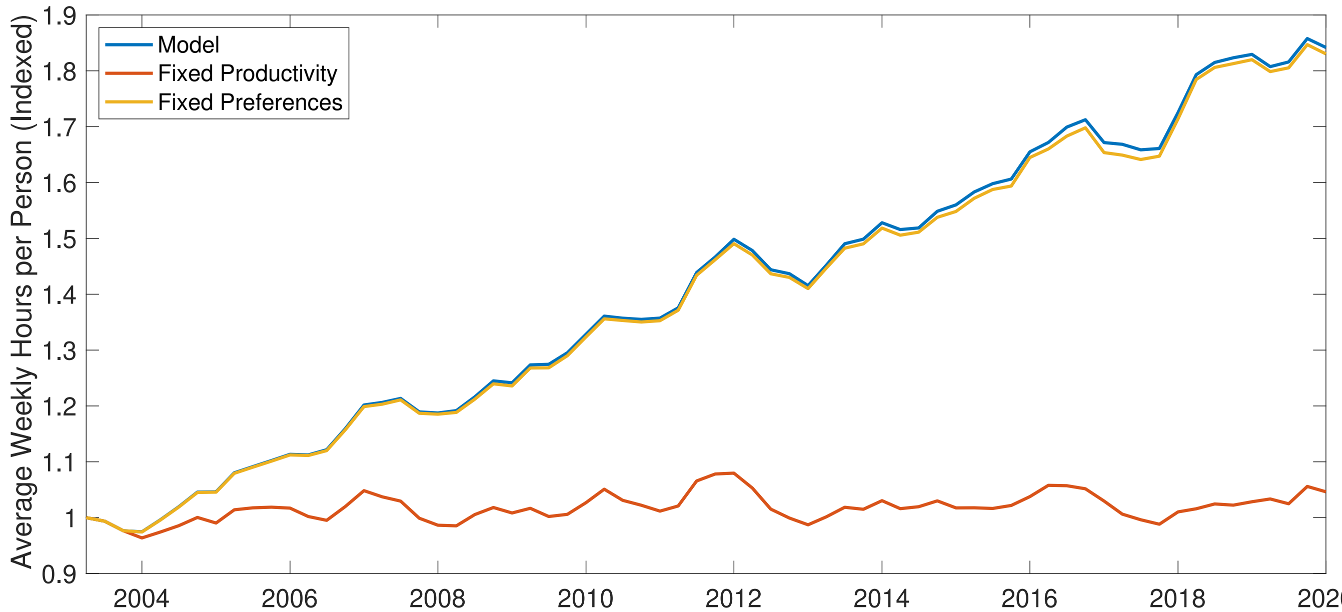
To understand the effect of changing preferences and productivity on weekly hours worked at home we construct two counterfactual hours worked at home series, one holding preferences (the relative disutility of working from home fixed) at their 2003 value and one holding productivities fixed at their 2003 values.

First we construct a counterfactual hours worked at home for each worker ($\tilde{h}^h_{ijt}$) using Equation 8 but set $\delta^\chi_i = 0$ for each demographic type i such that workers relative disutility of working is fixed at $\hat{\chi}^0_i$. Similarly, we construct a counterfactual cut of value for the relative productivity of working from home, $\tilde{\underline{\gamma}}_i$, below which the worker chooses not to work from home. Finally, we construct the counterfactual average weekly hours worked at home with fixed preferences as

$$\tilde{H}_t^h = \sum_{i,j} [1 - \hat{F}_{jt}(\underline{\tilde{\gamma}}_i)] \times \tilde{h}_{ijt}^h \times wgt_{ijt}. \tag{27}$$

Similarly to construct the counterfactual average weekly hours worked at home per worker when productivity is fixed we first predict individual hours worked but set $\delta_j^k = 0$ for each occupation j such that the scale parameter of the relative productivity of working from home distribution is fixed at θ_j^0. Then we construct the probability and observing someone work from home and aggregate up to weekly hours worked at home per worker as before.

Figure 8: Counterfactual: Preferences vs Productivity



Note: The figure plots the average weekly hours worked at home per worker predicted by the model (blue), when productivity is held fixed (orange), i.e. $\delta_j^k = 0$ for each j, and when preferences are held fixed (yellow), i.e. $\delta_i^\chi = 0$ for each i. Each series is indexed to 1 at its 2003 value

Figure 8 plots the counterfactual average weekly hours worked at home per worker series and the model predicted series each indexed at their 2003 values. The figure clearly shows that changes in worker preferences played little role in the increase in hours worked at home. If worker preferences had not changed since 2003 hours worked at home in 2019 would be nearly identical to what they are now. Changes in the relative productivity of working from home, on the other hand, played a substantial role. The counterfactual series holding productivity fixed shows that if the relative productivity of working from home had not changed since 2003, hours worked at home would have remained unchanged from their 2003 value.

5.2 Demographic vs Occupational Composition

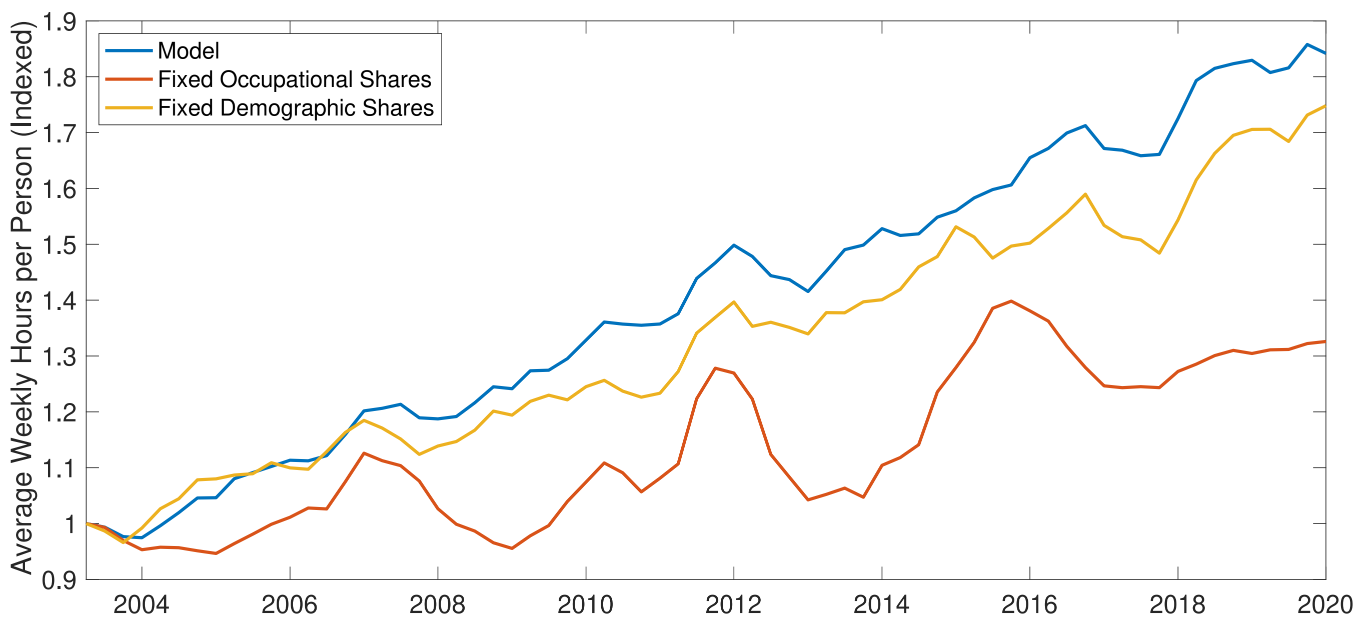
Changes in the composition of the workforce can also cause changes in the aggregate hours worked at home. Both changes in the composition across demographic types and employment across occupations can lead to increases in the observed measure. In this section, we construct two counterfactual series of aggregate hours worked at home, one in which we hold the employment composition across demographic groups fixed, and one in which we hold the employment composition across occupations fixed.

As before we construct predicted hours worked from home for each worker in the sample ($\hat{h}^h_{ijt}$) using Equation 8 and the model's estimated parameters and probability we observed the worker not working from home ($\hat{P}^{h^h=0}_{ijt}$) as in Equation 24. We then construct the counterfactual average weekly hours worked at home per worker as

$$\sum_{i,j}(1 - \hat{P}^{h^h=0}_{ijt}) \times \hat{h}^h_{ijt} \times \tilde{wgt}_{ijt}, \tag{28}$$

where $\tilde{wgt}_{ijt}$ is the counterfactual weight that holds either demographic or occupational employment shares fixed. A detailed explanation of how these weights are constructed can be found in Appendix A.4.

Figure 9: Counterfactual: Demographic vs Occupational Composition



Note: The figure plots the average weekly hours worked at home per worker predicted by the model (blue), when occupational employment shares are held fixed at their 2003 values (orange), and when demographic employment shares are held fixed at their 2003 values (yellow).

Figure 9 plots the counterfactual average weekly hours worked at home per worker series and the model predicted series each indexed at their 2003 values. The yellow line in the figure shows that, if the demographic composition were fixed at its 2003 distribution, hours worked at home would have evolved similarly, implying that changes in the demographic composition of the workforce since 2003 played little role in the observed increase in work from home. The occupational composition, on the other hand, played a larger role. If the occupational employment composition was fixed at its 2003 value, hours worked at home would have increased by 30%, 50 percentage points less than the observed increase, implying that occupation employment changes since 2003 account for around 60% of the observed increase in hours worked at home.

Overall the two counterfactual exercises show that worker preferences and demographic change in the workforce played little to no role in the rise of working from home. The rise can be attributed instead to a combination of increases in the occupational relative productivity of working from home and increases in the number of workers employed in occupations with higher relative productivity or working from home. In fact, since 2017, the entire increase in hours worked at home is accounted for by higher employment in occupations better suited to working from home.

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 nearly doubled using data from the American Time Use Survey. We constructed a mode in which workers optimally choose how much and where to work depending on the relative productivity of working from home, which is determined by the occupation they are employed in. We estimate the model using observations on the ratio of hours worked at home to the workplace and identify relative productivity as the residual needed to match the hours worked choices of workers within occupations, conditional on observable characteristics.

Using the estimated model we show changes in worker preferences and the demographic composition of the workforce played little role in the rise of work from home. We show that, instead, both within occupation increases in the relative productivity of working from home and changes in the employment composition across occupations account for the full increase in hours worked at home.

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A Appendix

A.1 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.5 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.5: 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

The left hand side variable of regression Equation 11 is constructed using information on the number of days worked at home per month and total days worked per month. Respondents are asked *"How often do you work only at home?"* and responses are binned into categories, 5 or more days per week, 3 to 4 days per week, 1 to 2 days per week, at least once per week, once every 2 weeks, once per month, or less than once per month. Table A.6 shows how these binned answers are converted to days worked at home per month, d^h. Total days worked per month come from the survey variable *lrdays*, which reports the usual number of days per week that the respondent works. We multiply *lrdays* by 4.5 to get usual days worked per month. The days ratio is constructed as,

$$\frac{d^h}{d^w} = \frac{d^h}{4.5 \times lrdays - d^h} \tag{A.29}$$

Table A.6: Days Worked at Home per Month

Response	d^h
5 or more days per week	4.5×5
3 to 4 days per week	4.5×3.5
1 to 2 days per week	4.5×1.5
at least once per week	4.5×1
once every 2 weeks	4.5×0.5
once per month	1
less than once per month	0.5

Table A.7 reports summary statistics for the days ratio constructed from the JFL module and the hours ratio constructed from the ATUS for workers who report spending both time working in the office and at home. The two statistics have a similar distribution, both skewed to the right. The mean and median of both statistics are similar. Although we do not observe information about hours worked at home in the JFL module, the proxy we construct using days worked at home as a similar distribution.

Table A.7: Summary Statistics: Hours ratio and Days ratio

	Minimum	25th percentile	Median	Mean	75th percentile	Max
Hours Ratio	0.0012	0.0531	0.1333	0.4758	0.3131	95.0000
Days Ratio	0.0161	0.0465	0.1111	0.6086	0.4286	10.0000

A.2 Estimated Parameters

Table A.8 reports the estimate parameters for the relative productivity of working from home distributions for each occupation. k is the estimated shape parameter, θ is the estimated scale parameter, and δ^{θ} is the estimated linear trend in the scale parameter. Standard errors are calculated using the Hessian of the estimation.

Table A.9 reports the relative disutility of working from home for each demographic group. χ is the estimated disutility of working from home in 2003 and δ^{χ} is the estimate linear trend in the relative disutility. Standard errors are calculated using the hessian of the estimation.

Figure A.10 plots the estimated relative disutility of working from home for each demographic group over time. The disutility is calculated using the estimates from Table A.9 and $\chi_{it} = \chi_i + \delta_i^{\chi} t$, where t is the year relative to 2003.

A.3 Counterfactual Weights

To construct the counterfactual weights used in subsection 5.2 we first find the percent of each demographic group g in 2003

$$\phi_g = \frac{\sum_{i \in g} wgt_{ij,2003}}{\sum_i wgt_{ij,2003}}. \tag{A.30}$$

Then the counterfactual weight for each group is constructed such that the percent in each subsequent year is held fixed at the 2003 fraction. That is,

$$\tilde{wgt}_{ijt} = \phi_g \times \sum_i wgt_{ijt} \tag{A.31}$$

for each i in group g. The counterfactual weights that hold the occupational employment composition fixed at the 2003 value are constructed analogously.

A.4 American Time Use Survey Sampling Weights

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.

Table A.8: Estimates: Relative Productivity of WFH Distribution Parameters

	k	θ	δ^{θ}
architecture and engineering	0.284	0.912	0.029
	[0.126,0.478]	[0.645, 2.074]	[0.0146, 0.0929]
arts, design, entertainment, sports, and media	0.296	2.203	0.015
	[0.152,0.483]	[1.294, 6.173]	[0.0045, 0.0565]
building and grounds cleaning and maintenance	0.136	0.980	0.018
	[0.056,0.230]	[0.676, 2.974]	[0.0086, 0.0583]
business and financial operations	0.218	1.480	0.091
	[0.100,0.355]	[0.971, 4.366]	[0.0439, 0.4593]
community and social service	0.287	2.837	-0.042
	[0.131,0.473]	[1.524,12.375]	[-0.2078,-0.0135]
computer and mathematical science	0.317	1.311	0.104
	[0.159,0.502]	[0.913, 2.944]	[0.0478, 0.4092]
construction and extraction	0.278	0.612	0.008
	[0.133,0.443]	[0.457, 1.383]	[0.0057, 0.0084]
education, training, and library	0.430	1.236	0.017
	[0.206,0.707]	[0.813, 2.743]	[0.0075, 0.0734]
farming, fishing, and forestry	0.213	1.647	-0.023
	[0.103,0.326]	[1.021, 6.965]	[-0.2377,-0.0047]
food preparation and serving related	0.231	0.812	-0.001
	[0.094,0.415]	[0.536, 2.351]	[-0.0096, 0.0002]
healthcare practitioner and technical	0.290	1.053	0.044
	[0.127,0.489]	[0.719, 1.905]	[0.0204, 0.2927]
healthcare support	0.241	1.059	-0.012
	[0.099,0.415]	[0.700, 3.325]	[-0.0513,-0.0075]
installation, maintenance, and repair	0.203	0.814	0.046
	[0.120,0.370]	[0.596, 1.890]	[0.0051, 0.0535]
legal	0.317	1.493	0.014
	[0.152,0.514]	[0.974, 4.865]	[-0.0713, 0.0577]
life, physical, and social science	0.308	1.254	0.020
	[0.131,0.502]	[0.864, 3.141]	[0.0083, 0.2121]
management	0.331	1.266	0.050
	[0.156,0.530]	[0.854, 2.988]	[0.0244, 0.2394]
office and administrative support	0.224	0.835	0.026
	[0.093,0.376]	[0.591, 2.154]	[0.0148, 0.1070]
personal care and service	0.197	3.477	-0.083
	[0.091,0.305]	[1.955,19.485]	[-0.4175,-0.0352]
production	0.297	0.505	0.002
	[0.126,0.491]	[0.386, 1.151]	[-0.0049, 0.0023]
protective service	0.247	1.309	-0.008
	[0.112,0.413]	[0.838, 3.876]	[-0.0362,-0.0038]
sales and related	0.288	1.365	0.049
	[0.146,0.442]	[1.023, 3.278]	[0.0160, 0.1865]
transportation and material moving	0.263	0.781	-0.000
	[0.121,0.419]	[0.582, 1.826]	[-0.0007, 0.0012]

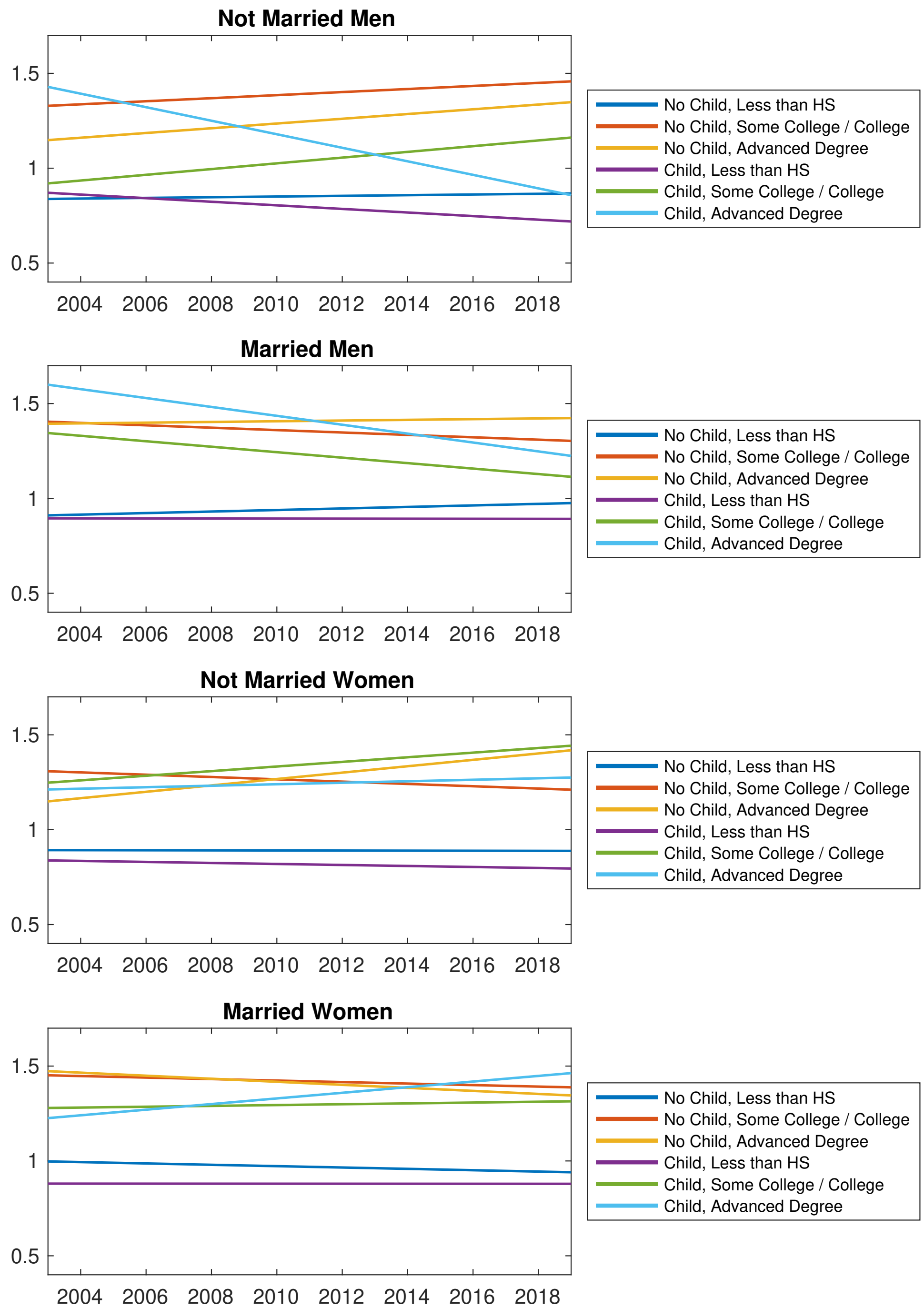
Note: The tables reports parameter estimates for the distribution of relative productivity of working from home and the 5th and 95th percentile of 500 bootstrapped estimates. First, ρ is estimated on 500 samples of the JFL data with replacement using Equation 11, then the log-likelihood is maximized using each estimate of rho and one sample of the ATUS data sampled with replacement. ATUS sample weighted used. The weights adjusted so that each day is $1/5^{th}$ of our subsample.

Table A.9: Estimates: Relative Disutility of WFH

	Men		Women	
	χ	δ^{χ}	χ	δ^{χ}
Not Married, No Child, Less than HS	0.838	0.002	0.892	-0.000
	[0.718,1.013]	[0.0010, 0.0042]	[0.742,1.157]	[-0.0012, 0.0001]
Not Married, No Child, Some College / College	1.329	0.008	1.308	-0.006
	[1.268,1.365]	[0.0010, 0.0124]	[1.121,1.442]	[-0.0069, 0.0015]
Not Married, No Child, Advanced Degree	1.148	0.012	1.149	0.017
	[1.103,1.353]	[-0.0002, 0.0128]	[1.044,1.270]	[0.0140, 0.0198]
Not Married, Child, Less than HS	0.870	-0.009	0.838	-0.003
	[0.734,1.080]	[-0.0134,-0.0047]	[0.719,1.074]	[-0.0045,-0.0015]
Not Married, Child, Some College / College	0.920	0.015	1.248	0.012
	[0.898,1.109]	[0.0058, 0.0152]	[1.135,1.371]	[0.0118, 0.0141]
Not Married, Child, Advanced Degree	1.428	-0.036	1.212	0.004
	[1.423,1.534]	[-0.0413,-0.0331]	[1.021,1.288]	[-0.0007, 0.0437]
Married, No Child, Less than HS	0.911	0.004	0.998	-0.004
	[0.766,1.049]	[0.0028, 0.0049]	[0.800,1.213]	[-0.0038,-0.0021]
Married, No Child, Some College / College	1.404	-0.006	1.451	-0.004
	[1.300,1.412]	[-0.0074,-0.0043]	[1.257,1.510]	[-0.0044,-0.0029]
Married, No Child, Advanced Degree	1.394	0.002	1.473	-0.008
	[1.315,1.402]	[-0.0008, 0.0253]	[1.344,1.501]	[-0.0089,-0.0028]
Married, Child, Less than HS	0.895	-0.000	0.880	-0.000
	[0.746,1.036]	[-0.0008, 0.0022]	[0.743,1.073]	[-0.0002, 0.0002]
Married, Child, Some College / College	1.345	-0.014	1.279	0.002
	[1.176,1.359]	[-0.0146,-0.0007]	[1.160,1.354]	[-0.0000, 0.0049]
Married, Child, Advanced Degree	1.599	-0.023	1.226	0.015
	[1.453,1.628]	[-0.0289,-0.0032]	[1.223,1.349]	[0.0063, 0.0151]

Note: The tables reports parameter estimates for the relative disutility of working from home and the 5th and 95th percentile of 500 bootstrapped estimates. First, ρ is estimated on 500 samples of the JFL data with replacement using Equation 11, then the log-likelihood is maximized using each estimate of rho and one sample of the ATUS data sampled with replacement. ATUS sample weighted used. The weights adjusted so that each day is $1/5^{th}$ of our subsample.

Figure A.10: Relative Disutility of WFH by Demographic Group



Note: The figure plots the estimated estimated relative disutility of work $\hat{\chi}_{it} = \hat{\chi}_i^0 + \hat{\delta}_i^{\chi} t$ *using the estimates from Table A.9.*