# Measuring the Productivity of Working from Home

Christine Braun[*] Travis Cyronek[†] Peter Rupert[‡]

December 9, 2021

**Abstract**

We estimate occupation level relative productivities of working from home using a model in which workers choose the location (home or workplace) and quantity of hours. The resulting estimates show that aggregate relative productivity of working from home has increased by 27% since 2003 which is driven by within occupation increases in relative productivity rather than changes in the employment composition across occupations. Using the estimated model, we decompose the increase in weekly hours worked at home since 2003, finding that two-thirds of the increase stems from increases in relative productivity and one-third from changes in employment composition.

[*]University of Warwick: christine.braun@warwick.ac.uk
[†]Bureau of Labor Statistics: cyronek.travis@bls.gov
[‡]University of California, Santa Barbara: peter.rupert@ucsb.edu

# 1 Introduction

Are we more productive working at home? 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 at home has affected individuals productivity. In this paper we estimate the productivity of working from home prior to the pandemic, document how it has changed over time and across occupations and how these changes have affected how much people decide to work at home.

We document a considerable rise in weekly hours worked at home using data from the American Time Use Survey (ATUS) 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 for 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 at home. By the end of 2019, the average hours at the workplace decreased to 45 hours per week and hours worked at 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 difference 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].

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 prefect substitutes in the production

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

of a labor unit, but the productivity of an hour worked at home, relative to an hour at the workplace differs across occupations. The model produces a ratio of hours worked at home to the workplace which is a function of worker preferences and the relative productivity of work. Using individual level ddata from the ATUS we estimate the parameters of the model by maximizing the likelihood of 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 at home in computer and mathematical occupations is about 80% as productive as an hour at the workplace, whereas an hour at home for production occupations is about 25% as productive as an hour at the workplace. We also show that some occupations have seen a substantial increase in the the relative productivity of working from home (computer and mathematical science occupations increased from 60% to nearly 93%) whereas others saw no increase since 2003. Overall, aggregate relative productivity of WFH has increased by 27%, from 40% as productive at the workplace in 2003 to 52% 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. 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 rely largely on worker or firms surveys and also vary in results. Morikawa [2021] on a survey or workers and firms in Japan finds productivity at 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 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 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]. We differ from these previous studies by estimating productivity from worker's 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 it's definition does not differ across workers in the model, in contrast to self reported productivity where difference in reported productivity can stem from disparities in the understanding of what productivity is.

Further, our approach allows us to use the model to decompose changes in aggregate relative productivity of working from home into changes in within occupation relative productivities and changes in the employment composition across occupations. Doing so, we find that within occupation increases in the relative productivity of working from home is the main driver of aggregate increases, accounting for 86% of the rise in aggregate relative productivity. Similarly we decompose the rise in average weekly hours worked at home and find that 36% of the increase is accounted for by changes in the employment composition across occupations and the rest by within occupation increases in the relative productivity of WFH.

In the next section we outline aggregate trends in hours worked at the workplace vs at 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 to 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 at 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), that, 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 about 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*

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 variables "Worked" summarizes the number of people that reported spending some time working on the interview day.*

*the work place* 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 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,

[2]ATUS activity code 50101.

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 respondents home.

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 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 summarizes the average hours spend in the the activity across all respondents, and conditional hours summarizes the hours spent in the activity across all respondents that participated.*

Table 2 contains summary statistics about time at work. Panel (a) summarizes all work (work at the work place and work at home), 85% of the sample participated in any work on the interview day. The average time spent working

[3] ATUS activity code 120308.

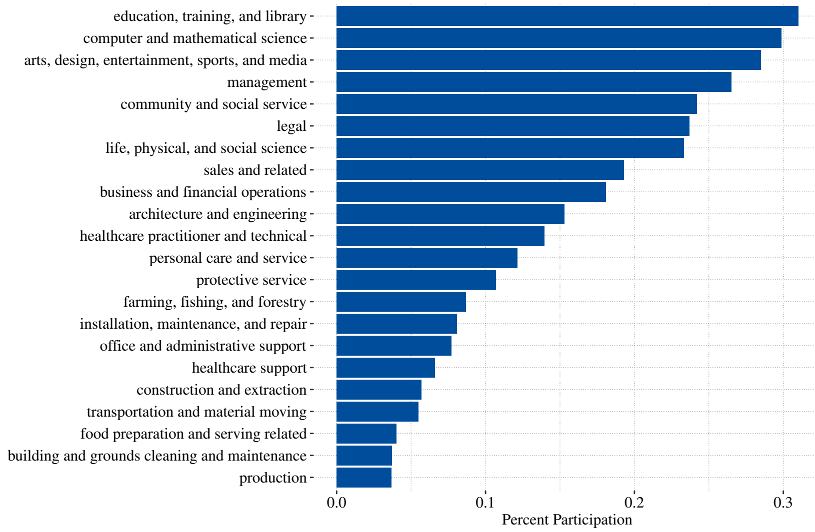
is about 7 hours and, conditional on participating in some work, the average hours worked on the interview day is 8.15. Panel (b) summarizes time spent working at the workplace, which 79% of the respondents did on the interview day. Among the entire sample the average time spent working at the workplace 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. Unconditionally, 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). 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.

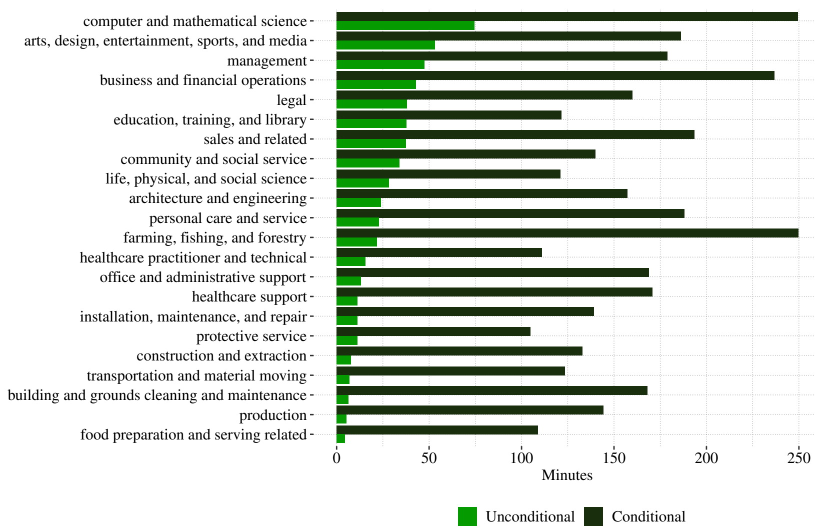
## 2.1 Trends in Hours Worked

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 ($h^w_{it}$)

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.*

and the ATUS sample weight ($wgt_{it}$) for each quarter $t$:

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

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 total employed.

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

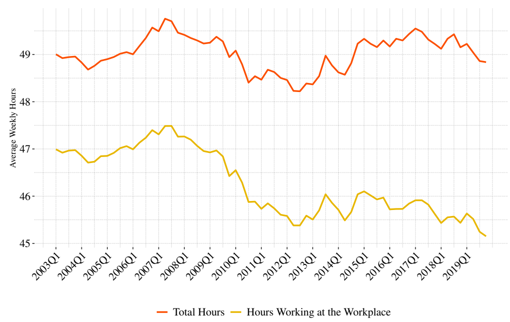
$$\bar{H}_t^h = \frac{\sum_i h_{it}^h \times wgt_{it}}{13 \times E_t} \tag{4}$$

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

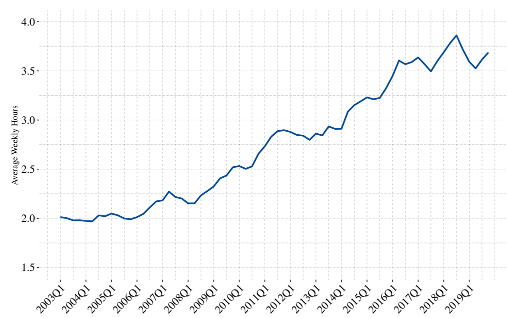
where $h_{it}^h$ is individual $i$'s hours worked at home. All resulting series are smoothed using a 12-quarter simple moving average.

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.

Figure 2: Average Weekly Hours per Worker




(a) Total Hours Working and Hours at the Workplace



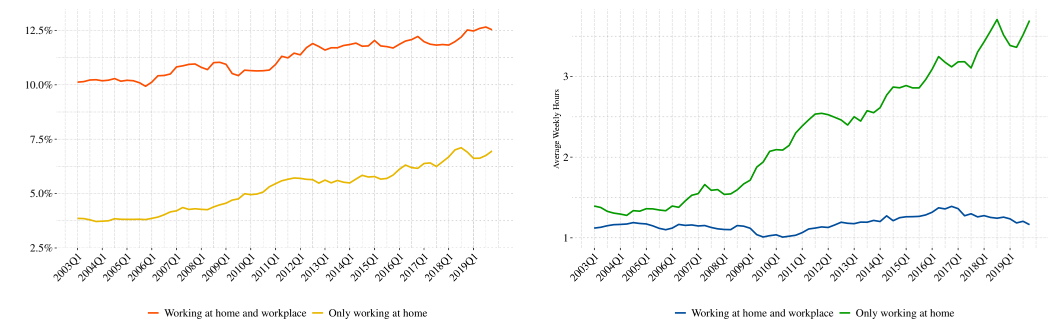

(b) Work from Home

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

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 the 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. Panel (a) also plots the fraction of workers who worked from 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.

# 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 $\alpha$:

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

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

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

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

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

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

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, $\gamma \sim F_{j,t}(\gamma)$ where $F_{j,t}$ is the cdf of the relative productivity distribution for occupation $j$ at time $t$.

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

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

## 3.2 Workers

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

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

where $h^h_{ijt}$ is the hours worked at home and $h^w_{ijt}$ is the hours worked at the workplace by individual $i$ in occupation $j$ in year $t$. Workers are heterogeneous in their disutility of working $\eta_i$ and their preferences between hours at home and at the workplace $\rho_i$. The utility of working is decreasing in both hours at home and hours at the workplace and we restrict $\rho_i \geq 1$ for each $i$ such that the indifference curves are concave to the origin.

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 $\gamma_{ijt}$. That is, a worker $i$'s labor input in occupation $j$ and year $t$ is $\ell_{ijt} = h^w_{ijt} + \gamma_{ijt} h^h_{ijt}$.

Workers maximize utility subject to their budget constraint,

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

The first order conditions for hours worked are

$$\frac{1}{h^w_{ijt} + \gamma_{ijt} h^h_{ijt}} - \eta_i [(h^h_{ijt})^{\rho_i} + (h^w_{ijt})^{\rho_i}]^{\frac{1}{\rho_i}-1} (h^w_{ijt})^{\sigma_i - 1} = 0$$
$$\frac{\gamma_{ijt}}{h^w_{ijt} + \gamma_{ijt} h^h_{ijt}} - \eta_i [(h^h_{ijt})^{\rho_i} + (h^w_{ijt})^{\rho_i}]^{\frac{1}{\sigma_i}-1} (h^h_{ijt})^{\rho_i - 1} = 0$$

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

$$\frac{h^h_{ijt}}{h^w_{ijt}} = \gamma_{ijt}^{\frac{1}{\rho_i - 1}}. \tag{7}$$

. Total hours at home and at the workplace are

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

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.

# 4 Estimation

We estimate the 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 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 worker's 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 an optimal hours at home less than one minute. Using Equation 8 and solving for the relative productivity of work from home such that $h_{ijt}^{h} < 1/60$ gives

$$\gamma_{ijt} < \left[ \left( \frac{60}{\eta} \right)^{\rho_i} - 1 \right]^{\frac{1-\rho_i}{\rho_i}} \equiv \underline{\gamma}_i, \tag{10}$$

where $\underline{\gamma}_i$ 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 an optimal hours at the workplace less than one minute. Using Equation 9, and solving for the relative productivity of work from home such that $h_{ijt}^{w} < 1/60$ gives

$$\gamma_{ijt} > \left[ \left( \frac{60}{\eta} \right)^{\rho_i} - 1 \right]^{\frac{\rho_i-1}{\rho_i}} \equiv \bar{\gamma}_i, \tag{11}$$

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

We allow the substitution parameter to vary by observable characteristics, $X_i$, that includes sex, age, age squared, education, race, marital status, an indicator for having a child and an interaction between sex and the child indicator. To ensure that the estimate of the substitution parameter is greater than 1, we specify the parameter as $\rho_i = 1 + exp(\beta_1 X_i)$ and estimate the effect of each characteristic, that is, the vector $\beta_1$. The disutility of work parameter $\eta_i$ determines the level of hours worked. Although we do not match levels in the estimation, $\eta_i$ determines the probability of observing a worker reporting either no time worked at home or at the workplace, Equation 10 and Equation 11. Therefore, we allow $\eta_i$ to vary by observables $Z_i$, which includes an indicator if the worker is full time and day of the week indicators for the diary day. To ensure that the estimate of the utility of work remains negative we specify the parameter as $\eta_i = exp(\beta_2 Z_i)$ and estimate the vector $\beta_2$. We fix the preference parameters to be constant over time, making the preference parameters identified by variation in the hours ratio across types over the full sample.

We specify the distribution of relative productivity of work from home as log-normal. This assumption is analogous to the assumption about TFP when estimating a Solow residual. We allow the distribution of relative productivities to vary by occupation and its mean to vary over time, that is, $\gamma \sim \ln N(\mu_{j,t}, \sigma_j)$. We estimate a time varying mean for each occupation using a linear trend, $\mu_{jt} = \mu_j^0 + \delta_j t$. Unlike a Solow residual, we are able to identify a mean productivity level for each occupation by matching the hours ratio. Taking the log of Equation 7 shows that the hours ratio is a transformation of relative productivity, specifically, it is a scaling of a normal random variable, $\ln \gamma$. Therefore, the mean relative productivity $\mu_{jt}$ is identified by the mean hours ratio within occupations over time and the standard deviation $\sigma_j$ is identified by the residual within-occupation dispersion of the hours ratio, conditional on worker characteristics.

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 $\underline{\gamma}_i$, that is,

$$\begin{aligned} P(h^h_{ijt}/h^w_{ijt} = 0|X_i, Z_i) &= P(\gamma_{ijt} < \underline{\gamma}_i|X_i, Z_i) \\ &= \Phi\left(\frac{\ln \underline{\gamma}_i - \mu_{jt}}{\sigma_j}\right), \end{aligned} \tag{12}$$

where $\Phi$ is the standard normal cdf. Similarly, observing a worker in occupation $j$ in year $t$ choosing to work no time at the workplace is equal to

$$\begin{aligned} P(h^h_{ijt}/h^w_{ijt} = \infty|X_i, Z_i) &= P(\gamma_{ijt} > \bar{\gamma}_i|X_i, Z_i) \\ &= 1 - \Phi\left(\frac{\ln \bar{\gamma}_i - \mu_{jt}}{\sigma_j}\right). \end{aligned} \tag{13}$$

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

$$P(h^h_{ijt}/h^w_{ijt} = \tilde{h}_{ijt}|X_i, Z_i) = \frac{d}{d\,\tilde{h}_{ijt}} P\left(\gamma_{ijt}^{\frac{1}{\rho_i - 1}} < \tilde{h} \middle| X_i, Z_i\right) \tag{14}$$

$$= P(\gamma_{ijt} = \tilde{h}_{ijt}^{\rho_i - 1}|X_i, Z_i)(\rho_i - 1)\tilde{h}_{ijt}^{\rho_i - 2} \tag{15}$$

$$= \frac{(\rho_i - 1)}{\tilde{h}_{ijt}} \times \phi\left(\frac{(\rho_i - 1)\ln \tilde{h}_{ijt} - \mu_{jt}}{\sigma_j}\right), \tag{16}$$

where $\phi$ is the standard normal pdf.

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

$$P(h^h_{ijt}/h^w_{ijt}|X_i,Z_i) = [P(\gamma_{ijt} < \underline{\gamma}_i|X_i,Z_i)]^{\mathbb{1}(h^h_{ijt}=0)} \times [P(\gamma_{ijt} > \bar{\gamma}_i|X_i,Z_i)]^{\mathbb{1}(h^w_{ijt}=0)} \\ \times [\{P(\gamma_{ijt} < \bar{\gamma}_i|X_i,Z_i) - P(\gamma_{ijt} < \underline{\gamma}_i|X_i,Z_i)\}P(h^h_{ijt}/h^w_{ijt} = \tilde{h}_{ijt}|X_i)]^{\mathbb{1}(h^w_{ijt}>0,h^h_{ijt}>0)} \quad (17)$$

and the log likelihood function is

$$\mathcal{L}(\beta_1,\beta_2,\{\mu^0\}_j,\{\delta\}_j,\{\sigma\}_j;X_i,Z_i,h^h_{ijt},h^w_{ijt}) = \sum_{i=1}^{N} \ln P(h^h_{ijt}/h^w_{ijt}|X_i,Z_i). \quad (18)$$

Maximizing Equation 18 gives estimates of the effect of the worker characteristics on the substitution parameter ($\beta_1$) and the relative disutility of work ($\beta_2$), the time varying mean of the relative productivity distribution for each occupation ($\mu^0_j$ and $\delta_j$) and the standard deviation of the relative productivity distribution for each occupation ($\sigma_j$).

## 4.1 Estimation Results

Table 3 reports the estimated effects of observable characteristics on the substitution parameter and the relative disutility of working. Table 4 reports the estimated parameters of the relative productivity distribution for each occupation. The estimated means of the log relative productivity in 2003, $\mu^0_j$, are all negative, implying an average log productivity less than zero, or equivalently a relative productivity less than one for all occupation in 2003. The estimates of $\delta$ vary across occupations and are both positive and negative, implying that the relative productivity has increased in some occupations and decreased in others. The largest increases in the relative productivity of working from home was experienced by computer and mathematical science and business and financial operations occupations. The largest decrease in the relative

Table 3: Estimates: Demographic Effects on Substitution Parameter

| Substiution Parameter | | Scale Parameter | |
|---|---|---|---|
| | $\beta_1$ | | $\beta_2$ |
| Female | -0.078 | Full Time | -0.118 |
| | (0.0004) | | (0.000) |
| Age | 0.001 | Tuesday | -0.013 |
| | (0.0000) | | (0.000) |
| Married | 0.013 | Wednesday | -0.031 |
| | (0.0003) | | (0.000) |
| Child | 0.016 | Thursday | -0.029 |
| | (0.0003) | | (0.000) |
| Female X Child | 0.018 | Friday | 0.062 |
| | (0.0005) | | (0.000) |
| High School | 0.120 | Constant | 3.474 |
| | (0.0006) | | (0.000) |
| Some College | 0.241 | | |
| | (0.0006) | | |
| College | 0.356 | | |
| | (0.0005) | | |
| Advance Degree | 0.454 | | |
| | (0.0006) | | |
| Black | -0.046 | | |
| | (0.0004) | | |
| Other | 0.087 | | |
| | (0.0005) | | |
| Constant | -0.749 | | |
| | (0.0007) | | |
| Log-Likelihood Value | | | -3.610e+07 |
| Observations | | | 40652 |

*Note: The tables reports parameter estimates for the distribution of relative productivity of working from home and standard errors. AUTS sample weighted used. The weights adjusted so that each day is* $1/5^{th}$ *of our subsample.*

Table 4: Estimates: Relative Productivity of WFH Distribution Parameters

| | $\mu^0$ | $\delta$ | $\sigma$ |
|---|---|---|---|
| architecture and engineering | -1.631 | 0.015 | 1.106 |
| | (0.001) | (0.0002) | (0.001) |
| arts, design, entertainment, sports, and media | -1.190 | 0.006 | 1.235 |
| | (0.001) | (0.0002) | (0.001) |
| building and grounds cleaning and maintenance | -2.034 | 0.022 | 0.967 |
| | (0.002) | (0.0002) | (0.001) |
| business and financial operations | -1.655 | 0.025 | 1.265 |
| | (0.001) | (0.0002) | (0.001) |
| community and social service | -1.018 | -0.008 | 1.169 |
| | (0.001) | (0.0002) | (0.001) |
| computer and mathematical science | -1.342 | 0.028 | 1.287 |
| | (0.001) | (0.0002) | (0.001) |
| construction and extraction | -1.725 | 0.007 | 0.923 |
| | (0.001) | (0.0002) | (0.001) |
| education, training, and library | -1.038 | 0.008 | 1.030 |
| | (0.001) | (0.0001) | (0.001) |
| farming, fishing, and forestry | -1.532 | -0.003 | 1.129 |
| | (0.005) | (0.0005) | (0.002) |
| food preparation and serving related | -1.667 | -0.000 | 0.936 |
| | (0.002) | (0.0002) | (0.001) |
| healthcare practitioner and technical | -1.478 | 0.015 | 1.096 |
| | (0.001) | (0.0002) | (0.001) |
| healthcare support | -1.560 | -0.016 | 1.073 |
| | (0.002) | (0.0003) | (0.001) |
| installation, maintenance, and repair | -1.565 | 0.000 | 0.942 |
| | (0.001) | (0.0002) | (0.001) |
| legal | -1.330 | 0.002 | 1.207 |
| | (0.002) | (0.0003) | (0.001) |
| life, physical, and social science | -1.380 | -0.003 | 1.175 |
| | (0.001) | (0.0002) | (0.001) |
| management | -1.310 | 0.017 | 1.182 |
| | (0.001) | (0.0001) | (0.001) |
| office and administrative support | -1.851 | 0.018 | 1.086 |
| | (0.001) | (0.0003) | (0.001) |
| personal care and service | -1.317 | -0.008 | 1.259 |
| | (0.002) | (0.0003) | (0.002) |
| production | -1.645 | -0.002 | 0.814 |
| | (0.001) | (0.0002) | (0.001) |
| protective service | -1.465 | -0.004 | 1.074 |
| | (0.001) | (0.0002) | (0.001) |
| sales and related | -1.276 | 0.012 | 1.067 |
| | (0.001) | (0.0003) | (0.001) |
| transportation and material moving | -1.588 | -0.003 | 0.941 |
| | (0.001) | (0.0003) | (0.001) |



*Note: The tables reports parameter estimates for the distribution of relative productivity of working from home and standard errors. AUTS sample weighted used. The weights adjusted so that each day is $1/5^{th}$ of our subsample.*

productivity of working from home was experienced by health care support occupations.

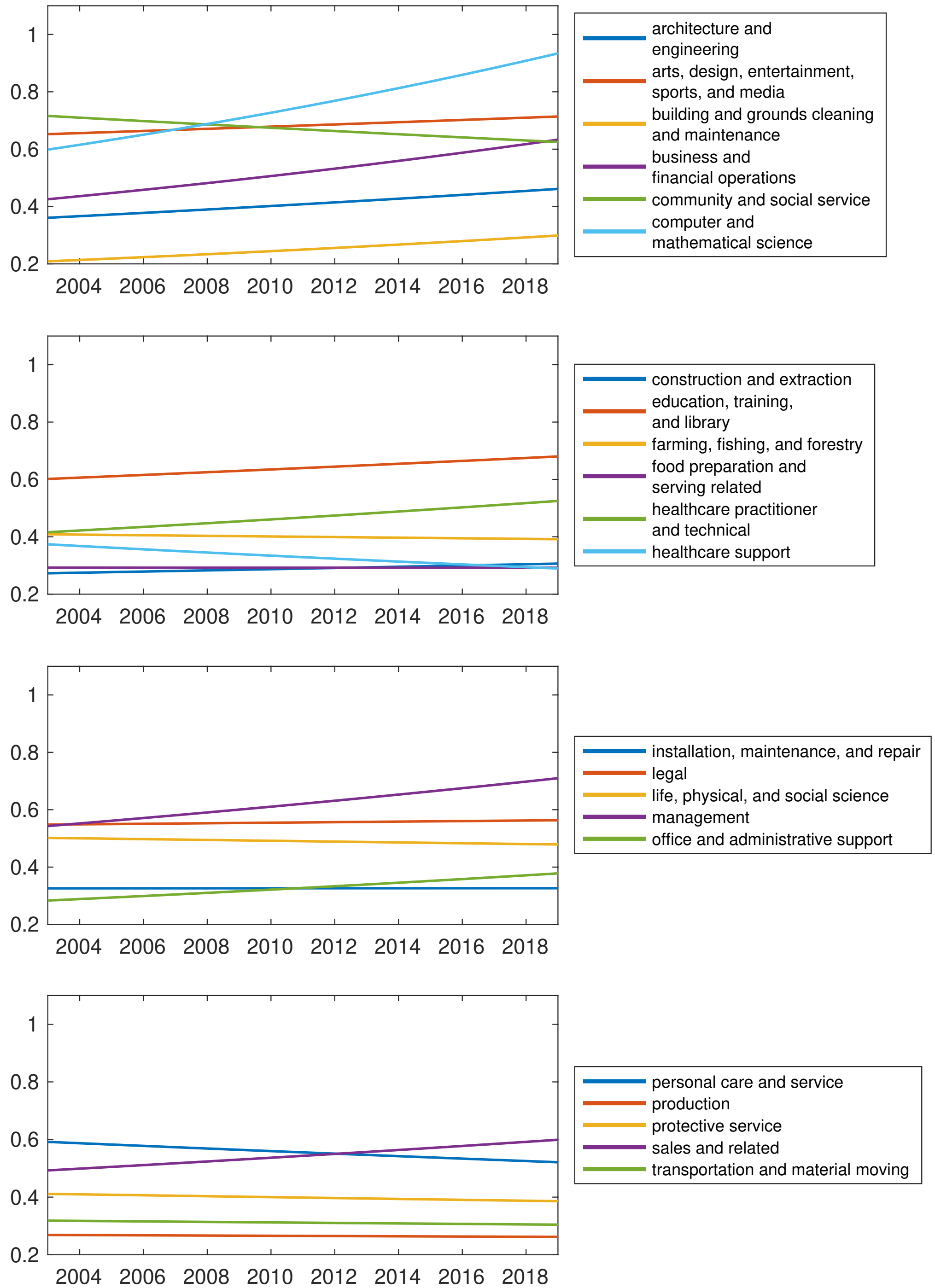
The mean of the relative productivity distribution is

$$E[\gamma_{jt}] = exp\left(\hat{\mu}_j^0 + \hat{\delta}_j t + \frac{\hat{\sigma}_j^2}{2}\right). \tag{19}$$

Figure 4 plots the mean relative productivity over time for each occupation. The figure compares both the levels and the increases in relative productivity of WFH across occupations. Computer and mathematical sciences had a relative productivity of about 0.6 in 2003, lower only than community and social service and arts, design, entertainment, sports and media occupations, and increased to reach a relative productivity of nearly 1 by the end of the sample. Business and financial occupations, architecture and engineering occupations, and management occupations also saw a large increase in their relative productivity of working from home.

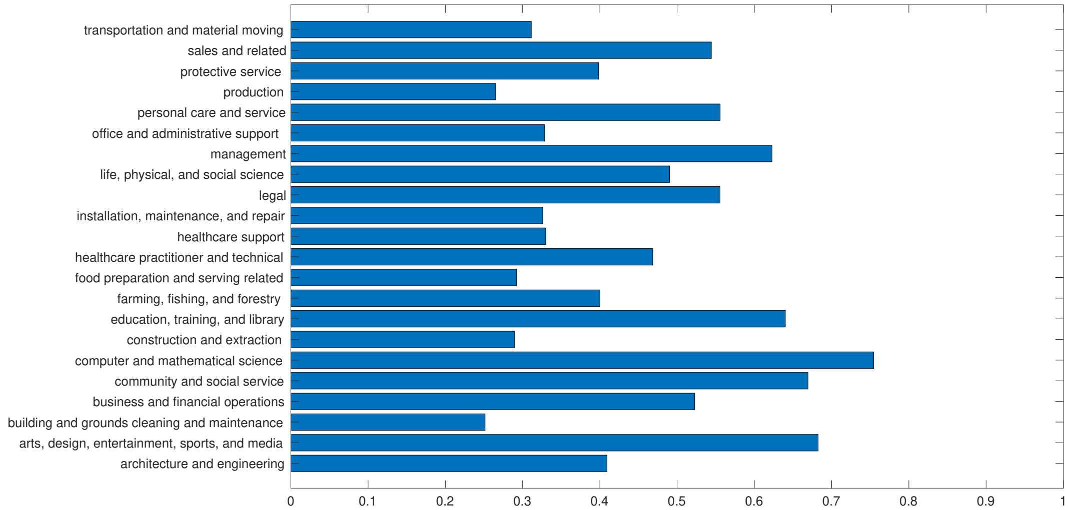
Figure 8 plots the average relative productivity for each occupation from 2003 to 2019. As expected, occupations that tend to be more "hands on" have a lower overall relative productivity. For example, the construction and extraction occupation, food preparation and serving related occupations, and production occupations have relative productivity below 0.3, implying that an hour at home is less than 30% less productive than an average hour at the workplace for these occupations. Figure 4 shows that these occupations also saw little growth in the average relative productivity of working from home over the period.

Figure 4: Relative Productivity of WFH by Occupation




*Note: The figure plots the estimated mean relative productivity of working from home, calculated using Equation 19.*

Figure 5: Average Relative Productivity of WFH by Occupation




*Note: The figure plots the average expected relative productivity (Equation 19) of working from home for each occupations from 2003 to 2019.*

# 5 Counterfactuals

Using the parameter estimate of the model we run two counterfactual exercises. First, we explore how aggregate relative productivity of working from home has changed over time and if the changes have come from within-occupation changes or changes in the composition of employment across different occupations. Second, we explore how average weekly hours worked at home per worker would have changed if there had been no within-occupational changes in the relative productivity of work from home.

To calculate the aggregate relative productivity of working from home we take the employment weighted average of each occupations expected relative productivity, Equation 19, that is

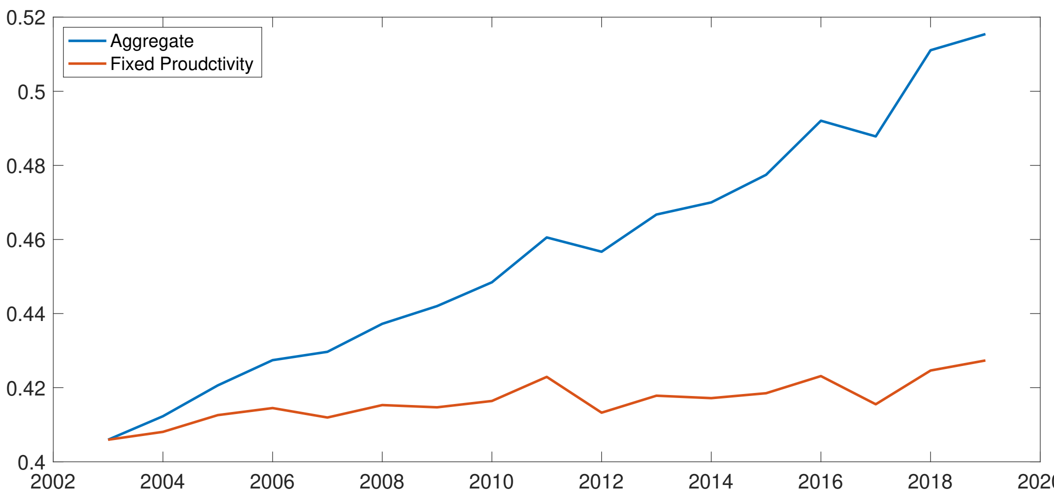
$$E[\gamma_t] = \sum_{j=1}^{22} e_{jt} \times exp\left(\hat{\mu}_j^0 + \hat{\delta}_j t + \frac{\hat{\sigma}_j^2}{2}\right), \tag{20}$$

where $e_{jt}$ is the share of employment in occupation $j$ in year $t$ calculated using the sample weights as follows:

$$e_{jt} = \frac{\sum_{i \in j,t} wgt_{ijt}}{\sum_{i \in t} wgt_{ijt}}. \tag{21}$$

The counterfactual aggregate relative productivity of working from home if there had been no within occupational change is calculated using Equation 20 and setting $\hat{\delta}_j = 0$ for each occupation. Any remaining growth in the relative productivity of working from home is then driven by changes in the occupation composition of employment.

Figure 6: Aggregate Relative WFH Productivity Decomposition




*Note: The figure plots the aggregate relative productivity of working from home, constructed by taking the employment weighted average across occupations in each year, Equation 20, in blue. The counterfactual relative productivity of working from home, in which there is no within occupation growth ($\delta_j = 0$) is plotted in orange.*

Figure 8 plots the estimated aggregate relative productivity of working from home (blue). In 2003 the estimated productivity is about 0.4 and increases steadily to 0.52 by the end of 2019. Plotted in orange is the counterfactual aggregate relative productivity where all within-occupation relative productivity is fixed at its 2003 level. The counterfactual productivity increases from 0.4 in 2003 to 0.43 in 2019, implying that about 14% of the increase in aggregate relative productivity was driven by a shift of employment in occupations with higher relative productivities and 86% of the increase was due to within-occupation increases in relative productivity.

Next, we construct a counterfactual weekly hours worked at home series holding fixed the change in within-occupation changes in the relative productivity of work from home. This allows us to decompose the observed increase in hours worked from home into changes in productivity and changes in the employment composition across occupations. To construct the model's weekly hours worked at home we predict the expected hours ratio for each individual as

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

where $\hat{F}_{jt}$ is the estimated cdf of the relative productivity of working from home in occupation $j$ in year $t$. Next we construct the estimated probability that each individual would report a positive number of hours worked at home and at the workplace,

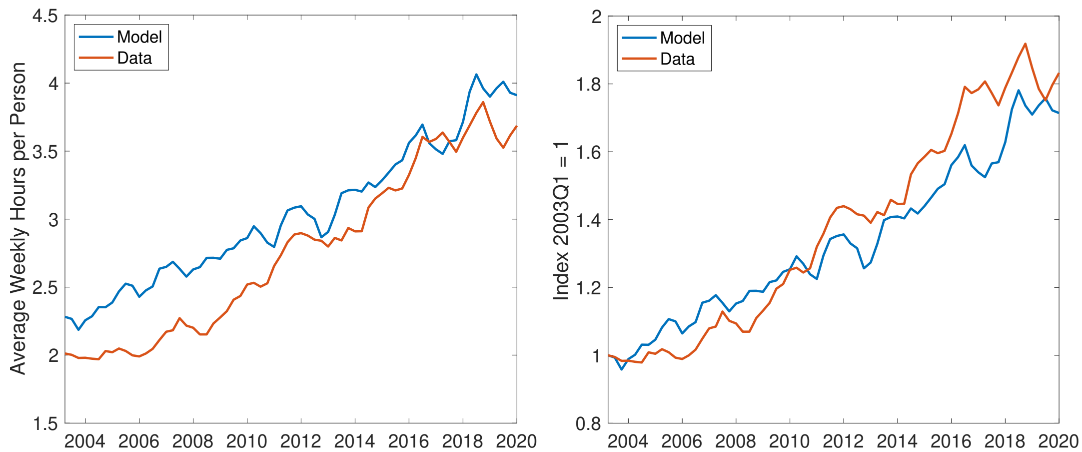
$$\hat{P}_{ijt} = \hat{F}_{jt}(\hat{\bar{\gamma}}_i) - \hat{F}_{jt}(\underline{\hat{\gamma}}_i), \tag{23}$$

where $\hat{\bar{\gamma}}_i$ and $\underline{\hat{\gamma}}_i$ are the estimated upper and lower bounds of reporting positive hours worked at home and the workplace, Equation 10 and Equation 11. Since we do not match the level of hours worked in our estimation we construct predicted average weekly hours of work from home as follows,

$$\widehat{\bar{H}^h}_t = \bar{H}^w_t \times \sum_{i,j} \hat{P}_{ijt} \times \widehat{\frac{h^h_{ijt}}{h^w_{jt}}} \times wgt_{ijt}, \tag{24}$$

where $\bar{H}^w_t$ is the average weekly hours worked at the workplace per worker, Equation 2, plotted in yellow in Figure 2. That is, we first construct a weighted average of expected hours ratios per period $t$, and then to match the levels we multiply by the weekly hours worked at the workplace per person observed in the data.

Figure 7: Average Weekly Hours Worked From



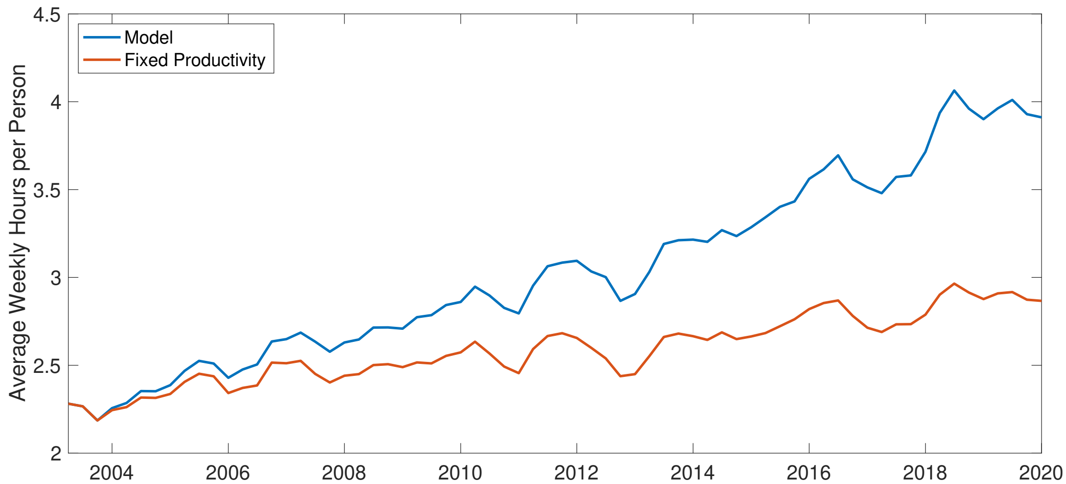

(a) Levels (b) Indexed

*Note: Panel (a) plots in orange the average weekly hours of work from home per person, constructed from the ATUS data following Equation 5 and in blue the predicted model equivalent constructed using Equation 24, both in levels. Panel (b) plots the same series each indexed to 1 in the first quarter of 2003.*

Panel (a) of Figure 7 plots the resulting predicted and observed average weekly hours worked at home per person. The predicted hours worked at home follows the trend of observed hours worked at home closely. This can also be seen from panel (b) which plots the same series indexed to 1 in the first quarter of 2003. Overall the predicted hours worked at home matches the observed data well.

Next, we construct the counterfactual series analogously, i.e. using Equation 24, but setting $\hat{\delta}_j = 0$ in the predicted mean of each relative productivity distribution for each occupation. The resulting counterfactual average weekly hours worked at home and the model predicted series are plotted in Figure 8. Similar to the observed data, the model predicted hours worked at home increased from about 2.25 hours per week in 2003 to nearly 4 hours by 2019, nearly doubling. The counterfactual "fixed productivity" series increased to

Figure 8: Counterfactual: Average Weekly Hours Worked From Home




*Note: The figure plots in blue the predicted model equivalent constructed using Equation 24 and in orange the counterfactual weekly hours when there is no within occupation growth in the relative productivity of working from home ($\delta_j = 0$) for each occupation.*

about 3 hours by 2019. The counterfactual hours worked at home series shows that 36% of the increase in hours worked at home was due to changes in the employment composition across occupations. The remaining increase was driven by the within-occupational increase in the relative productivity of 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 both 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 when facing a relative productivity of working from home determined by which 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 choices of workers within occupations, conditional on observable characteristics.

Using the estimated model we show that since 2003, the aggregate relative productivity of working from home increased by nearly 30% and that this increase was driven by within-occupational increases in the relative productivity of working from home, rather than changes in the employment composition across occupations. Finally we decompose the rise in hours worked at home into productivity changes and employment changes and show that about two-thirds of the increase in work from home was driven by the increase in the relative productivity of working from home.

# References


Abigail Adams-Prassl, Teodora Boneva, Marta Golin, and Christopher Rauh. Work That Can Be Done from Home: Evidence on Variation within and across Occupations and Industries. IZA Discussion Papers 13374, Institute of Labor Economics (IZA), June 2020. URL https://ideas.repec.org/p/iza/izadps/dp13374.html.

Jose Maria Barrero, Nick Bloom, and Steven J. Davis. Why Working From Home Will Stick. SocArXiv wfdbe, Center for Open Science, December 2020. URL https://ideas.repec.org/p/osf/socarx/wfdbe.html.

Alexander Bick, Adam Blandin, and Karel Mertens. Work from home after the covid-19 outbreak. *Federal Reserve Bank of Dallas, Working Papers*, 2020, 07 2020. doi: 10.24149/wp2017r1.

Nicholas Bloom, James Liang, John Roberts, and Zhichun Jenny Ying. Does Working from Home Work? Evidence from a Chinese Experiment. *The Quarterly Journal of Economics*, 130(1):165–218, 2014.

Jonathan I Dingel and Brent Neiman. How many jobs can be done at home? Working Paper 26948, National Bureau of Economic Research, April 2020. URL http://www.nber.org/papers/w26948.

Ben Etheridge, Yikai Wang, and Li Tang. Worker productivity during lockdown and working from home: evidence from self-reports. ISER Working Paper Series 2020-12, Institute for Social and Economic Research, October 2020. URL https://ideas.repec.org/p/ese/iserwp/2020-12.html.

Harley Frazis and Jay Stewart. Is the workweek really overestimated? *Monthly Lab. Rev.*, 127:1, 2004.

Lena Hensvik, Thomas Le Barbanchon, and Roland Rathelot. Which Jobs Are Done from Home? Evidence from the American Time Use Survey. IZA Discussion Papers 13138, Institute of Labor Economics (IZA), April 2020. URL https://ideas.repec.org/p/iza/izadps/dp13138.html.

Alexandre Mas and Amanda Pallais. Alternative Work Arrangements. NBER Working Papers 26605, National Bureau of Economic Research, Inc, January 2020. URL https://ideas.repec.org/p/nbr/nberwo/26605.html.

Petr J. Mateyka, Melanie Rapino, and Liana Christin Landivar. Home-based workers in the united states: 2010. *U.S. Census Bureau, Current Population Reports*, 2012.

Natália P. Monteiro, Odd Rune Straume, and Marieta Valente. Does Remote Work Improve or Impair Firm Labour Productivity? Longitudinal Evidence from Portugal. CESifo Working Paper Series 7991, CESifo, 2019. URL https://ideas.repec.org/p/ces/ceswps/_7991.html.

Masayuki Morikawa. Work-from-home productivity during the covid-19 pandemic: Evidence from japan. *Economic Inquiry*, Nov 2021. doi: https://doi.org/10.1111/ecin.13056. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/ecin.13056.