On-the-job Leisure and Work from Home: Measuring the Productivity of Work

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Abstract

We document a considerable rise in hours worked at home and a small decline in hours not working at work brought about by the 2008 recession. In 2019, workers spent on average 4.5 hours per week working from home and 2.15 hours not working at work. We show that the increase in working from home cannot be accounted for by changes between occupations, but rather by increased computer use within occupations. We also document a substantial increase in the productivity of working from home relative to at the workplace. In 2003, an hour worked at home was about 2% less productive than an hour at the workplace, but in 2019 an hour at home was 12% more productive. The increase in relative productivity can be accounted for by less work from home occurring while also providing childcare and more work from home occurring during standard business hours rather than in the early morning or late evening. Finally, 10% of the increase in labor productivity since 2009 can be attributed to the substitution from working at the office to working from home.

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1 Introduction

Not all hours are created equal. Some hours at work are spent are spent socializing, while some hours at home are spent working. We document a considerable rise in hours worked at home and a small decline in hours not working at work brought about by the 2008 recession. The move toward more hours worked at home is coupled with an increase in the relative productivity of working from home. What brought about this shift from the workplace to home and why are workers now 12% more productive at home?

To answer these questions we use data from the American Time Use Survey (ATUS) and the Occupational Information Network (O*Net). The ATUS contains detailed accounts of where and how Americans spend their time. We construct data on how long people were at their workplaces, how long they worked at work, how long they took leisure on the job (non-work at work), and for how long they worked at home. Prior to the 2008 recession, the average worker spent 37.5 hours per week at their workplace but about 2 and a half hours of that time was spent doing non-work related activities. However, workers were working about 2 hours and 45 minutes at home, making total productive work time (which we define as working at work and working at home) slightly more than time spent at work. The 2008 recession induced a shift from the office to the home and, by 2019, the average worker spent 36 hours per week at the office, taking 2 hours of leisure on the job, and working 4 and half hours from home.[1]

There are large differences in the propensity and duration of work from home across occupations, which have, of recent, gathered attention in response to the COVID-19 pandemic [Dingel and Neiman, 2020, Hensvik et al., 2020, Adams-Prassl et al., 2020, Bick et al., 2020]. Similar to Burda et al. [2020], we show that occupations also differ with respect to workers' propensity and duration of on-the-job leisure. Changes in the occupational employment distribution cannot account for any of the increase in work from home that occurred through 2016; thereafter, further increases in working from home are almost entirely explained by such changes. The small decrease in on-the-job leisure cannot be attributed to occupational change. In fact, occupational employment shifts during the 2008 recession mitigated a larger decrease in average weekly hours of on-the job leisure.

We also look at changes within occupations, focusing on the increasing reliance on computers at work from the O*Net data. We show that as an occupation increases its reliance on computers, the probability a worker takes any on the job leisure decreases, suggesting significant monitoring effects of computers. The overall increase in computer use can account for about 23% of the decrease

[1]These trends are consistent with the increased proportion of workers who primarily work from home [Mateyka et al., 2012]. Also see Mas and Pallais [2020] for a nice review of the trends in alternative work arrangements in the US.

in aggregate on-the-job leisure. On the other hand, increased computer use within an occupation, significantly increase both the probability and duration of work from home. The overall increase in computer usage since 2003 can account for about 43% of the increase in average weekly hours of work from home.

Using an aggregate production function in which labor input is the sum of hours worked at the office, at home, and on-the-job leisure, we estimate the productivity of an hour worked at home and an hour of leisure on-the-job relative to working at the workplace. On average, one hour of on-the-job leisure is about 85% less productive than working at the workplace. Prior to the 2008 recession working from home was about 2% less productive than working at the workplace. However, during the recession and its recovery, productivity at home increased substantially, peaking at 30% more productive than working at the workplace in 2016. Since 2016, productivity at home has decreased but in 2019 an hour worked at home remains, on average, 12% more productive than an hour worked at the office. We show that 10% of the increase in labor productivity since 2009 can be attributed to the substitution of working at the office to working from home.

To better understand the rapid increase in productivity at home we show that the fraction of time workers spend working from home while providing childcare has decreased from about 10% to 6.5% since the onset of the 2008 recession. We show that this decline is associated with an increase in relative productivity of about 5 percentage points. We show that before the recession, about 40% of hours worked at home were worked between 9am and 5pm, and by 2019, 55% of work at home was occurring during usual business hours. The shift towards working at home during the day is associated with a 22 percentage point increase in the relative productivity of an hour worked at home. Together, the changes in how and when workers worked from home can account for nearly the entire increase in the relative productivity of working from home.

Our paper contributes to the literature documenting trends in remote work and telecommuting, for example, Oettinger [2011], Mateyka et al. [2012], and Mas and Pallais [2017]. Existing studies focus on changes in the extensive margin, that is, the fraction of workers working exclusively from home. We show that the rise in work from home is not concentrated among fully remote workers. We document similar increases in the extensive margin among people who continue to go to a physical workplace. Further, we also document a substantial increase in the intensive margin (total hours worked at home), again the increase is also present for workers that continue to go the office. We add to the literature studying how increases in information and communication technologies affect these trends, such as Gaspar and Glaeser [1998], Viete and Erdsiek [2015], and Jerbashian and Vilalta-Bufi [2020], by showing that computers also increase the intensive margin of work from home.

Finally, our paper contributes to the literature studying productivity of remote work. Most of these studies focus on within firm effects. For example, Bloom et al. [2015] conduct a teleworking experiment in China and find that workers are about 4% more productive per hour at home.[2] However, using firm level data from Portugal, Monteiro et al. [2019], suggest that such productivity effects may differ across firms. To the best of our knowledge we are the first to study how and why the shift towards work from home has affected aggregate US productivity.

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, contain 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. Our sample includes people age 16 or older in either private or public employment.

Table 1 contains summary statistics for demographic characteristics, job characteristics and whether or not the interviewee went to work on the diary day. Since the ATUS oversamples on weekends, only 62% of the sample went to work on the diary day.

2.1 Work and On-the-job Leisure

There are three measures of work we are interested in. First, if the respondent went to work on the diary day, we construct *total time at work* by summing the duration of all activities done at the workplace, this includes work and non-work (on-the-job leisure) 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.[3] 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."[4] Alternatively, if the computer was used to do online shopping the activity is recorded as "Shopping (Store, Telephone, Internet)."[5] Similar structures are used for other activities that could

[2] Also see Cornelissen et al. [2017] and Dutcher and Saral [2012].
[3] ATUS category 50101.
[4] ATUS category 120308.
[5] ATUS categories 070101-070199.

be done for multiple purposes. Second, we measure total *on-the-job leisure (OJL)* as the duration of activities done at the respondent's workplace that were not work-related. Lastly, we measure total *work from home (WFH)* as the duration of work, either for the main job or any other jobs, done anywhere outside of the respondent's workplace.

Table 2 contains summary statistics about time at work, OJL, and WFH. The average time spent at work is 312 minutes (5 hours and 12 minutes). The fraction of respondents that participated in OJL is 0.43 (conditional on having gone to work on the interview day participation is 0.68) and conditional in participating in OJL, the average duration is roughly three quarters of an hour. The fraction of workers who participated in any work from home is 16% and conditional on working from home, the average worker spends about 190 minutes (3 hours and 10 minutes) doing so.

We define *productive hours* h^p worked as the sum of time spent working at work (time at work net of OJL) plus time spent working at home, that is for each respondent:

$$h_{it}^p = h_{it}^w - h_{it}^l + h_{it}^h, \tag{1}$$

where h_{it}^p is total productive hours for person i in period t, h_{it}^w is hours at the office, h_{it}^l is hours of on-the-job leisure, and h_{it}^h is hours worked from home. We also define hours worked at the workplace (office) as $h_{it}^o = h_{it}^w - h_{it}^l$. In what follows we use lowercase letters to denote individual values and uppercase to denote aggregate values. The average time spent doing productive work is 324 minutes (5 hours and 50 minutes). On average, workers spent about 10 minutes more doing productive work than time spent at work.

The difference between time at work and productive hours worked for the full sample is, in part, caused by workers who, on the diary day, did not go to work but spent some time working from home. Figure 1 plots the densities of productive hours and hours at work for the full sample. The density of productive hours shows a shift to the right, as well as a decrease in the fraction of workers that spent no time working. About 8% of workers did not go to work on the diary day but worked from home, and worked on average 271 minutes (4 hours and 31 minutes) from home.

Work from home and on-the-job leisure vary markedly, both in participation and minutes, across occupations. Panel (a) of Figure 2 plots the participation probabilities of WFH and OJL across occupations. Education, training, and library occupations have the highest probability of observing a person working from home (0.35) and production occupations have the lowest (0.05). Panel (b) plots the unconditional average minutes of WFH and OJL by occupation. Again we see substantial differences across occupations. The figure shows how productive hours, relative to time at work, differ across occupations. For example, education, training and library occupations have 26 minutes of productive work more on average than time at work, whereas production occupations spend 35 minutes more at work than doing productive work on average.

2.2 Aggregate Hours

Using our measure of productive hours worked at the individual level we aggregate to a measure of average weekly hours per worker per quarter and compare productive hours worked to other standard hours worked measures for the economy. We compare our measure of productive hours worked to reported hours worked from the Current Employment Statistics (CES), the Current Population Survey (CPS), and a composite measure created by the Bureau of Labor Statistics (BLS).

In the ATUS the sample weights aggregate measures of daily time spent in each activity to total quarterly time spent. To construct total productive hours in our sample we sum the product of individual productive hours and the ATUS sample weight (wgt_{it}) for each quarter t:

$$H_t^p = \sum_i h_{it}^p \times wgt_{it}. \tag{2}$$

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

$$\bar{H}_t^p = \frac{H_t^p}{13 \times E_t} \tag{3}$$

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

$$E_t = \sum_i \frac{wgt_{it}}{91.5}. \tag{4}$$

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 ($\bar{H}^h$), average weekly hours of on-the-job leisure per worker ($\bar{H}^l$), and average weekly time at work per worker ($\bar{H}^w$) as:

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

$$\bar{H}_t^l = \frac{\sum_i h_{it}^l \times wgt_{it}}{13 \times E_t} \tag{6}$$

$$\bar{H}_t^w = \frac{\sum_i h_{it}^w \times wgt_{it}}{13 \times E_t}. \tag{7}$$

All resulting series are smoothed using a 12 quarter simple moving average.

Panel (a) of Figure 3 plots the average weekly productive hours per worker and the average weekly time at work per worker. Productive hours and time at work follow similar trends through the end of the 2008 recession. Productive hours begin to increase and are above their pre-recession max by 2014. Time at work, on the other hand, never reaches its pre-recession max, continuing to decline through the end of the sample period. The diverging trends in productive hours and time at work are driven by a rise in work from home and a small decline in on-the-job leisure.

Panel (b) of Figure 3 shows that before the 2008 recession workers on average worked about 3 hours at home. Recovery from the recession brought with it a substantial substitution of working in the office to working from home. Hours worked at home have increased gradually from about 3 hours in 2009 to almost 4 and a half hours in 2019. Pre-recession about 7% of productive hours per week were done at home, and in 2019 about 12% of productive hours were worked at home. On-the-job leisure has been stable around 2 and a half hours per week, with a small decrease beginning in 2014. Although time at work also begins to decrease at the same time, leisure at work as a percent of time spent at work decreases from about 6.4% before the recession to 5.8% in 2019.

Figure 4 show that the rise in work from home is not solely driven by teleworkers, that is, workers who exclusively work from home. Panel (a) plots the fraction of workers who went to work on the interview day that also worked from home, either before or after going to work. The fraction is stable at 11% of workers before the 2008 recession, increasing rapidly after the recession, reaching 13.5% by 2019. Panel (b) plots the average weekly hours of work from home by workers who also went to work. Prior to the recession workers who went to work also worked about one and half hours at home. Time worked at home falls during the recession but increases rapidly with the recovery and through the end of the sample, increasing by about 30 minutes per week from the trough in the third quarter of 2009 to the end of 2019.

There are two main measures of hours worked for the US; the first from a household level survey (CPS) and the second from an establishment level survey (CES). Using these two measures the Bureau of Labor Statistics also publishes a composite measure that combines both measures and other labor market indicators; we refer to this measure as the BLS measure.[6] We construct the CPS hours series using the monthly outgoing rotation group (CPS ORG) usual weekly hours question. The CES contains information about average weekly hours from all production workers and average weekly hours from all private workers starting in 2006. Respondents in the ATUS are also asked the same usual hours question as in the CPS, from which we construct an ATUS usual weekly hours series.

Panel (a) of Figure 5 plots the six measures of average weekly hours. There are large level differences

[6]Information about how the BLS measure is constructed can be found at https://www.bls.gov/opub/hom/inp/data.htm

between the hours series; hours constructed from the CES and the BLS composite are on average around 34 hours per week, whereas hours constructed from the CPS ORG are on average 36 hours per week and hours constructed from the ATUS usual hours question are on average 40 hours per week. Our measure of productive hours worked is on average 38 hours per week. These level differences can be accounted for in large part by the differences in the sample population, as well as the hours concept (paid hours vs all hours worked), see Frazis and Stewart [2004] for a discussion.

Panel (b) of Figure 5 plots the trend of each hours measure, each series is indexed to 2006Q1. The trends are similar before the 2008 recession, diverging after the recession. The CES Production measure and the BLS composite measure do not grow after the recession, never reaching their pre-recession max. The CPS ORG measure and the CES private measure both recover from the recession and are growing at similar rates toward the end of the sample, however, the recovery in hours worked in the CES private sample is much quicker than the CPS ORG sample. Unlike the level differences, the differences in trends can not be accounted for by differences in the sample population [Frazis and Stewart, 2010].

The best comparison for our productive hours measures remains the ATUS usual hours worked since the measures come from the same sample. The measures have nearly identical trends through the 2008 recession after which they begin to diverge. Productive hours worked increase rapidly after the end of the recession, growing about 3% from the start of 2010 to 2017, after which, similar to other measures, the growth in productive hours slows. Reported usual hours, on the other hand continue to decline after the end of the recession, recovering slightly beginning in 2015, but not reaching their pre-recession levels. Comparing these divergent trends to the trend in hours worked from home and on-the-job leisure suggest that respondents are likely omitting some work from home and including non-work at work in their answers to the usual weekly hours worked question.

3 Trends in WFH and OJL

The previous section documented the rise in work from home and a slight decrease in on-the-job leisure since 2009, as well as substantial differences in the uptake and duration of each across occupations. Next we decompose the changes in aggregate WFH and OJL through changes in the employment composition across occupations. While movements across occupations can account for some of the increase in work from home beginning in 2016, none of the shift towards working from home during the recession and recovery can be accounted for by employment changes. To further understand the trends, we study how changes in the reliance on computers for work within occupations have affected WFH and OJL. To do so we combine the ATUS data with data from the Occupational Information Network (O*NET).

3.1 Across Occupations

To decompose how changes in employment shares across occupations have contributed to the trends in WFH and OJL, we construct 1,000 bootstrapped samples of the full ATUS data, holding the occupational employment distribution fixed at the 2003Q1 distribution. We calculate average weekly hours of WFH and OJL in each sample as in section 2. We construct a counterfactual WFH and OJL series by taking the mean of our bootstrapped series and smoothing the final series with a 12 quarter simple moving average. Figure 6 plots the resulting "Fixed Occupation" series and the original series ("Data").

Panel (a) of Figure 6 shows that changes in the occupational distribution cannot account for much of the increase in WFH through 2016. The counterfactual fixed occupation WFH series increases rapidly following the great recession, from about 2 and a half hours per week to 4 hours per week by 2015Q4. Starting in 2016 the counterfactual series diverges from the actual series, with the counterfactual series reaching about 4 hours and 15 minutes of weekly work from home. This implies that changes in the occupational employment distribution can account for about 15 minutes, about half, of the increase in work from home since 2016.

Panel (b) shows the actual and counterfactual weekly hours of on-the-job leisure. The series are nearly identical until the end of 2006, after which the counterfactual series begins to decrease faster than the actual average weekly hours of on-the-job leisure. The majority of the divergence between the two series occurs during the 2008 recession. This implies that occupational change during the recession led to a slower decrease in on-the-job leisure than otherwise would have occurred. The counterfactual OJL series shows that occupational change can not account for any of the decrease in OJL observed since 2003, in fact, it mitigated a larger decline.

3.2 Within Occupations

Next we explore how changes in computer usage within occupations affected the uptake and duration of WFH and OJL. Data on computer usage by occupation comes for O*Net 5.0 - 24.0. The O*Net data were released approximately once per year from 2004 to 2019 and collect data on worker attributes and job characteristics for nearly 1,000 occupations. Our measure of computers comes from the O*Net work activities - work output questions, which contain information on what work activities are performed, what equipment and vehicles are operated/controlled, and what complex/technical activities are accomplished as job outputs.

We use all 9 measures in the work output section of O*Net in our analysis, but our measure of interest is the importance of interacting with computers.[7] The specific question about computers is,

[7] The remaining activities are: Controlling Machines and Processes, Documenting/Recording Information, Drafting, Laying

"How important is working with computers to the performance of the occupation?" Each occupation has a score between 1-5, 1 being not important and 5 being very important. Responses are at the 4-digit occupation level, however O*Net does not include values for each 4-digit occupation and not all occupations are updated in each edition.[8] Figure 7 plots how reliance on computers varies across and within aggregated 2-digit occupations over time, and shows an overall increase in the reliance of computers. Using the occupational level data on reliance on computers we explore the effect of computers on OJL and WFH using the individual level data from the ATUS. The sample period we focus on is 2004-2019 since the O*Net Edition 4, which includes 2003, is not directly comparable to later editions. We look at the effect of computers on the expensive margin, uptake of WFH and OJL, and the intensive margin, conditional minutes, separately.[9]

Theoretically the effect of computer usage on on-the-job leisure is ambiguous. An increase in computer usage could increase the uptake and minutes of OJL by increasing downtime at work through efficiency gains from computer, or by increasing the amount of distractions at work. Alternatively, employers may be better able to monitor workers' activities, discouraging them from taking on-the-job leisure. To establish the effect on uptake, we estimate a Logit model on an indicator if a worker from the ATUS participated in any on-the-job leisure. We control for all observable worker and job characteristics contained in the ATUS data, see Table 1, and a month and diary day fixed effect. Our final specification for the uptake in OJL is:

$$P(y_{ito} = 1 | x_{ito}, C_{to}, A_{to}, \gamma_o) = \frac{\exp(\beta_0 + x'_{ito}\beta + \delta_1 C_{to} + \delta_2 A_{to} + \gamma_o)}{1 - \exp(\beta_0 + x'_{ito}\beta + \delta_1 C_{to} + \delta_2 A_{to} + \gamma_o)} \tag{8}$$

where y_{ito} is an indicator that takes the value 1 if worker i in period t and occupation o participated in OJL and zero otherwise. x_{ito} are the worker and job characteristics, and month and day fixed effects. γ_o is an occupation fixed effect. C_{to} is the standardized measure of importance of computers in period t and occupation o from O*Net. A_{to} are the remaining standardized measure of worker output activities. We also look at the effect of computers on OJL within a year, across occupations, in which case γ_o is a year fixed effect.

We estimate the effect of computers on the intensive margin of OJL by regressing minutes of OJL on the same set of observables and fixed effects as the extensive margin, but limit the sample to the

Out, and Specifying Technical Devices, Parts, and Equipment, Handling and Moving Objects, Interacting With Computers, Operating Vehicles, Mechanized Devices, or Equipment, Performing General Physical Activities, Repairing and Maintaining Electronic Equipment, Repairing and Maintaining Mechanical Equipment.

[8] See Appendix C for details on how we compute missing values and interpolate between editions.

[9] Stewart [2009] shows that when using time use data, at Tobit model preforms worse than a two part estimation procedure as we use here.

subset of workers that participated. Our final specification for minutes of OJL is:

$$m_{ito} = \beta_0 + x'_{ito}\beta + \delta_1 C_{to} + \delta_2 A_{to} + \gamma_o + \varepsilon_{ito} \tag{9}$$

where m_{ito} is the minutes of on-the-job leisure taken by worker i in period t and occupation o, and the rest are as above.

Column (1) of Table 3 reports the estimates from the Logit across occupations. The estimated effect of computers across occupations is small and statistically insignificant, implying that within a year, workers in occupations that have a higher reliance on computers do not take more or less leisure on the job than workers in occupations with a lower reliance on computers. Column (2) reports the effect within occupations; the estimated coefficient on computers is -0.327 and statistically significant, implying that within an occupation, as interacting with computers becomes more important the probability of observing a worker taking any OJL decreases. A one standard deviation increase in reliance on computers decreases the probability of OJL by about 0.08 relative to the mean probability of 0.68. Columns (3) - (6) report the results from the intensive margin (with and without eating time included in on-the-job leisure). We find no effect of computer use on the intensive margin of OJL. However we find a small increase in OJL without eating time (column 6), implying that computers may lead to workers substituting leisure at work away from eating toward other activities. Our estimates of demographic characteristics on OJL are consistent with Hamermesh et al. [2017] and Burda et al. [2020].

Theoretically the effect of computer usage on working from home is also ambiguous. Again, if computers make work more efficient, there may be less need to take work that remains unfinished at the end of the day home. On the other hand, an increase in computers may decrease the reliance of face-to-face interactions or the necessity of working at an office, as well as increase the ability to work from home by allowing access to work through the internet. We look at the effect of computers on the uptake of work from home through a Logit model analogous to Equation 8, and the duration of work from home through OLS on minutes of work from home on the subset of workers that participated, analogous to Equation 9.

Column (1) of Table 4 reports the estimates from the Logit of WFH across occupations. The estimated effect of computers across occupations is small and insignificant, implying that within a year, workers in occupations that have a higher reliance on computers do not work from home more often than workers in occupations that rely less on computers, nor spend more or less time when taking work home (column 3). Within occupations we find a large and significant effect of computers on the uptake and duration of work from home. Column (2) reports the estimated effects on WFH uptake within occupations (0.261) implying that when as an occupation increases its reliance on computers by one standard deviation, the probability of observing a worker work from home increases 0.04. Relative to the average WFH uptake of 0.16, the effect is about 25% of the mean. Column (4) reports the intensive margin effect of computers on WFH, with a one standard deviation increase in computers implying an increase of 32 minutes of work from home. The positive effect of computers on working from home are consistent with estimates from other countries, see Viete and Erdsiek [2015] and Jerbashian and Vilalta-Bufi [2020] for estimates in Germany and the EU.

To see how much the increase in computer use within occupations can account for the aggregate trends in WFH and OJL we use the estimated parameters from the "within" occupations model to predict OJL and WFH. For each person in the ATUS we predict the probability and number of minutes:

$$\hat{p}_{it}^k = \frac{\exp(\hat{\beta}_0 + x_{ito}'\hat{\beta} + \hat{\delta}_1 C_{to} + \hat{\delta}_2 A_{to} + \hat{\gamma}_o)}{1 - \exp(\hat{\beta}_0 + x_{ito}'\hat{\beta} + \hat{\delta}_1 C_{to} + \hat{\delta}_2 A_{to} + \hat{\gamma}_o)} \tag{10}$$

$$\hat{m}_{it}^k = \hat{\beta}_0 + x_{ito}'\hat{\beta} + \hat{\delta}_1 C_{to} + \hat{\delta}_2 A_{to} + \hat{\gamma}_o \tag{11}$$

for $k \in \{h, l\}$. Then we construct the aggregate expected minutes of work from home and on-the-job leisure as follows:

$$\hat{H}_t^h = \sum_i \hat{p}_{it}^h \times \hat{m}_{it}^h \times wgh_{it} \tag{12}$$

$$\hat{H}_t^l = \sum_i \hat{p}_{it}^l \times \hat{m}_{it}^l \times wgh_{it}. \tag{13}$$

Then we calculate average weekly hours of each and smooth using a 12 quarter simple moving average as in section 2. We predict average weekly hours of WFH and OJL for the full data as well as for a counter factual data set in which the importance of computers is held fixed in each occupation at its 2004 values.

Panel (a) of Figure 8 plots the resulting predicted average weekly hours worked at home as well as the series constructed in section 2. The predicted model captures about 72% of the increase in average weekly hours worked at home observed in the data. The predicted model increases relatively smoothly over the period, whereas the data has a sharp increase during the 2008 recession, implying that our model can not account for the changes that occurred during the recession that lead to this sharp increase. Comparing the predicted model to the predicted counterfactual show that the increase in computers can account for about 60% of the increase within the model. Panel (b) of Figure 8 plots the resulting predicted average weekly hours of on-the-job leisure and the data. The predicted model captures the full decline in OJL. Comparing the predicted model to the predicted counterfactual show that the increase in computers can account for about 23% of the decrease within the model.

4 Relative Productivity of WFH and OJL

In section 2 we documented a shift from working at the office towards working more at home. In this section we use a simple aggregate production function where labor input is a combination of hours worked in the office, at home, and leisure on the job, to measure the relative productivity of each hour of work. Although an hour of on-the-job leisure may not be a standard productive hour of work, as in, directly leading to output, it may have some productivity benefits. For example, socializing with co-workers may lead to discussions about work, therefore indirectly affecting output. For this reason, we include on-the-job leisure in the aggregate production function.

We consider a Cobb-Douglas production function where aggregate output Y is a function of the capital stock K and total labor input L. Labor input is the sum of hours worked in the office (H_o), at home (H_h), and on-the-job leisure (H_l). That is,

$$Y = K^{\alpha} L^{1-\alpha} \tag{14}$$

$$L = H_o + A_h H_h + A_l H_l \tag{15}$$

where A_h is the productivity of an hour worked at home relative to an hour at the office and A_l is the productivity of an hour of on-the-job leisure relative to an hour of work at the office.

To find the relative productivities of work from home and on-the-job leisure we use the first order conditions of a competitive firm. Taking wages a given, the firm's optimality conditions imply the following relationship between the relative income shares of each hour worked and relative supply:

$$\frac{s_h}{s_o} = A_h \times \frac{H_h}{H_o} \tag{16}$$

$$\frac{s_l}{s_o} = A_l \times \frac{H_l}{H_o} \tag{17}$$

where s_o, s_h and s_l are the income shares of hours worked at the office, at home, and leisure on the job. For the relative supply of hours we use the aggregate hours series constructed in section 2.

We calculate the relative income shares of each type of work using the individual level data from the ATUS on hours of each type of work and reported hourly earnings. For each worker i in period t

we calculate the fraction of time they spend working from home and on-the-job leisure:

$$\theta^h_{it} = \frac{h^h_{it}}{h^o_{it} + h^h_{it} + h^l_{it}} \tag{18}$$

$$\theta^l_{it} = \frac{h^l_{it}}{h^o_{it} + h^h_{it} + h^l_{it}} \tag{19}$$

We calculate the income share of hours worked at home as the weighted sum of hours worked at home times the reported hourly wage, where the weight is the fraction of hours worked at home, similarly for one-the-job leisure and hours at the office. That is:

$$s^h_t = \sum_i w_{it} \times \theta^h_{it} \times h^h_{it} \times wgt_{it} \tag{20}$$

$$s^l_t = \sum_i w_{it} \times \theta^l_{it} \times h^l_{it} \times wgt_{it} \tag{21}$$

$$s^o_t = \sum_i w_{it} \times (1 - \theta^h_{it} - \theta^l_{it}) \times h^o_{it} \times wgt_{it}, \tag{22}$$

where w_{it} is the reported hourly wage of worker i in period t and wgt_{it} is the ATUS sampling weight.

Figure 9 plots the relative supply of hours worked and the relative income shares for WFH and OJL. Prior to the 2008 recession, the relative supply and income share for work from home were stable around 0.08, implying similar productivities of an hour at home vs an hour at the office. Beginning in 2008 the relative income share of hours at home begins to rise quickly reaching nearly 0.16 by 2019. The relative supply of hours at home begins to rise 2 year later, beginning in 2010 and reaching nearly 0.14 by 2019. The rise in total payments to hours worked from home is consistent with evidence that workers are not willing to take pay cuts for flexible work conditions Mas and Pallais [2017]. Oettinger [2011] shows that the pay penalty of working from home declined significantly from 1980-2000, and more recently Pabilonia and Vernon [2020] find that some teleworkers earn wage premiums.

Figure 10 plots the corresponding relative productivities. Prior to the 2008 recession, an hour at home was on average 98% as productive as an hour at the workplace, increasing to about 117% as productive by the end of the recession. The relative productivity of an hour at home peaks in 2016 at 125%. Hours at home remain more productive in 2019 than hours at the workplace.

The relative supply of on-the-job leisure is stable at 0.065 until 2012, after which it begins to decrease, hitting its trough in 2018 around 0.06. However, the relative supply of OJL remains above its relative income share throughout, implying that on-the-job leisure is on average about 15% as productive as an hour of work at the office. Panel (b) of Figure 10 plots the relative productivity of leisure on the job which increased slightly during the recovery from the recession, however falling quickly back to its precession level of about 13%. Since 2015, the relative productivity of leisure on the job has increased from about 13% to 16%.

4.1 Changes in Working From Home

Given the substantial increase in the productivity of an hour worked at home since the 2008 recession, we look at some characteristics of work from home. Since 2004, the ATUS has collected data on childcare as a secondary activity. With this addition it is possible to see if a person working from home is simultaneously responsible for caring for a child that is younger than 13, and for how long. For each person we calculate the total hours of work from home while also caring for a child, $\tilde{h}^h_{it}$, then we calculate the fraction of time worked at home while caring for a child as:

$$\frac{\tilde{H}^h_t}{H^h_t} = \frac{\sum_i \tilde{h}^h_{it} \times wgt_{it}}{\sum_i h^h_{it} \times wgt_{it}}. \tag{23}$$

The resulting series is smoothed using a 12 quarter simple moving average.

Figure 11 plots the fraction of hours worked from home while caring for children. On average, before the 2008 recession, about 9% of hours worked from home where while caring for children, peaking right before the recession's start at 10%. Since the recession, the fraction of hours worked at home while caring for a child has dropped to about 6.5% in 2019. The decreasing trend in child care while working from home is in line with the increase in the relative productivity of an hour worked at home.

We also explore changes in the time of day that people are working from home. If people are more productive at the beginning of the day than at night after a full day of work, then changes in the time of day that people are working from home could affect the relative productivity. In the ATUS, the start time of each activity is recorded. In our sample of workers who did any work from home, about 61% did so for only one uninterrupted spell. Figure 12 shows the distribution over the time of day that people started their first spell of working from home. The distribution is clearly bimodal with one mode in the morning and the other at night.

To gauge how this distribution has changed over time, and what affect it could have had on the productivity of an hour worked at home, we construct a measure of usual business hours at home. That is, the fraction of hours worked at home between 9am and 5pm. Let $\dot{h}^h_{it}$ be the number of hours worker i in period t worked at home between 9am and 5pm, then average weekly hours of usual business hours work from home per worker is:

$$\dot{H}^h_t = \frac{\sum_i \dot{h}^h_{it} \times wgt_{it}}{13 \times E_t}. \tag{24}$$

The resulting series is smoothed using a 12 quarter simple moving average. Similarly we calculate the average weekly hours outside of 9am to 5pm.

Panel (a) of Figure 13 plots the average weekly hours of work from home between 9am and 5pm and outside of usual business hours. Prior to the 2008 recession, both series are flat, with more hours per week being worked outside of business hours at home, 1.1 hours between 9am and 5pm and 1.6 hours outside of 9am to 5pm. During, and following the end of the recession, both series begin to increase, however, working from home during business hours increased faster, reaching 2.5 hours per week in 2019, whereas work outside of 9am and 5pm increased to about 2 hours per week by 2019. Panel (b) plot the percent of business hours at home ($\dot{H}_t^h/H_t^h$) which increased from 40% in 2003 to 55% in 2019. Although work from home increased both during and outside of usual business hours, the increase in average weekly hours of work from home is primarily driven by working at home between 9am and 5pm.

The decrease in working from home while being the primary caretaker of children could have had a positive effect on the productive of work from home if working with children present is less efficient than without. Similarly, if working at home during the day is more productive than working at home at night, after a full day of work, then the observed change in the timing of work from home could have had a positive effect on the relative productivity of WFH. To estimate these effects we regress our estimated relative productivity of WFH on the fraction of hours worked from home while providing childcare and the fraction of hours worked during business hours. We control for changes in the demographic aspects by constructing the fraction of hours worked at home by each demographic variable (in Table 1) identically to Equation 23 and the fraction of work from home by each 2-digit occupation. Our final specification is:

$$\hat{A}_t^h = \alpha_1 \dot{H}_t^h/H_t^h + \alpha_2 \tilde{H}_t^h/H_t^h + \beta D_t + \gamma O_t + \varepsilon_t \tag{25}$$

where D_t are the shares of hours worked from home by demographic group and O_t are the shares of hours worked from home by occupation.

Column (1) of Table 5 shows the estimated coefficients without controlling for occupations shares. The estimated coefficient on WFH between 9am and 5pm is 0.892 and statistically significant, implying that increases in the share of hours worked at home during business hours is positively correlated with the increase in the relative productivity of working from home. WFH while providing childcare is negatively correlated with productivity, however the estimate is far from significant. When controlling for occupational shares (column 2) the estimated coefficients on 9am-5pm and WFH with childcare both increase in magnitude, however only the positive correlation between WFH 9am-5pm and productivity is significant.

The fraction of hours worked at home between 9am and 5pm is, no doubt, endogenous to the changing productivity of work from home since there are only so many hours in the day, and as productivity at home rises, more hours will be worked at home. In Column (3) of Table 5 shows estimated coefficients when instrumenting for the fraction of hours worked at home between 9am and 5pm with its one quarter lagged value. The coefficient on work from home between 9am and 5pm is 1.47, implying that a 1pp increase in the share of WFH occurring during business hours increases relative productivity by 0.0147. Given the 15pp increase in WFH between 9am and 5pm since 2003, all else equal, relative productivity at home would have increased by nearly 0.22, almost the entire estimated increase. The coefficient on working from home while providing childcare is -1.77, and statistically significant, implying a 1pp decrease in the time spent working from home while providing childcare, increases relative productivity by 0.0177. Given the 3pp decrease in time working from home while providing childcare, all else equal, relative productivity at home would have increased by 0.05.

The only significant coefficient on the share of hours worked by different demographic groups is the coefficient for hours worked by women. The estimated coefficient is -0.684, implying that as the share of hours worked at home by women increases, relative productive of work at home decreases. The negative effect could be stemming from women multi-tasking more than men when working from home. Unfortunately, childcare activities are the only multi-tasking activities tracked by the ATUS. However, recent studies suggest there exist significant gender differences in the enjoyment of working from home [Gimenez-Nadal and Velilla, 2020] and the share of childcare responsibilities [Hupkau and Petrongolo, 2020], both of which could contribute to women having lower productivities at home. However, since 2003 there has not been a significant trend in the percent of hours worked at home by women so it can not account for the changes in relative productivity.

Over all the data suggest that prior to the 2008 recession, when a majority of the work at home was occurring either early in the morning or late in the evening, work from home was slightly less productive than working at the office. The recession and rise in reliance on computers brought about a shift in the time at which people work at home, spending less time at the workplace and working more hours at home during usual business hours. This change can account for nearly the entire increase in the relative productivity in work from home, impling that, while workers are less productive working from home in the morning and evening, they are much more productive at home during standard business hours, especially when not needing to simultaneously provide childcare.

4.2 Effects on Labor Proudctivity

Lastly we construct and compare two measures of labor productivity. The first measure we construct is the standard measure of labor productivity: real output per hour. That is, real output per total hours at the workplace ($H^o + H^l$) plus all hours worked at home H^h. We compare this measure to real output per labor input, Equation 15, where A^h and A^l are those plotted in Figure 10.

Figure 14 plots the resulting real output per hour and labor input, indexed to 2009 Q1. The figure shows that real output per hour worked has increased by 20% since 2009 and real output per labor input has increased by 18%. This implies that 2 percentage points (10%) of the increase in real output per hour worked as can be attributed to the substitution of working at the workplace to working from home.

5 Conclusion

We have documented a significant rise in the share of hours worked at home, which can be attributed to the rise of computer use within occupations and, since 2016, occupational employment changes. The small decline in on-the-job leisure can, in part, be accounted for by the increased use of computers but not by occupational employment changes. We have shown that with the rise in work from home came substantial increases in the relative productivity of working from home. The rise in productivity at home can be attributed to fewer hours worked at home while simultaneously providing childcare and a shift in the time of day people work from home, working more during standard business hours. The rise in the relative productivity of working from home can account for 10% of the increase in real output per hour experienced since the 2008 recession.

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A Tables

Table 1: Demographic Summary Statistics: ATUS 2003-2019

Characteristic	Sample Mean	Characteristic	Sample Mean
Female	0.48	White	0.82
Married	0.55	Black	0.11
Age	40.41	Other	0.07
Child	0.43	Government	0.17
High School	0.28	Full Time	0.80
Some College	0.27	Paid Hourly	0.59
Advanced Degree	0.12	One Job	0.87
College	0.22	At Work	0.62
Less than HS	0.10		
Total number of Observations			110,717
Number of people at work on interview day			55,152

Note: ATUS weights used in all calculations.

Table 2: Work and Leisure at Work Summary Statistics: ATUS 2003-2019

	Sample Average
Time at Work (h^w)	312.71
On-the-job Leisure (h^l)	
Participation	0.43
Unconditional Min.	19.87
Conditional Min.	46.74
Work from Home (h^h)	
Participation	0.16
Unconditional Min.	30.92
Conditional Min.	190.84
Productive Work (h^p)	323.76

Note: ATUS weights used in all calculations. Unconditional minutes are calculated for the full sample and conditional minutes are calculated for the sample conditional on participating in either on-the-job leisure or work from home.

Table 3: Computer and On-the-job Leisure

	Probability of OJL		Minutes of OJL		Minutes of OJL w/o eating	
	Across	Within	Across	Within	Across	Within
	(1)	(2)	(3)	(4)	(5)	(6)
Interacting with Computers	0.018	-0.327	-0.827	0.641	-0.100	3.047
	(0.036)	(0.072)	(0.824)	(1.475)	(0.703)	(1.379)
log(Hours at work)	1.961	2.046	31.256	31.747	11.711	12.407
	(0.053)	(0.054)	(1.590)	(1.599)	(1.311)	(1.310)
Female	0.069	0.039	-0.215	-0.104	-0.544	-0.554
	(0.031)	(0.034)	(0.624)	(0.677)	(0.536)	(0.602)
Child	-0.011	-0.020	-1.062	-0.834	-0.771	-0.377
	(0.030)	(0.031)	(0.588)	(0.579)	(0.514)	(0.506)
Age	-0.001	-0.001	0.062	0.065	0.025	0.027
	(0.001)	(0.001)	(0.022)	(0.022)	(0.019)	(0.019)
Married	-0.003	0.007	-1.547	-1.356	-2.182	-2.044
	(0.030)	(0.031)	(0.594)	(0.581)	(0.504)	(0.491)
Race - Other	0.075	0.077	1.728	1.148	-0.990	-0.725
	(0.072)	(0.073)	(1.550)	(1.521)	(1.500)	(1.438)
Race - White	-0.337	-0.323	-1.947	-1.450	-2.841	-1.835
	(0.042)	(0.044)	(0.743)	(0.756)	(0.654)	(0.670)
Less than High School	0.426	0.287	5.594	5.014	3.999	4.062
	(0.068)	(0.076)	(1.227)	(1.325)	(1.070)	(1.173)
High School	0.241	0.193	3.926	4.134	3.941	4.427
	(0.050)	(0.058)	(0.983)	(1.087)	(0.816)	(0.920)
Some College	0.056	0.050	2.800	3.142	3.531	4.101
	(0.046)	(0.053)	(0.915)	(1.057)	(0.723)	(0.880)
College	0.084	0.060	0.932	1.507	0.775	1.617
	(0.044)	(0.049)	(0.844)	(0.907)	(0.674)	(0.761)
Government	0.237	0.163	2.651	1.620	2.131	0.902
	(0.038)	(0.044)	(0.654)	(0.773)	(0.557)	(0.647)
Part Time	-0.126	-0.095	1.681	1.264	4.221	3.610
	(0.043)	(0.045)	(1.187)	(1.197)	(1.129)	(1.126)
Paid Hourly	0.497	0.374	2.594	1.537	3.173	2.424
	(0.032)	(0.034)	(0.641)	(0.640)	(0.530)	(0.537)
Occupation FE		✓		✓		✓
Year FE	✓		✓		✓	
Month FE	✓	✓	✓	✓	✓	✓
Diary Day FE	✓	✓	✓	✓	✓	✓
Mean Dependent Variable	0.682	0.682	46.229	46.229	17.878	17.878
N	48,824	48,824	32,352	32,352	32,352	32,352

Note: ATUS weights used in all calculations. Robust standard errors given in parentheses.

Table 4: Computers and Work from Home

	Probability of WFH		Minutes of WFH	
	Across	Within	Across	Within
Interacting with Computers	-0.054	0.261	-1.478	32.271
	(0.038)	(0.066)	(5.387)	(8.975)
At Work	0.633	0.607	-64.277	-63.312
	(0.079)	(0.078)	(9.385)	(9.154)
At Work × log(Hours at work)	-0.928	-0.925	-89.986	-87.978
	(0.037)	(0.037)	(4.370)	(4.272)
Female	-0.156	-0.087	-12.130	-7.917
	(0.028)	(0.030)	(3.804)	(3.956)
Age	0.011	0.010	0.308	0.340
	(0.001)	(0.001)	(0.160)	(0.159)
Married	0.085	0.046	-5.227	-4.829
	(0.028)	(0.029)	(4.064)	(3.951)
Race - Other	0.193	0.228	-12.277	-12.685
	(0.064)	(0.066)	(8.873)	(8.846)
Race - White	0.290	0.273	-16.032	-13.358
	(0.044)	(0.045)	(6.361)	(6.343)
Less than High School	-1.563	-1.170	43.120	40.161
	(0.078)	(0.084)	(11.682)	(12.425)
High School	-1.213	-0.879	20.614	19.250
	(0.045)	(0.050)	(6.644)	(7.081)
Some College	-0.847	-0.577	3.448	4.816
	(0.038)	(0.044)	(4.937)	(5.338)
College	-0.402	-0.262	-2.761	-2.473
	(0.032)	(0.036)	(4.038)	(4.248)
Government	-0.103	-0.244	-18.644	-16.792
	(0.033)	(0.040)	(4.281)	(4.848)
Part Time	-0.448	-0.446	-110.186	-108.600
	(0.041)	(0.044)	(5.336)	(5.528)
Paid Hourly	-0.728	-0.479	-8.174	-8.640
	(0.030)	(0.032)	(4.346)	(4.500)
Occupation FE		✓		✓
Year FE	✓		✓	
Month FE	✓	✓	✓	✓
Diary Day FE	✓	✓	✓	✓
Mean Dependent Variable	0.163	0.163	191.880	191.880
N	99,403	99,403	16,517	16,517

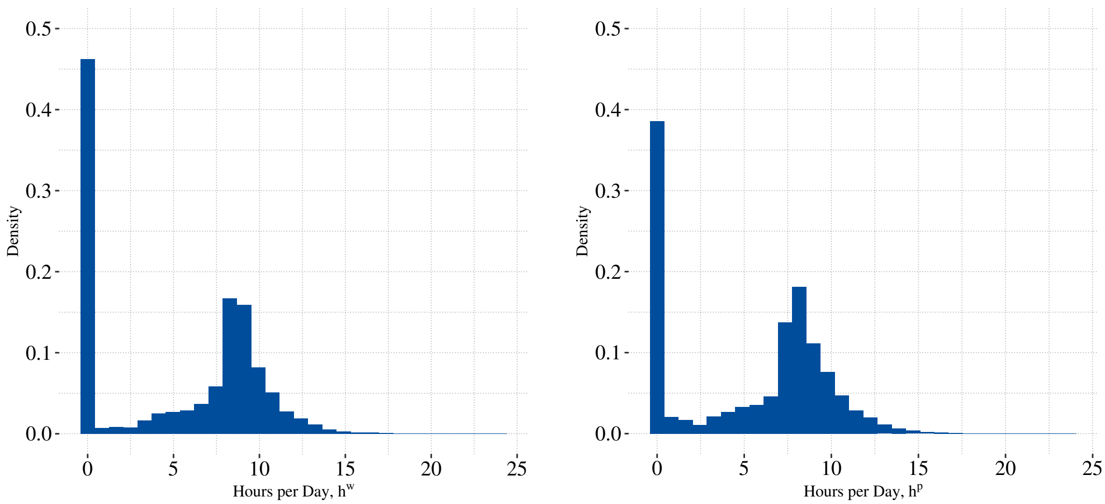
Note: ATUS weights used in all calculations. Robust standard errors given in parentheses.

Table 5: Relative Productivity of Work from Home

	Relative Productivity of WFH		
	OLS		IV
	(1)	(2)	(3)
WFH 9am-5pm	0.892	1.053	1.471
	(0.246)	(0.323)	(0.540)
WFH providing Childcare	-0.557	-1.011	-1.770
	(0.795)	(1.127)	(0.721)
Female	-0.657	-0.460	-0.684
	(0.334)	(0.565)	(0.347)
Married	0.156	0.184	0.649
	(0.355)	(0.530)	(0.483)
Child	0.152	0.345	0.257
	(0.442)	(0.611)	(0.439)
Government	-0.470	0.047	-0.041
	(0.364)	(0.707)	(0.502)
Full Time	-0.611	-0.396	-0.484
	(0.438)	(0.615)	(0.395)
One Job	-0.161	-0.126	-0.075
	(0.369)	(0.490)	(0.291)
Paid Hourly	-0.830	-0.467	-0.184
	(0.320)	(0.465)	(0.284)
Some College	-0.020	-0.051	0.173
	(0.491)	(0.784)	(0.456)
College	0.214	0.037	0.265
	(0.491)	(0.899)	(0.559)
Advanced Degree	0.183	-1.277	-0.980
	(0.582)	(0.963)	(0.556)
Less than HS	0.396	1.567	1.680
	(0.785)	(1.109)	(0.848)
Race - Black	-0.133	0.146	0.004
	(0.502)	(0.610)	(0.354)
Race - Other	-0.521	-1.108	-0.872
	(0.599)	(0.744)	(0.453)
Age 25-39	-0.798	0.793	0.555
	(0.516)	(0.976)	(0.576)
Age 40-54	-0.249	1.325	1.009
	(0.608)	(1.084)	(0.729)
Age 55+	0.004	1.334	1.146
	(0.549)	(0.947)	(0.718)
Occupation Shares		✓	✓
First Stage F-stat			8.751
N	64	64	63

B Figures

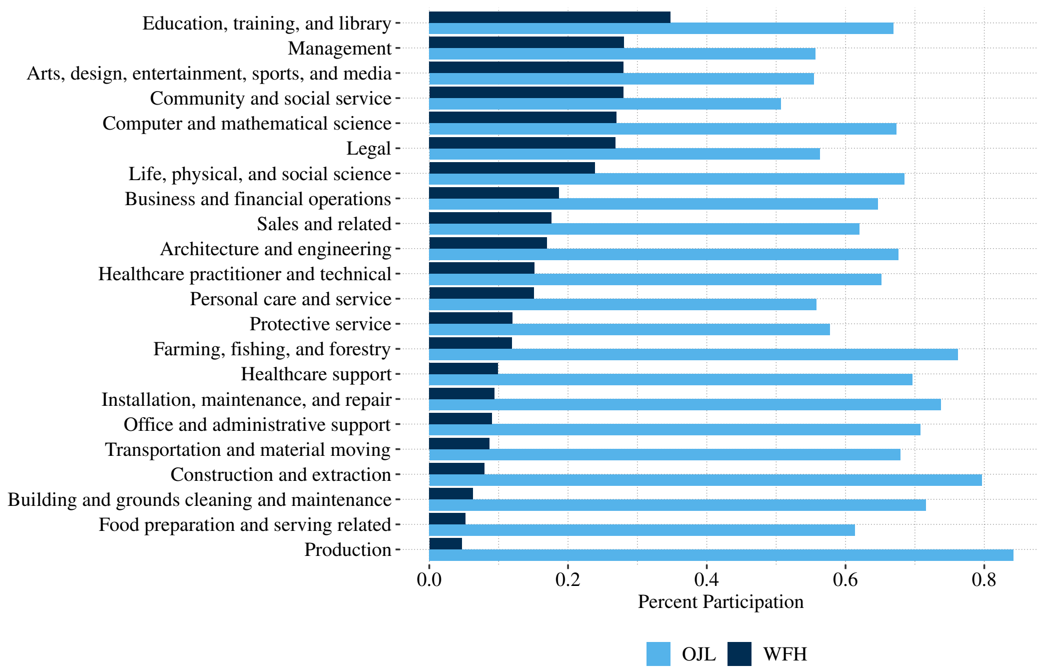
Figure 1: Hours at work and Productive hours worked: Full sample



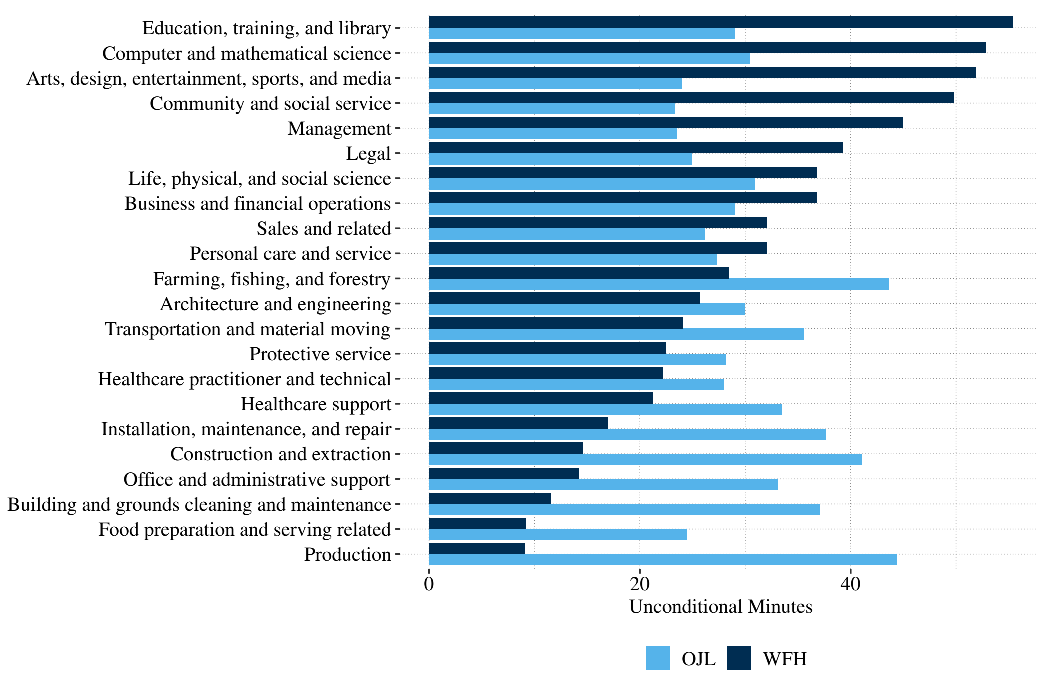
(a) Hours at Work, h^w (b) Productive Hours Worked, h^p

Note: ATUS weights used in all calculations.

Figure 2: Participation and Minutes of WFH and OJL



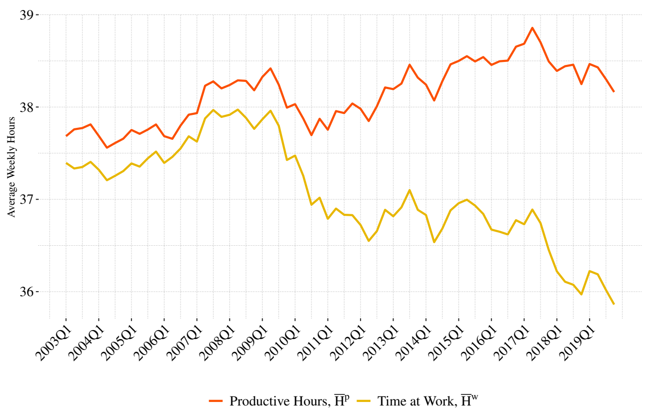
(a) Participations Percentage



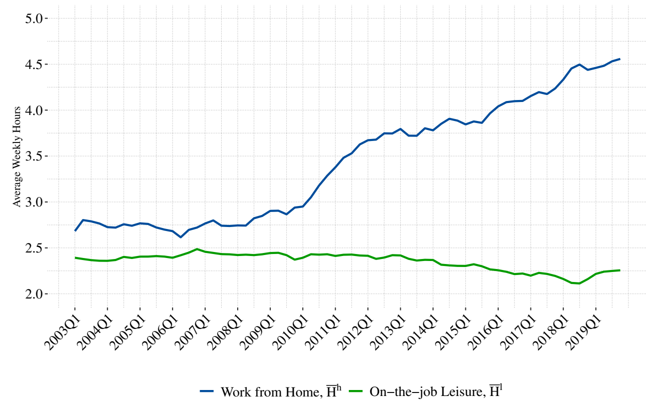
(b) Unconditional Minutes

Note: ATUS weights used in all calculations.

Figure 3: Average Weekly Hours per Worker



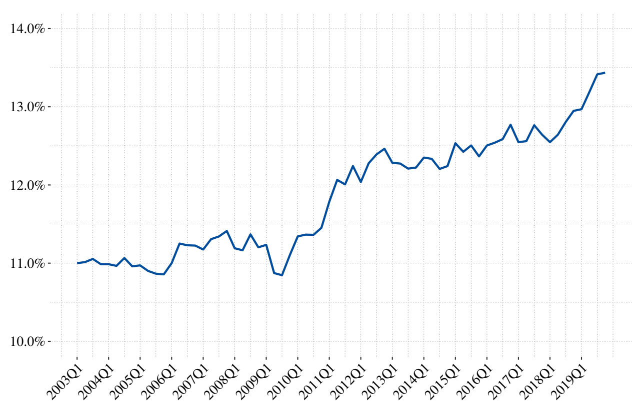
(a) Productive Hours ($\bar{H}^p$) and Time at Work ($\bar{H}^w$)



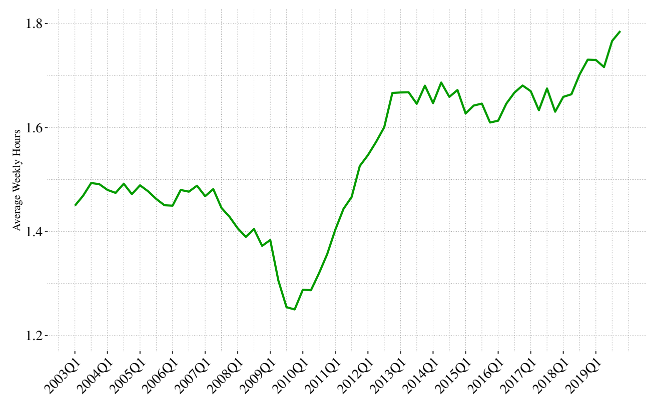
(b) Work from Home ($\bar{H}^h$) and On-the-job Leisure ($\bar{H}^l$)

Note: ATUS weights used in all calculations.

Figure 4: Work From Home by People who went to Work on Diary Day



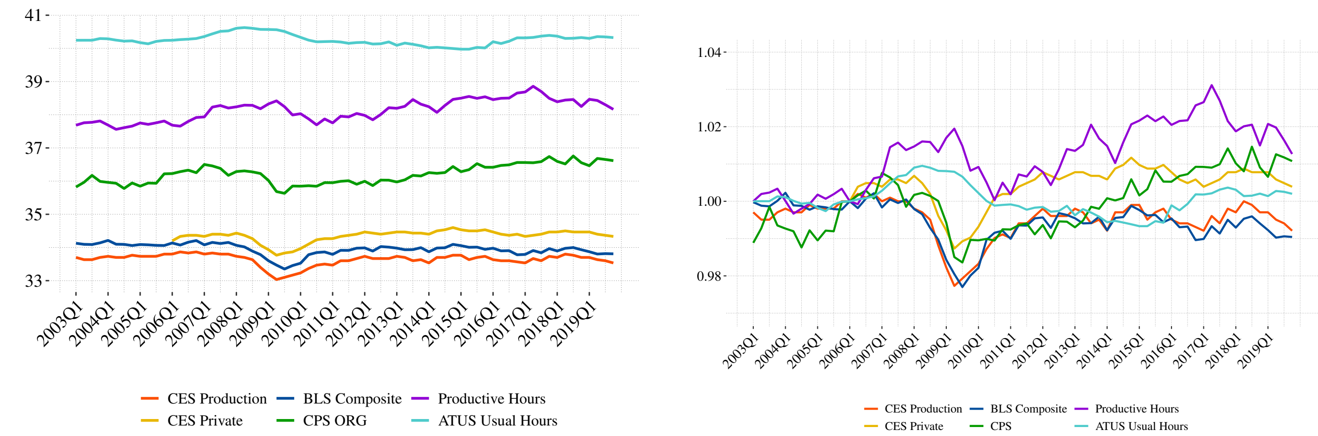
(a) Fraction Who Participated in WFH



(b) Average Weekly Hours of WFH

Note: ATUS weights are re-weighted such that each day of the week in the subsample of people who went to work in the interview day is 1/7 of the sample. The new weights are used to calculate averages.

Figure 5: Average Weekly Hours per Worker

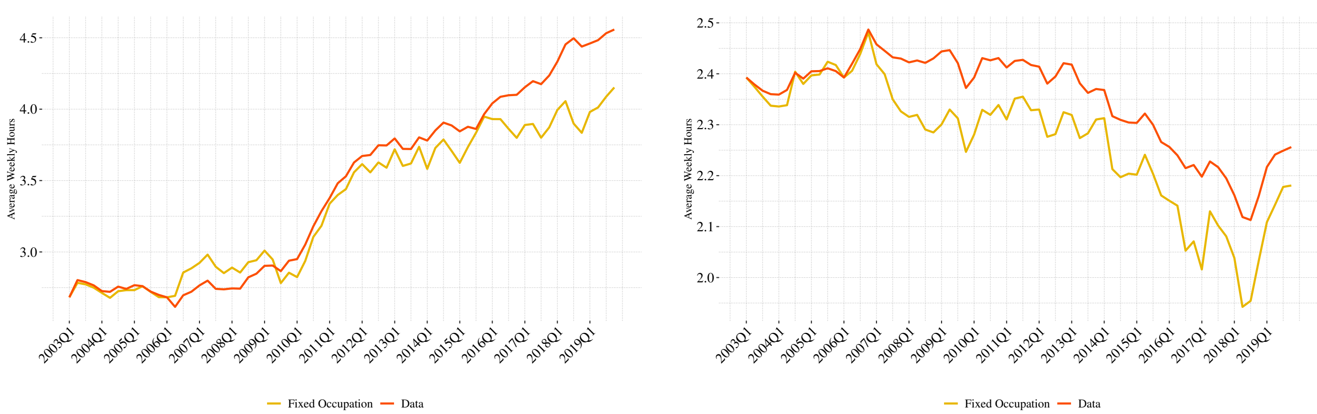


(a) Level

(b) Index 2006 Q1 = 1

Note: ATUS weights used in all calculations.

Figure 6: Across Occupation Decomposition

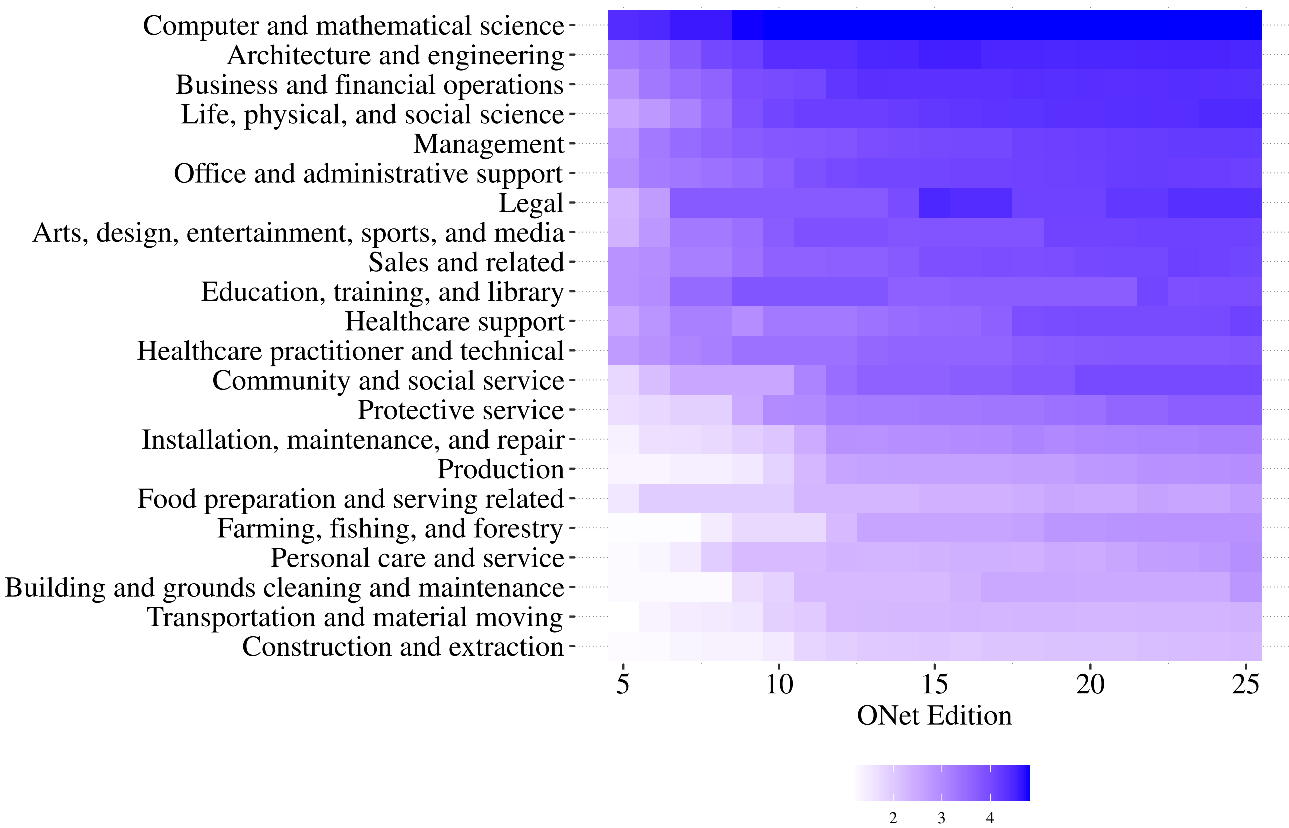


(a) Worked from Home

(b) On-the-job Leisure

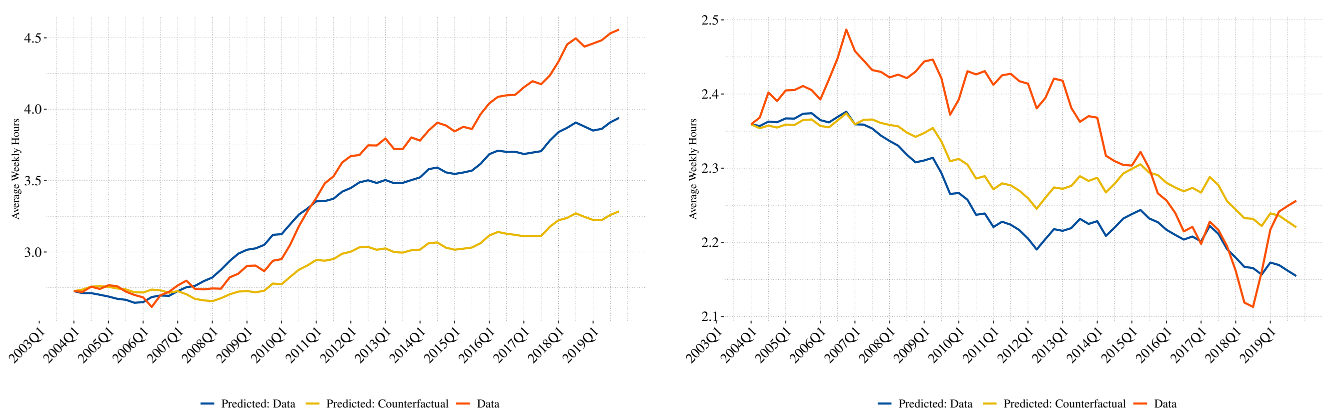
Note: ATUS weights used in all calculations. The “Data" series are average calculated from the full ATUS sample. The “Fixed Occupation” series is the mean values from 1,000 quarterly re-sampled data in which the employment distribution across occupations is fixed at its 2003Q1 distribution.

Figure 7: Reliance on Computers



*Note: The figure plot average responses to "How important is working with computers to the performance of the occupation?" within occupations across each O*Net Edition. 1 begin not important and 5 being very important*

Figure 8: Within Occupation Decomposition

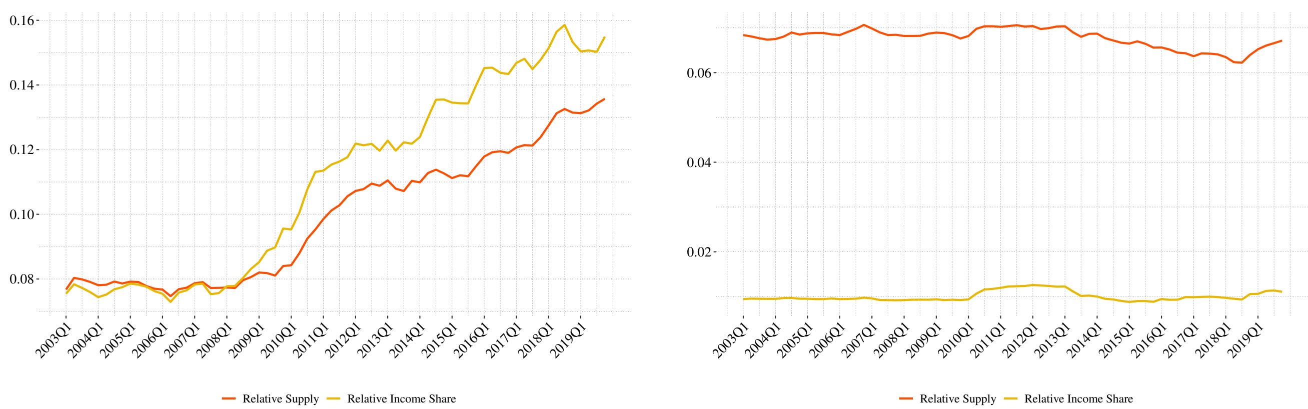


(a) Work from Home

(b) On-the-job Leisure

Note: ATUS weights used in all calculations. The "Data" series are average calculated from the full ATUS sample The "Predicted: Data" series are the average weekly hours of WFH and OJL predicted by the Logistic and OLS model in section 3. The "Predicted: Counterfactual" series are the average weekly hours of WFH and OJL predicted with the reliance on computers regressor fixed at its 2004 values for each occupation.

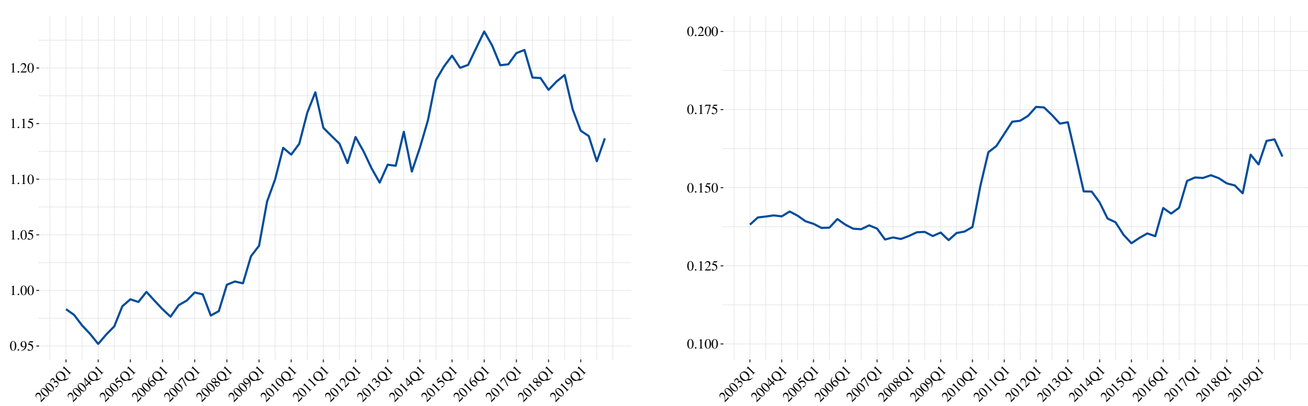
Figure 9: Relative Supply and Relative Income Share



(a) Work from Home (b) On-the-job Leisure

Note: ATUS weights used in all calculations. Plotted are the supply and income share of work from home and on-the-job leisure relative to working at the workplace.

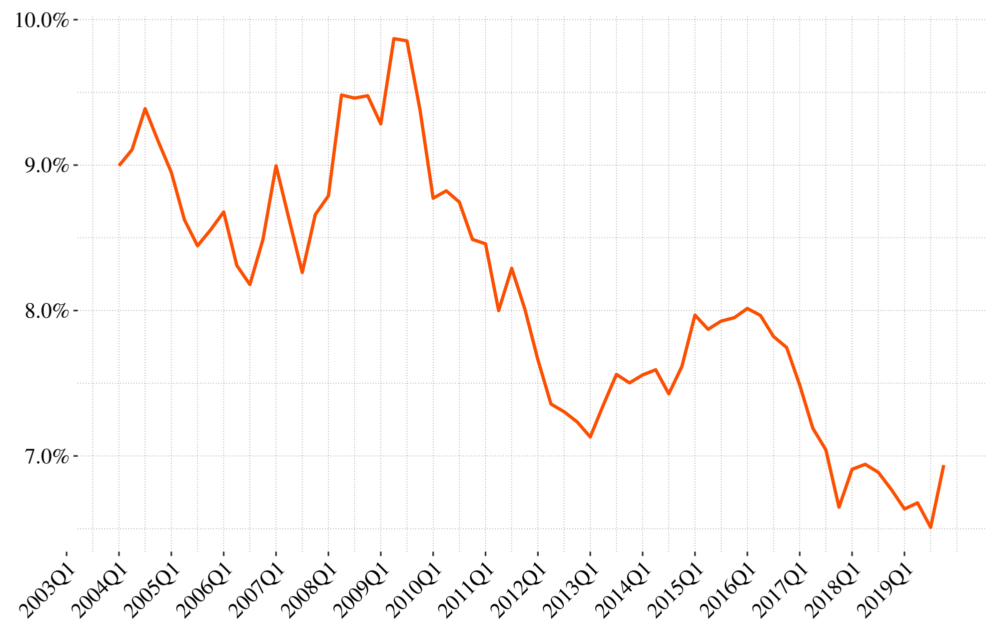
Figure 10: Relative Productivity



(a) Work from Home (b) On-the-job Leisure

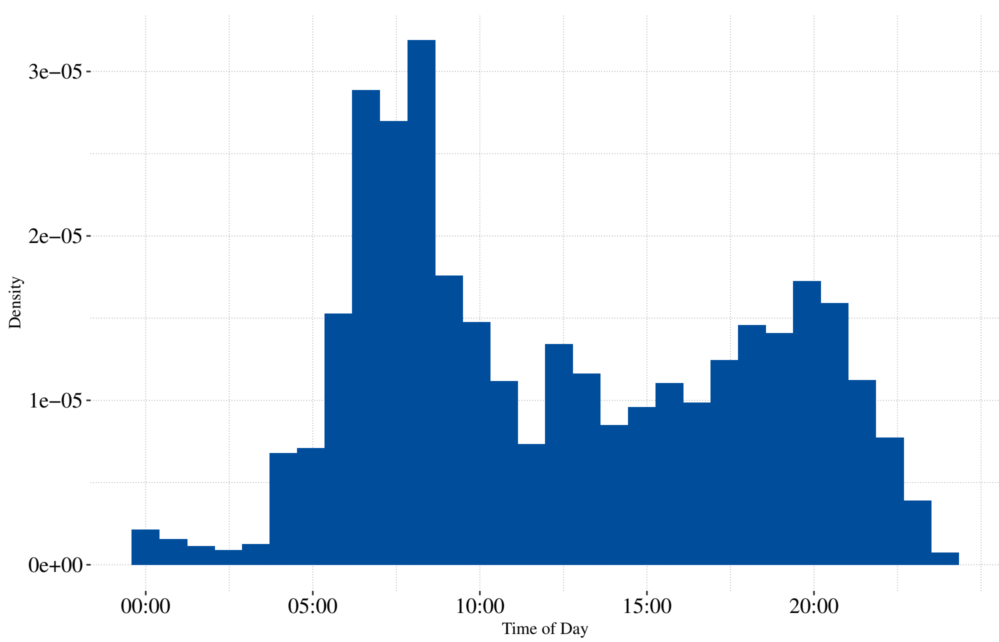
Note: ATUS weights used in all calculations. Plotted are the productivities of working from home and on-the-job leisure relative to working at the workplace.

Figure 11: Percent of Hours Worked from Home while caring for Children



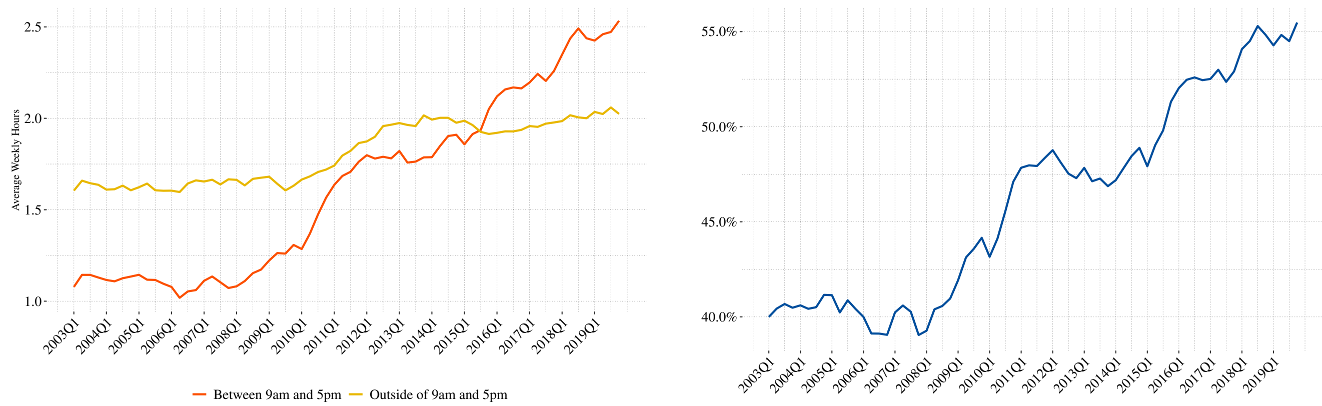
Note: ATUS weights used in all calculations.

Figure 12: Distribution of Start times of Working from Home



Note: ATUS weights used in all calculations.

Figure 13: Work from Home by Time of Day

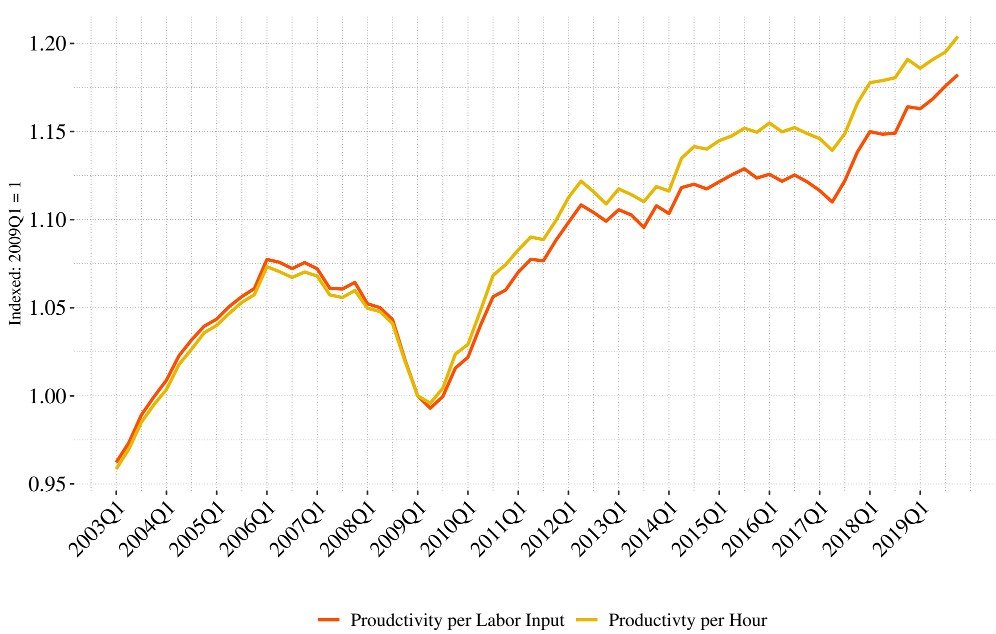


(a) Work from Home by Time of Day

(b) Fraction of Work from Home between 9am-5pm

Note: ATUS weights used in all calculations. Panel (a) plots the average weekly hours of work from home that are worked between 9am and 5pm and outside of 9am and 5pm. Panel (b) plots the fraction of total hours worked at home that were worked between 9am-5pm.

Figure 14: Real Output per Labor Input and Total Hours Worked



Note: Plotted is real output per total hours worked ($H^w + H^h$) and real output per unit of labor input, where labor input is define as in Equation 15.

C Data Processing

C.1 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 the subsample of workers who went to work on the interview day, we rescale the weights such that each day of the week is equally represented within each quarter of the subsample. The subsample and new weights are used to produce Figure 4.

Usual Hours Worked: There are a total of 4,953 (4.5%) missing responses to the ATUS usual hours worked question. We impute the missing responses by regressing usual hours worked on occupation fixed effects, industry fixed effects, state level unemployment rates and all the demographic and work characteristics from Table 1 for the subset of non-missing values. Using the estimates we predict usual hours worked for the missing responses.

C.2 O*Net

Imputing missing values: There are a total of 535 unique 4-digit occupational codes. The O*Net data does not contain information about all 535 codes in every year. For the missing values in each edition of the O*Net we take the 2-digit occupational average within edition and assign it to the missing 2 digit occupations. Table 6 below show how many missing values are imputed within each O*Net edition.

Interpolating: Each O*Net edition updated a subset of occupations each year. For each 4 digit occupation we linearly interpolate between updated values. The interpolation results in a monthly series for each occupation from January 2004 to December 2019. The final variables we use are the standardized interpolated values.

Table 6: O*Net Missing Occupation Values

Editions	Recorded	Imputed	Total
4-6	355	180	535
7-8	361	174	535
9	365	170	535
10	369	166	535
11	370	165	535
12	371	164	535
13	373	162	535
14-15	381	154	535
16	382	153	535
17	384	151	535
18	386	149	535
19-24	389	146	535