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**Which jobs are done from home?
Evidence from the American Time Use Survey?**

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[\(This paper also appears as CAGE Discussion Paper No: 466\)](#)

April 2020

No: 1261

Warwick Economics Research Papers

ISSN 2059-4283 (online)

ISSN 0083-7350 (print)

Which jobs are done from home?

Evidence from the American Time Use Survey

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April 13, 2020

Abstract

Which jobs are more likely to be affected by mobility restrictions due to the Covid-19 pandemic? This paper uses American Time Use Survey data to measure the share of the work hours that are spent at home for different job categories. We compute and provide home-working shares by occupation (US census classification, SOC and international ISCO classification), and by industry (US census classification, NAICS and international ISIC classification).

Keywords: home-working, remote work, time-use, COVID. **JEL Codes:** J22.

*Hensvik: Uppsala University. Le Barbanchon: Bocconi University. Rathelot: University of Warwick. Hensvik is also affiliated to IFAU, CEPR; Le Barbanchon to CEPR, IGIER, IZA, J-PAL; Rathelot to CAGE, CEPR, J-PAL. All remaining errors are our own. Code and data are available at <https://github.com/tlebarbanchon/home-working-ATUS>.

1 Introduction

As the COVID-19 pandemic started to spread, the government of many countries around the world have advised or required workers to work from home. The economic consequences of these measures are likely to depend on how easily workers can perform their jobs away from their workplace, which may vary across occupations, and industries.

This paper follows a data-driven approach to rate occupations and industries by their propensity to substitute home-working for workplace work. We rely on the American Time Use Survey (ATUS) and compute the prevalence of home-working between 2011 and 2018. From worker-level data, we aggregate the share of working hours at home by detailed occupations and industries. We provide ready-to-use datasets of the share of hours worked at home by detailed occupations and industries in both US and international classifications.

Between 2011 and 2018, we observe more than 30,000 workers. The large sample of the ATUS is essential to obtain precise home-working rates at detailed occupation and industry levels. We start by computing the share of hours worked at home at the 2010 Census Occupation Classification and the 2012 Census Industry Classification level, the finest categories directly available in the survey. We then convert our measures into the US Standard Occupation Classification (SOC2010) and the North American Industry Classification System (NAICS2012): we obtain ratings for around 800 6-digit SOC occupations and over 300 4-digit NAICS industries. To allow the use of our rankings outside of the US, we also convert US classifications into the International Standard Classification of Occupations (ISCO-08) and the International Standard Industrial Classification (ISIC revision 4.0).

We find that around 15% of working hours are performed at home in the US from 2011 to 2018. Obviously, this estimate provides a lower bound of the remaining labour in periods when workers are advised to stay home, as some firms will still require workers to be in their workplace. This also provides a lower bound in times of mandatory lock-down, like the one implemented in Italy on March 9 2020, for two reasons. First, even during lock-down, some industries are deemed essential and their workers are allowed to be in the workplace. Second, there may be extra substitution from workplace into home-working in lock-down compared to normal times.

We also find that there is substantial heterogeneity in home-working shares across occupations and industries, with standard deviations around 0.15. We argue that occupational and industrial heterogeneity in pre-COVID years is informative about their differential responses to the pandemic crisis.

Our paper contributes to the literature by providing estimates of the share of hours that worked from home at detailed occupation and industry levels, for both US and international classifications. The Bureau of Labour Statistics (BLS) publishes on their website hours worked at home vs in the workplace using the same ATUS data by broad occupations only (8 categories). We compute the home-working shares at the 6-digit SOC level of occupations (around 800 categories), and across industries.

Our paper is mostly related to [Office for National Statistics \(2020\)](#), who compute the share of British workers who work from home, and study the heterogeneity of this share, by sector, occupation, and workers' age. The main difference with respect to our work is that we document the intensive margin (the number of hours of home working) more precisely, and work on the US instead of the UK. Our paper is also related to [Dingel and Neiman \(2020\)](#) and [Boeri et al. \(2020\)](#). Both papers assess the tele-workability of occupations according to the description of their tasks. Our approach relies on the actual place of work declared by workers in surveys. Because we analyse worker-level data, we also directly aggregate home-working at the industry-level without relying on the occupational composition of industries, as in [Dingel and Neiman \(2020\)](#). This allows that the same occupation may be performed mostly at home in one industry and mostly at the workplace in another industry. In a horse race between occupations and industries to explain home working, we find that industry dummies are significant, and explain 3 percentage points of the variance in home-working, on top of the 13% explained by occupations.

Our home-working estimates can be used as core inputs for quantitative macro exercises of the economic consequences of social-distancing measures as in [Barrot et al. \(2020\)](#).

Section 2 describes the data. Section 3 provides summary statistics of where workers work by occupation and industries.

2 Data description

We use data from the American Time Use Survey in the US from 2011 to 2018. Over this period, the BLS reports respondents' occupation in their main job according to the 2010 census occupation classification (OCC10, 535 codes).¹ Since ATUS 2014, the industries of main jobs are reported according to the 2012 census industry classification.²

We select employed respondents who declare some work hours related to their main job during the survey day (or diary). The ATUS focuses on civilian employment, so that we exclude military occupations. This amounts to 30,250 respondents, around 3,800 every survey year. All statistics are obtained using survey weights.

For each work activity within the survey diary, workers declare the place of activity. We isolate two places – workplace and home – and group all other places in one residual category. Collapsing the data at the day level, we compute the number of work hours at the workplace, at home, and at other places. On the average day, workers spend 6.7 hours at their workplace, 0.7 hours at home and 0.3 hours at another place. Given the residual nature of the third category, we mainly focus on the workplace and the residence, and our main statistics of home-working prevalence is the share of hours worked at home over hours worked at the workplace and home.

Collapsing the data at the occupational or at the industry level, we obtain home-working estimates by occupation and by industry. To allow for across-survey and international use of our ranking, we also convert occupations into the SOC-2010 classification (at the 6-digit level, 840 codes) and the ISCO-08 classification (finer 4-digit level, 438 codes). We convert census industries into the NAICS-2012 classification (4-digit level, 310 codes) and the ISIC classification (4-digit level, 419 codes). Details are available in the Appendix.

¹Before 2010, the previous census classification is used, so that the occupational data is not easily comparable.

²From ATUS 2010 to 2013, the 2007 industry classification; before ATUS 2009, the 2002 vintage.

3 Descriptive statistics

3.1 Home-working by occupation

Figure 1 plots daily work hours at the workplace and at home by broad occupation group. Consistent with BLS publications, we find that workers in high-skilled occupations, such as management, business, financial, and professional occupations, work more hours at home than workers in less skilled occupations, except farmers. Furthermore, the share of hours worked at home is also larger in higher-skilled occupations.

Table 1 reports summary statistics of the working hours by place of work collapsed at the finer occupation level of the census occupation classification (OCC10). We find that around 15% of working hours are at home. 84% of workers work at their workplace, and 22% of workers spend some hours working at home per day (see Mas and Pallais, 2020, for comparable estimates). Note that the sum of these percentages is greater than 100% as some workers split their work day across different places. Consistent with Figure 1 at the broader level, we find a fair amount of heterogeneity in the home-working prevalence across finer occupations. The standard deviation of the home-working share amounts to 0.13 in Table 1. Figure 2 plots the distribution of home-working shares across detailed occupations (weighted by their size in US employment). It illustrates well the occupational heterogeneity, which is precisely estimated thanks to the large sample size of the ATUS. On average, there are 60 observations per occupational cell (see Table 1), and only 60 occupations over 500 have less than 4 observations.

Table 2 reports the top five and bottom five occupations in share of home-working (among occupations with at least 5 observations). For bottom occupations we randomly select them among the 57 occupations with no home-working. Intuitively, we find computer scientists among the top home-working occupations, and blue-collar work such as meter readers at the bottom.

Tables 3 and 4 report the same summary statistics for the SOC and ISCO classification respectively. Using wage data from the Occupational Employment Statistics produced by the BLS, we also compute wages obtained from home-working. Within each occupation, we proxy home-working wage as annual wage times the share of hours worked at home. We then obtain an average of 10,746 dollars, which

amounts to 17.7% of total annual wages. As home-working is more frequent among high-wage occupations, home-working wage represents a share of total wages that is 2-3 p.p. higher than the share of hours worked at home.

In Figure 5, we compare the average share of hours worked at home we produce for each SOC10 occupation with the teleworkability index of [Dingel and Neiman \(2020\)](#). Overall, the two measures are highly correlated: the rank correlation is .46.

3.2 Home-working by industry

Figure 3 plots daily work hours at the workplace and at home by broad industry group. Except agriculture, the broad industries with the most hours worked at home are information, financial activities, and professional and business services. The industries with the least home-working hours are transportation and utilities, and leisure and hospitality.

Table 5 reports summary statistics of home-working when the data are collapsed at the finer industry level of the US census industry classification (IND12). As in the occupational data, we find heterogeneity across detailed industries, as the distribution plotted in Figure 4 also illustrates. Table 6 shows the five top and five bottom industries in terms of home-working prevalence. Tables 7 and 8 report the same summary statistics for the NAICS and ISIC classification respectively.

One advantage of our industry-level data set is that we aggregate data directly from industry information at the worker-level. Namely, we do not need to assume that the same occupation has the same share of home-working hours in different industries (as in [Dingel and Neiman \(2020\)](#)). Using our individual level data, we regress the share of hours worked at home on occupation dummies as well as industry dummies. Table 9 shows that industry dummies are jointly highly statistically significant conditional on occupation with a value of the F-statistic similar to that of occupation dummies. In a regression with occupation dummies only, occupations explain 13.4% of the variance in the hours worked at home. When we add industries, we find that industry dummies explain 3 percentage points of the variance of home-working on top of the variance explained by occupations, which represents roughly a quarter of the variance explained by occupations.

4 Conclusion

In this paper, we compute the share of work hours that American workers from different occupations and industries spend at home between 2011 and 2018. While these figures could be indicative of the share of labour that would be used during a strict lock-down, there are a few reasons for the share of home-working in the past to be either a lower or an upper bound. On the one hand, firms might have adopted policies to change the substitutability of home vs. workplace work, making our estimates a lower bound of the share of labour resisting the lock-down. On the other hand, some occupations or sectors (for instance, those providing business-to-business services) might suffer from a large demand shock, which will reduce the labour demand for part of the home-working workers. Ex-post assessments of the crisis will allow a better understanding of these different mechanisms.

References

- BARROT, J.-N., B. GRASSI, AND J. SAUVAGNAT (2020): "Sectoral effects of social distancing," Working paper, SSRN.
- BOERI, T., A. CAIUMI, AND M. PACCAGNELLA (2020): "Mitigating the Work-Safety Trade-off," Working paper, CEPR.
- DINGEL, J. I. AND B. NEIMAN (2020): "How many jobs can be done at home?" Working Paper 26948, National Bureau of Economic Research.
- MAS, A. AND A. PALLAIS (2020): "Alternative Work Arrangements," NBER Working Paper 26605, forthcoming in the *Annual Review of Economics*.
- OFFICE FOR NATIONAL STATISTICS (2020): "Coronavirus and homeworking in the UK labour market: 2019," Released on 24 March 2020.
- SOLTAS, E. (2019): "Census–NAICS 2012 Industry Code Crosswalk," Harvard Dataverse, doi:10.7910/DVN/O7JLIC.

FIGURES

Figure 1: Daily hours worked by place of work and by major occupation groups

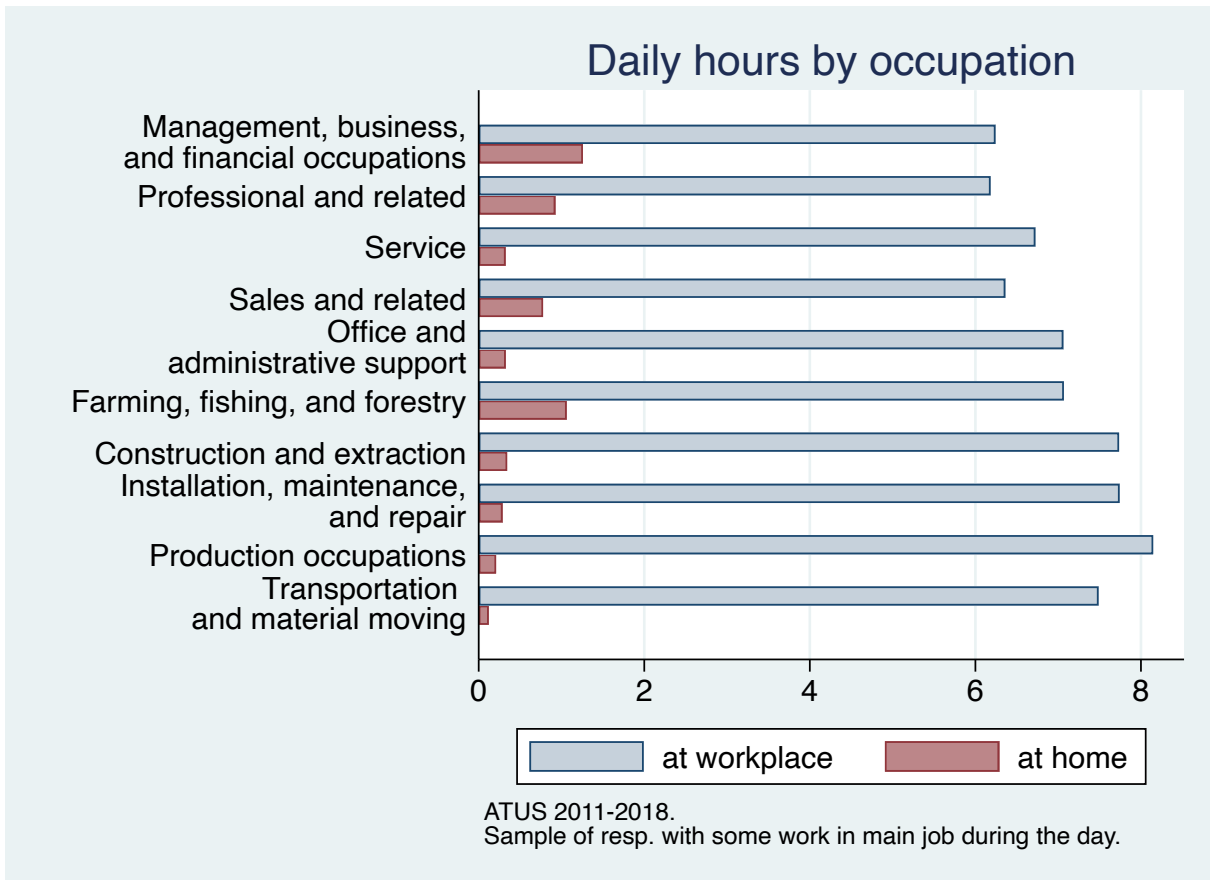
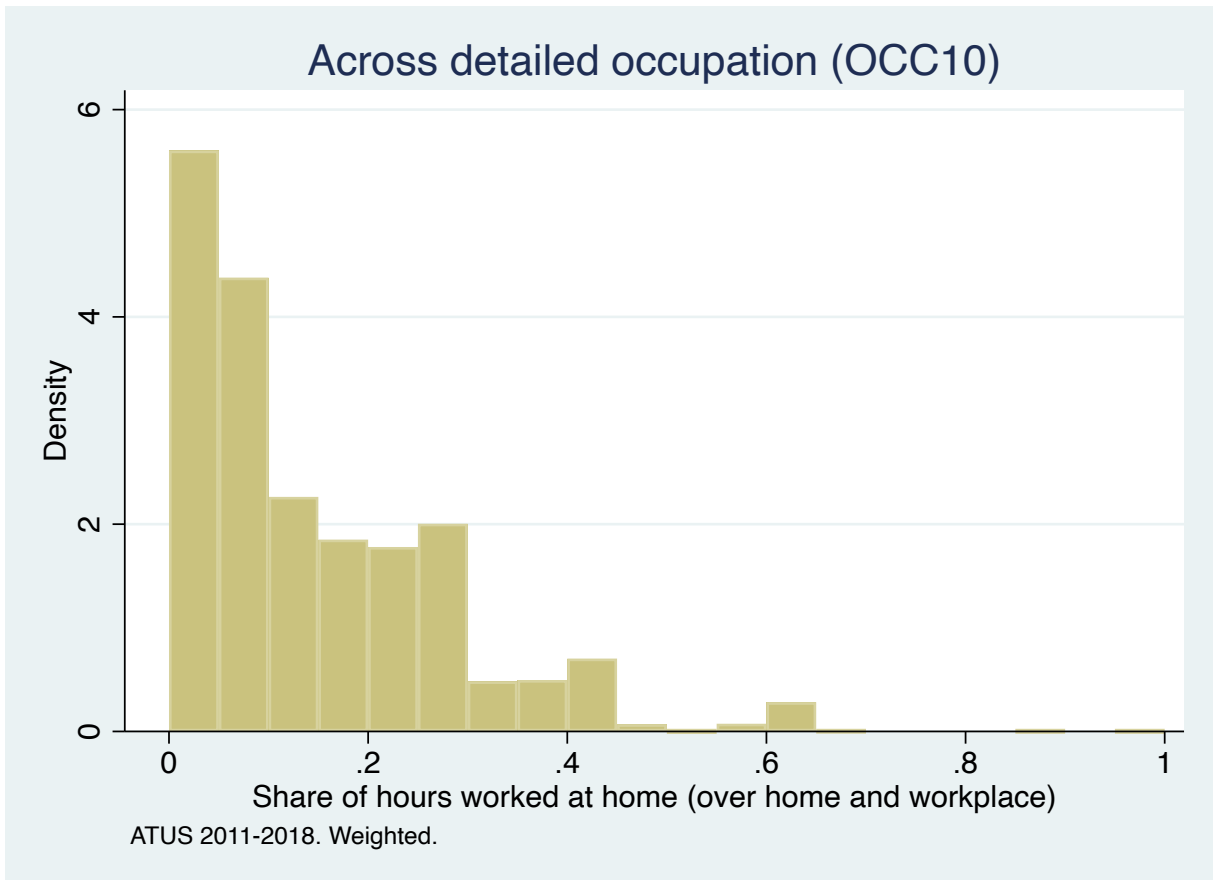


Figure 2: Share of home working by detailed US census occupations (OCC10)



Note: This figure shows the distribution of share of home-working hours by detailed occupation. We use the finer level of the US census occupation classification (500 codes). We use as weights the number of US workers in each occupation.

Figure 3: Daily hours worked by place of work and by major industry groups

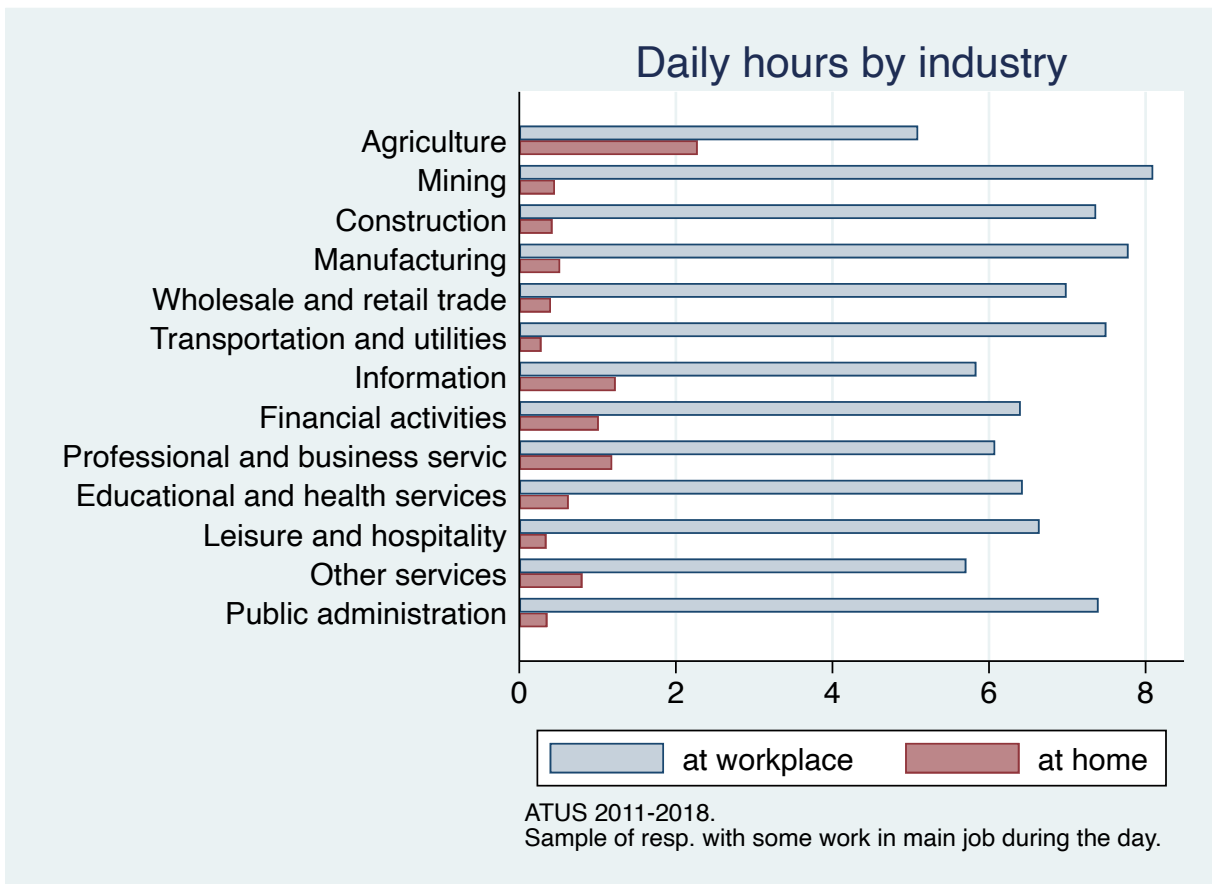
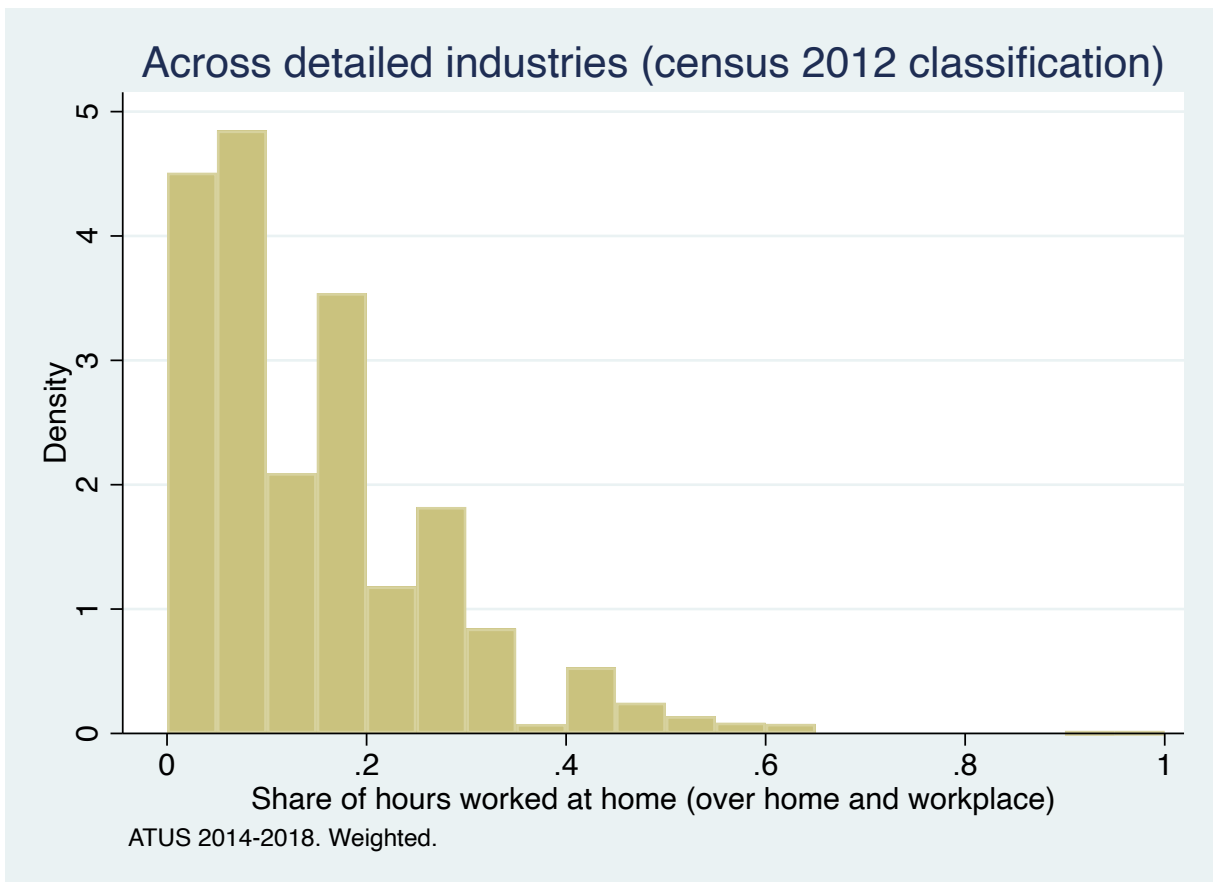
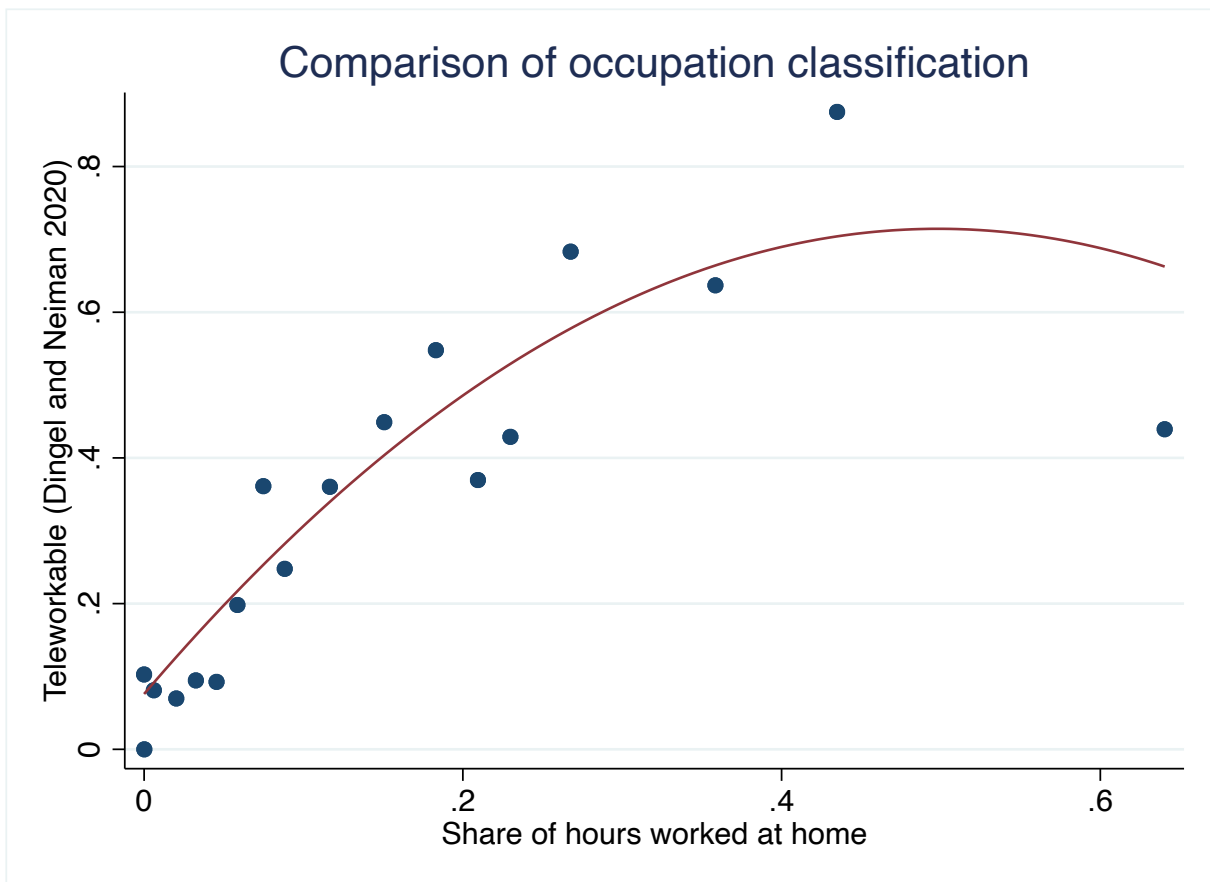


Figure 4: Share of home working by detailed US census industries (IND12)



Note: This figure shows the distribution of share of home-working hours by detailed industry. We use the finer level of the US census industry classification. We use the number of US workers in each occupation as weights.

Figure 5: Comparison: share of hours worked at home in ATUS vs. Dingel and Neiman's (2020) occupational tele-workability index



Note: Binscatter showing the relationship between the share of hours worked at home (x-axis) and the tele-workability index computed by Dingel and Neiman (2020). Observations are at the 6-digit SOC10 level.

TABLES

Table 1: Summary Statistics: US census occupation (OCC10)

Variable	Mean	Std. Dev.	N
Share of hours worked at home (over home and workplace)	0.147	0.132	497
Hours worked at the workplace per day	6.697	1.296	497
Hours worked at home per day	0.672	0.71	497
Worked from workplace	0.841	0.128	497
Worked from home	0.216	0.169	497
Number of ATUS observations	60.8	110.2	497
Number of workers	348352	631336	497

Note: In this table, we report summary statistics of hours worked at home vs at the workplace obtained from ATUS over years 2011 to 2018. We aggregate the data by occupation. This yields around 500 occupations from the finer level of the US census occupation classification (OCC10). We use ATUS weights when computing statistics, except when computing the average number of survey observations per occupation and the number of workers per occupation (last two rows).

Table 2: Top-5 and bottom-5 occupations in home-working (OCC10)

Code	Occupation Title	Share of hours worked at home	# workers	Rank
3646	Medical transcriptionists	0.885	20687	1
1005	Computer scientists	0.660	14113	2
1800	Economists	0.658	17176	3
205	Farmers, ranchers	0.649	1.513e+06	4
2600	Artists and related workers	0.631	339598	5
5410	Reservation and transport ticket agents	0	70953	395
6720	Hazardous materials removal workers	0	99689	396
5530	Meter readers, utilities	0	21842	397
8450	Upholsterers	0	20651	398
9150	Motor vehicle operators, all other	0	39201	399

Note: In this table, we report the five census occupations with the largest share of home-working hours and the five occupations with the least. As there are a few occupations with zeros hours worked at home, we randomly select five of them.

Table 3: Summary Statistics: US Standard Occupations (SOC10)

Variable	Mean	Std. Dev.	N
Share of hours worked at home (over home and workplace)	0.146	0.171	778
Hours worked at the workplace per day	6.874	2.044	778
Hours worked at home per day	0.609	0.786	778
Worked from workplace	0.846	0.171	778
Worked from home	0.215	0.209	778
Number of workers	189,259	433,022	776
Mean annual wage (2018)	60,785	34,000	772

Note: In this table, we report summary statistics of the home-working dataset at the 6-digit level of the SOC10 classification. Unweighted statistics. Number of workers and annual wage data are from the Occupational Employment Statistics (OES) Survey published by the BLS (year 2018).

Table 4: Summary Statistics: International Standard Occupations (ISCO-08)

Variable	Mean	Std. Dev.	N
Share of hours worked at home (over home and workplace)	0.153	0.145	427
Hours worked at the workplace per day	6.842	1.821	427
Hours worked at home per day	0.675	0.743	427
Worked from workplace	0.838	0.144	427
Worked from home	0.212	0.17	427

Note: In this table, we report summary statistics of the home-working dataset at the finest level of the ISCO-08 classification. Unweighted statistics.

Table 5: Summary Statistics: US Census Industries (IND2012)

Variable	Mean	Std. Dev.	N
Share of hours worked at home (over home and workplace)	0.153	0.175	259
Hours worked at the workplace per day	6.693	1.805	259
Hours worked at home per day	0.74	0.967	259
Worked from workplace	0.835	0.178	259
Worked from home	0.21	0.186	259
Number of ATUS observation	69	135	259
Number of workers	685,103	140,7193	259

Note: In this table, we report summary statistics of hours worked at home vs at the workplace obtained from ATUS over years 2014 to 2018. We aggregate the data by industries. This yields around 310 industries from the finer level of the US census industry classification (IND12). We use ATUS weights when computing statistics, except when computing the average number of survey observations per industry and the number of workers (last two rows).

Table 6: Top-5 and bottom-5 industries in home-working (IND12)

Code	Industry Title	Share of hours worked at home	# workers	Rank
6695	Data processing services	0.643	96316	1
7370	Specialized design services	0.621	549216	2
7490	Other professional services	0.598	588025	3
1590	Textile product mills	0.565	35528	4
8880	Personal goods maintenance	0.560	148006	5
590	Electric and gas	0	84524	230
2890	Coating, engraving	0	90699	231
3170	Metalworking machinery mfg.	0	163697	232
2480	Clay building material mfg.	0	59814	233
8780	Car washes	0	269958	234

Note: In this table, we report the five census industries with the largest share of home-working hours and the five industries with the least. As there are a few industries with zeros hours worked at home, we randomly select five of them.

Table 7: Summary Statistics: NAICS Industries

Variable	Mean	Std. Dev.	N
Share of hours worked at home (over home and workplace)	0.16	0.162	310
Hours worked at the workplace per day	6.72	1.663	310
Hours worked at home per day	0.802	0.978	310
Worked from workplace	0.827	0.165	310
Worked from home	0.222	0.173	310

Note: In this table, we report summary statistics of the home-working dataset at the 4-digit level of the NAICS classification. Unweighted statistics.

Table 8: Summary Statistics: International Industries (ISIC4.0)

Variable	Mean	Std. Dev.	N
Share of hours worked at home (over home and workplace)	0.173	0.143	419
Hours worked at the workplace per day	6.656	1.48	419
Hours worked at home per day	0.878	0.854	419
Worked from workplace	0.813	0.143	419
Worked from home	0.233	0.151	419

Note: In this table, we report summary statistics of the home-working dataset at the finest level of the ISIC classification. Unweighted statistics.

Table 9: Variance decomposition of share of hours worked at home

	(1)	(2)	(3)
	Share of hours worked at home		
Occupation F-test	10.05		5.163
Occ. p-value	0		0
Industry F-test		13.72	4.967
Ind. p-value		0	0
Observations	29,035	29,035	29,035
Adjusted R-squared	0.134	0.105	0.165
Occupation FE	Y		Y
Industry FE		Y	Y

Note: In this table, we regress the share of hours worked at home on occupational dummies in Column (1). In Column (2), we regress the home-working share on industry dummies. In Column (3), we have both occupation and industry dummies. There are 497 codes of the US census occupation classification, and 259 codes of the US census industry classification. Regressions at the worker level from ATUS 2011-2018.

Appendix

A Occupational classification

Occupations are available in the census 2010 classification in the public American Time Use Survey data sets. There are around 500 codes. We use crosswalks to convert census occupation classification (OCC10) to the other US standard classification (SOC10) and then to the international codes (ISCO-08). The SOC10 classification is more detailed than OCC10. Some OCC10 codes map into one broad SOC10 codes (either 3 or 5 digit). In those cases, we assign to all SOC10 6-digit codes of the broader SOC10 category the OCC10 statistics computed from the ATUS. This imputation helps the next mapping from the US classification into the international ISCO. We obtain from the BLS website a crosswalk from SOC10 to ISCO-08. At the finer 6 digit levels, SOC features over 800 codes, while ISCO has around 450 codes. Consequently, there are several SOC10 codes for each ISCO codes. We take the simple average across SOC10 codes to obtain the relevant home-working statistics at the ISCO-08 level.

B Industry classification

The ATUS uses the census industry classification to report industries of respondents main jobs. There are 269 codes at the finer level. We use crosswalks to convert census codes to the 4-digit NAICS, and then to the international ISIC classification (revision 4). From census industries to NAICS, we use the probabilistic crosswalk [Soltas \(2019\)](#) based on US employment. From NAICS to ISIC, available crosswalks do not have probabilistic weight. We thus take the simple average of NAICS codes corresponding to the same ISIC code.