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A tale of Work from Home in the aftermath of the Great Recession: Learning from high-frequency diaries

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Abstract

This study contributes to the growing literature on Work from Home (WfH), focusing on the responsiveness of the phenomenon to the business cycle. In particular, the Great Recession led many states to implement unprecedented and expansionary unemployment benefit measures (Extended Benefit, EB), which were often revoked when the recession resumed. EB measures differ widely in generosity and timing across states. We exploit this, for identification purposes, by linking the interview date of the respondents to the American Time Use Survey (ATUS) to the dates of implementation of EB programs, in the respondent's state of residence. ATUS provides unique cross-sectional information on WfH for a representative sample of Americans. Taking an approach inspired by a Regression Discontinuity Design, we find that recessions, as proxied by EB expansionary measures, significantly increase women's commuting. In contrast, women's remote work increases with economic recovery, as captured by EB contractionary measures. The evidence for men is less clear-cut.

Keywords Time allocation · Labor Supply · Work from Home · Great Recession

JEL codes J22 · J6 · J29

1 Introduction

This study adds to the growing literature on Work from Home (WfH), focusing on the responsiveness of the phenomenon to the business cycle. According to the literature, both labour demand (Sedlâcek and Shi, 2024) and supply factors (Harrington and Kahn, 2023), together with technological progress (Gershuny 2022), contribute to the spread of WfH. However, we know little to date on how the business cycle

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may come into play. Recessions destroy more men's jobs than women's jobs (Alon et al. 2020; Farber, 2017), and, thus, special attention will be paid to the heterogeneity of results by gender. Since the Covid-19 pandemic, WfH has boomed, structurally transforming the labour market, with about one in every three jobs worked remotely today in OECD countries (Barrero et al. 2021; Eurofund, 2023). Therefore, it is crucial to understand the possible effects on WfH of cyclical upswings and downswings in the economy.

Recessions may impact WfH because of both supply- and demand-side considerations. Employers may streamline production for fear of bankruptcy and if work done from home is less costly because of, for example, lower infrastructure and electricity costs, they may reorganize the location of work accordingly. When the labour market is slack, workers intensify work efforts for fear of losing their job (Lazear et al. 2016; Mulligan, 2011). Bringing work home (Eldridge and Pabilonia Wulff, 2007 and 2010), in the evenings or at the weekend, may be a means to increase work effort. On the other hand, if workers have higher reservation wages for jobs with longer commutes (Rupert et al. 2009), recessions may increase the take-up rate of jobs entailing commuting.

Here, the Great Recession (GR) of 2008, which sharply increased the level of unemployment, destroying many jobs (National Bureau of Economic Research, 2010; International Monetary Fund, 2009; Farber, 2017) will be exploited for identification purposes. In the aftermath of the GR, many states implemented Extended Benefit (EB) measures, increasing the duration of unemployment insurance benefits up to 99 weeks, from the usual 26 weeks. Years later, when the recession abated, many states implemented contractionary EB programs, cutting back unemployment insurance benefit durations. These EB measures were implemented at different times in different states, with varying increases (and later, reductions) in the duration of unemployment insurance benefits. These large cross-state variations in the timing and generosity of expansionary and contractionary EB measures enable us to identify the effects of ups and downs in the business cycle. In particular, many EB expansions occurred in 2009, while many EB contractions took place in 2012. Therefore, it is possible to examine separately the impact of EB expansions - which may proxy business cycle downturns - from that of EB contractions - which may capture upswings, with economic activity resuming, and the end of the recessionary period.

Earlier studies investigated the employment effects of variations in unemployment benefits duration (Card et al. 2015; Farber and Valletta 2015; Farber et al. 2015; Valletta, 2014). In particular, using 2008–2014 CPS, Farber et al. 2015 conclude that both benefit expansions and benefit contractions reduced labour force exits, by increasing labour market attachment, but neither had any impact on the job-finding rate. As they argue, because benefit expansions are implemented when the labour market is slack and benefit contractions when it is tight, labour demand conditions may mediate individual labour supply responses to benefit cuts and expansions. However, they did not consider the phenomenon of WfH.

Here, the dates of implementations of measures of EB expansion/contraction will be linked to the respondents' interview date and state of residency, using data drawn from the American Time Use Survey (ATUS). The ATUS provides information on the hours devoted to paid work (Hamermesh and Stancanelli, 2015), as well as information on the location of individuals when working (Pabilonia and Vernon, 2022), which enables us to investigate the effect of the business cycle on WfH. We use all ATUS data available, from 2003 to 2019. There are large variations in cross-state unemployment rates over the analysis period (see Figure A in the Online Appendix) that triggered measures of unemployment insurance benefits expansion/contraction throughout the period (see Table A in the Online Appendix for a summary of these measures). To avoid confounding effects, we do not examine the Covid-19-pandemic and post-pandemic data.

For the empirical analysis, ATUS 2003–2019 was linked to Current Population Surveys (CPS) and merged with state monthly unemployment rates, from Local Area Unemployment (LAU) statistics of the Bureau of Labor Statistics (BLS), and implementation dates of state Extended unemployment Benefit (EB) measures, collected by the Department of Labor's, Employment and Training Administration. The analysis sample includes over 150,000 individual observations. ATUS is a cross-sectional survey and each individual is interviewed only once. The empirical method mimics a Regression Discontinuity Design, in which the running variables are the days elapsed between the respondent's interview and the date at which the EB expansion/contraction measure was implemented, in the respondent's state of residence.[1]

We find that the Great Recession, as tracked by the substantial variation in unemployment rates across states, correlates with reduced overall employment, especially for men, but also with an increase in women's WfH. Nonetheless, the causal analysis points to recessions - as captured by EB expansionary measures - significantly increasing the commutes of women. In contrast, economic recoveries - as proxied by contractionary EB programs - significantly boost women's employment and remote work. Men's work appears to be less sensitive to the business cycle, in so far as it is not much responsive to EB measures. This finding contrasts with the fact that it is especially men's jobs that are lost due to recessions. A possible explanation is that EB expansionary measures only come into force once the recession is well under way, so men have already lost their jobs, while EB contractionary measures are put into place when the recession has already abated, so again, by then many men are back at work.

The structure of the paper is as follows. The analysis data are described first. The methodological approach is presented next. A discussion of the results of our estimations follows, with the final section presenting our conclusions.

2 The data

The main data for the analysis comes from the American Time Use Survey (ATUS), which is collected by the Bureau of the Census, for the Bureau of Labor Statistics. It covers a large and representative sample of the American population, with over 10,000 individuals being interviewed every year since 2003. The BLS provides individual weights, which we use throughout the analysis.

[1] We expect that people may hear it from a variety of sources: unemployed friends, neighbours, local news, employers, trade unions, job agencies, unemployment offices, local community counsellors, etc.

The ATUS collects detailed information on the location of individuals when performing daily activities. The following possible locations are reported in the diary for each activity: the workplace; the respondent's home; someone else's home; restaurant or bar; place of worship; grocery store; other store or mall; school; outdoors away from home; library; bank; gym, health club; post-office; other or unspecified place; car, truck or motorcycle (driver); car, truck or motorcycle (passenger); bus; subway, train; boat, ferry; taxi, limousine service; airplane; other mode of transportation; unspecified mode of transportation. This is on top of travel time to work, collected in a separate question, which we also analyse here. Therefore, we distinguish the following:

- total daily hours worked;
- hours worked from the workplace;
- hours worked from home;
- hours worked from elsewhere than home or workplace;
- commute.

We merged ATUS-CPS with data on unemployment by state taken from the Local Area Unemployment Statistics (LAUS), collected by the Bureau of Labor Statistics. In particular, we consider the level of the state unemployment rate in the month preceding the ATUS interview, in the respondent's state of residence. To capture the impact of business cycle changes, we use state policy measures targeted at increasing/reducing unemployment benefits duration, which are triggered by labor market slack (EB expansionary programs) and tightness (EB contractionary programs). The implementation date of state Extended unemployment Benefits (EB) programs is reported by state unemployment insurance program offices to the Department of Labor's Employment and Training Administration in the data labelled "ETA 539", which is publicly available. We match records on the implementation date (day, month, year) of state EB expansionary and contractionary measures to our data, based on ATUS respondents' interview day, month and year, and state of residence.

Specifically, we count 60 EB expansionary policy measures and 70 EB contractionary policy measures, across 41 different states and the District of Columbia, during the time span of our data, with most of them occurring in the period 2009–2012 (see online Appendix Table A). More specifically, to each ATUS respondent, we link information on their state of residence EB expansionary or contractionary program closest to their interview date. ATUS is a cross-sectional, yearly survey and each respondent is interviewed only once. Generally, we cannot observe for the same respondent both an expansionary and a contractionary measure.

The analysis data drawn from ATUS 2003–2019 and merged with LAU and ETA covers over 210,000 respondents. Restricting the analysis sample to individuals aged under age 70[2], not self-employed or in full-time education, not employed in agriculture or in the military sector, yields a total analysis sample of over 150,000 observations.

[2] Although the normal retirement age in the U.S. is 65-67, there is no compulsory retirement age in the US. Restricting the sample to individuals who did some paid work on the interview day, about 96% of them were aged under 67 years and an additional 1% were aged 67 to 69 years. The latter group includes 1,248 respondents (461 respondents aged 67, 437 aged 68, and 350 aged 69) and we see no good reason to drop them from the sample. A remaining 3.5% of workers were aged 70 to 85 and are excluded from the analysis in line with standard practice.

Considering a bandwidth of 365 days, the estimation sample for the EB-start model includes over 21,000 observations and that for the EB-end model over 27,000. This difference in sample size is because many states started EB programs in 2008–2009 and many ended them in 2009–2012, with ATUS sample size having been increased in 2009–2010, for reasons totally independent from the EB measures (see Online Appendix Figures B and C for graphical checks of the continuity of sample participation and sample composition, respectively).

As regards the location of work, we find that:

- 80% of the workers (excluding students, people aged 70 and above, the self-employed, the military, and those employed in agriculture) work about 6.5 h per day from the employer's premises;
- 26% of the workers work over half an hour per day from their home;
- 17% work over twenty minutes per day from other locations/transportations;
- 75% work while commuting for over half an hour per day.

Therefore, of the 8 h worked, on average, per person and per day, 6.5 h are worked from the employer's premises and 1.5 h from locations other than the workplace (home, elsewhere, or commuting).

Nonetheless, one limitation of this study is that, during the period studied, working from home only involved a small and highly heterogenous group of workers. About 9% of women and about 11% of men were doing some work from home, on the day of the ATUS interview. We only observe respondents on a given random day, when they answered the time use diary. We do not know how often they work from home on a regular basis. However, the ATUS sample is drawn from the CPS sample and it is a random sample, representative of the US population. Earlier work established that work documented in ATUS corresponds well to work from other sources.

3 Methodological approach

We first specify an empirical model of work done at different places as a function of the lagged monthly state unemployment rate (measured a month before the date of the respondent's ATUS interview), a yearly time trend, and month, state, and industry fixed effects, as well as a weekend dummy and controls for individual socio-demographics, as follows.

$$W_i = \gamma U_{i,s,t-1} + \lambda V_i + \rho X_i + \psi_t + u_i \quad (1)$$

We define W as individual i's outcome. The outcomes considered are work done from the workplace, from home, elsewhere, or commuting. Both the extensive and intensive margin are considered. For the intensive margin, the sample is restricted to individuals who performed some work on the day of the interview.[3] The key

[3] We are aware that restricting the sample to workers may potentially raise selection issues. We could not think of any variable that may affect employment probability but not the hours worked, from the various locations. Therefore, we do not explicitly model selection but we do control for a wide range of variables and fixed effects in all the regressions.

explanatory variable is U, which denotes the unemployment rate of individual i's state of residence in the month before. The vector V includes state fixed effects, month fixed effects, and four-digit industry fixed effects, while the vector X includes individual socio-demographic characteristics (gender, age, race, family composition, education level, household income, home ownership, whether living in a hotel or mobile home or boarding/rooming house), a dummy for residing in a metropolitan area, and a weekend dummy (taking the value one for individuals interviewed on a weekend day and zero otherwise). The yearly time trend is denoted by t. This model will be estimated by Ordinary Least Squares, clustering the standard errors at the state level and using robust standard errors. This will enable pinning down correlations between the large variation in unemployment rates, especially high during the great recession, and the location of work.

Next, we exploit the timing of state measures of expansion/contraction in unemployment insurance benefits (i.e., Extended Benefits) to pin down the effect of ups and downs in the business cycle. Large expansions in the duration of unemployment benefits across states were notably triggered by the Great Recession, with corresponding large contractions when the recession resumed. We allow EB program expansions to have a different impact than EB program contractions. We specify and estimate separate models for EB expansions and contractions. Respondents who answered the survey in the days before the implementation of an unemployment insurance expansion/contraction program serve as a counterfactual for those who were interviewed in the days after. We assume that whether a respondent answered the ATUS survey before or after a given program was implemented is random. To ensure this, we check the continuity of survey participation ((McCrary, 2008; see Figure B in the Online Appendix) around the cut-off (the day of the implementation of the program). We also check the continuity of survey participants' characteristics around the cut-off (see Figure C in the Online Appendix). In particular, since we include several controls in the model, we predict the outcomes as a function of these controls and plot them against the running variable (as done, for instance, in Card et al., 2015, to check the continuity of the covariates at the cut-off). As required for the validity of our empirical approach, which is inspired by Regression Discontinuity Design (Imbens and Lemieux, 2007; Lee and Lemieux, 2010), we find no discontinuity in survey participation (Figure B in the Online Appendix) or sample composition (Figure C in the Online Appendix). To gather preliminary insights into the data, we plot the raw data outcomes against the days elapsed since EB implementation dates (see Figure D in the Online Appendix). There is only moderate variation in the outcomes at the cut-off. Plots of non-parametric, triangular, Kernel estimates of the impact of EB expansions/contractions on hours worked - controlling also for state, year, month, weekend day, industry fixed effect, and individual socio-demographics heterogeneity (i.e. plotting the hours residuals from regressions including all the covariates; see online Appendix Figure 4) - show that EB contractions cause a significant increase in overall hours worked,[4] while EB expansions induce a decrease, although the latter is not statistically significant at the 5% level (the 95% confidence intervals drawn around the triangular Kernel estimates overlap).

[4] These findings are not driven by discontinuity in covariates; we already tested for those and found no evidence for discontinuity (see Figure C).

We include controls in the models and opt for a parametric specification to be able to cluster the standard errors, both at the level of the running variable and at the level of the state. Our empirical model is the following:

$$W_i = \zeta T_i + \tau f(D_i) T_i + \mu f(D_i)(1 - T_i) + \eta V_i + \rho X_i + \pi t + \omega_i \tag{2}$$

The impact of the EB expansion/contraction measures on the outcome W (i.e., hours worked from home) is captured by the 'treatment' T, which takes value one in the days after the EB program implementation, and zero in the days before. The running variable is defined as the days elapsed since the EB program implementation and is labelled D; and f(D) is a polynomial function of the running variable, which is also interacted with the treatment dummy *T*, to allow for different effects on either side of the cut-off. The polynomial f(.) is taken to be quadratic in our empirical specifications, and we test for a linear specification, as well as higher degree polynomials. We use the procedure in Calonico et al. (2017) to determine the optimal bandwidth, which gives a bandwidth that varies with the outcomes but is never larger than 365 days. We set the bandwidth equal to 365 days for all the outcomes, to stay within a meaningful calendar bandwidth, as individuals (and also employers) may use the year as a time horizon for their labor decisions. We test the robustness of the estimates to varying the bandwidth. The standard errors are robust and clustered at the level of both the running variable and the state of residence. We test for the robustness of the estimates to dropping observations located at different distances from the bandwidth (as suggested, for instance, by Barreca et al. 2011), by dropping, first, observations closer to the cut-off and then, progressively farther away. Moreover, we test for the sensitivity of the estimation results to eliminating observations for a given state (dropping states one by one).

4 Estimation results

We present estimation results for the sample and by gender, motivated by the conclusions of earlier work that recessions affect the employment of men and women differentially (Farber, 2017; Alon et al., 2020). We are interested in the effects of ups and downs in the business cycle on WfH. To set this into the picture, the outcomes we consider are: overall employment; work done at the employer's premises; work done from home; work done from other locations (e.g., a café, a library, someone else' home); work done while commuting to work. We examine the effects at the extensive margin (defined as the probability of working a positive number of hours from a given location) and at the intensive margin, focusing on hour responses conditional on doing some paid work (i.e., restricting the sample to those with positive hours on the day of the ATUS interview).

Table 1 presents, the results of estimation of the baseline model specified in Equation 1 of Section 2. We find that an increase in the unemployment rate is negatively associated with the overall probability of working (see Specification 1 in Table 1) and especially so for men (see Specification 3 in Table 1). The probability of working remotely is significantly and positively associated with an increase in the level of the unemployment rate, and especially so for women. These findings are corroborated by the intensive margin results in the bottom block of Table 1, which

Table 1 Results of estimation of the Great Recession and hours worked at different places

	Outcome: probability of working a positive number of hours				
	Any work	at workplace	from home	elsewhere	commute
1) **Analysis sample**					
state U rate	−0.201*** (0.0574)	−0.315*** (0.0757)	0.102* (0.0545)	−0.123*** (0.0407)	−0.117* (0.0635)
Observations	*150,731*	*150,731*	*150,731*	*150,731*	*150,731*
R squared	*0.365*	*0.342*	*0.088*	*0.052*	*0.303*
2) **Women**					
state U rate	−0.0603 (0.110)	−0.171 (0.113)	0.146** (0.0553)	−0.0630 (0.0643)	−0.0770 (0.102)
Observations	*84,868*	*84,868*	*84,868*	*84,868*	*84,868*
R squared	*0.364*	*0.340*	*0.086*	*0.059*	*0.305*
3) **Men**					
state U rate	−0.362*** (0.102)	−0.481*** (0.115)	0.0469 (0.0774)	−0.180** (0.0719)	−0.167 (0.105)
Observations	*65,863*	*65,863*	*65,863*	*65,863*	*65,863*
R squared	*0.358*	*0.339*	*0.099*	*0.058*	*0.296*

Outcome: minutes worked per day (including only individuals with positive hours of work)					
	total minutes	at workplace	from home	elsewhere	commute
4) **Analysis sample**					
state U rate	−68.43 (48.37)	−139.6** (54.95)	57.30 (34.52)	7.031 (16.21)	6.793 (12.78)
Observations	62,314	62,314	62,314	62,314	62,314
R squared	0.148	0.155	0.071	0.022	0.061
5) **Women**					
state U rate	−69.67 (48.75)	−150.1** (67.19)	70.06* (41.33)	−9.634 (67.19)	−0.730 (12.30)
Observations	30,878	30,878	30,878	30,878	30,878
R squared	0.149	0.165	0.079	0.165	0.063
6 **Men**					
state U rate	−55.34 (77.73)	−129.6 (87.29)	45.24 (35. 83)	11.78 (28.03)	17.25 (21.11)
Observations	31,436	31,436	31,436	31,436	31,436
R squared	0.139	0.149	0.178	0.027	0.063

The outcomes are, respectively, the probability of working a positive number of hours from each place (that varies between zero and one) and the hours worked at each place (measured in minutes per day and set equal to zero for individuals not working). All models are estimated by OLS and include controls for gender, race and ethnicity, marital status, number and age of kids, education, a quadratic in age, total household income in brackets, home ownership, a dummy for living in a hotel or mobilome or boarding/rooming house, weekend diary dummy, a linear year trend and fixed effects for state, metropolitan area, (four-digit) industry, and month of the year when the diary was filled in. The state unemployment rate is lagged one month and its average value is 0.06. Standard errors are robust and clustered at the state level

ATUS weights are applied

suggest that the unemployment rate correlates positively with hours worked from home by women. In particular, for women, a one percentage point increase in the unemployment rate is associated with a decline in hours worked from the workplace by about two and a half hours per day (150 min) and an increase in the probability of working from home by over an hour, on average (Specification 5 in Table 1). Overall, these findings suggest that the Great Recession, as tracked by the large variation in unemployment rates across states (see Fig. A in the online Appendix), hit men's employment more strongly than women's employment, which is in line with earlier literature, but was also associated with a significant increase in work done for pay from home by women, a fact which had hitherto gone unnoticed.

Next, we exploit, for identification purposes, state measures of expansions/contractions in the duration of state unemployment insurance benefits, which are triggered by unemployment peaks and troughs. During the great recession, many states dramatically expanded the duration of unemployment insurance benefits, from the usual 26 weeks up to 99 weeks. Years later, when the recession abated, states cut back the duration of unemployment insurance benefits. The timing (i.e., the implementation date) and generosity (as captured by the duration of the benefits) of these expansionary and contractionary benefit measures varied substantially across states. Certain states implemented this type of measure at different points in time than the great recession (as shown in Table A in the Online Appendix). We take an RDD type of approach, in which the running variable is the days elapsed before and after the implementation of state EB measures, relative to the ATUS respondent's interview date, in the respondent's state of residence.

Tables 2 and 3 provide the estimates of the effects of, respectively, state EB expansions/contractions. We find no significant effect of state EB expansions, except for women's probability to work, which increases by over 6 percentage points (only significant at the ten per cent level), corresponding to a 15% increase. Women's work done while commuting also increases by 20% at the extensive margin (see Specification 2 in Table 2). However, none of the estimates are significant for men. This is possibly explained by the fact that, by the time states implemented expansionary benefit measures, the recession was well under way and the unemployment rate was soaring, and many men had already lost their jobs. Specifically, the Great Recession began in December 2007, and most states implemented measures of expansionary benefit duration in 2009 (see Table A of the Online Appendix).

EB contractions led to a strongly significant increase of 8.5 percentage points (corresponding to a 15% increase) in women's overall employment (Specification 2 in Table 3). Work from home increased by almost 5 percentage points (corresponding to an increase of over 50%) and work from the workplace by almost 7 percentage points (corresponding to an increase of less than 20%). The probability of women working while commuting also increased by almost 6 percentage points (i.e., by about 17%). In contrast, at the intensive margin, the latter declined significantly by 7 percentage points (i.e., by 50%; Specification 5 in Table 3). At the intensive margin, the hours worked by men declined significantly, by almost 40 min per day, corresponding to a drop of about 13% (see Specification 6 in Table 3). Thus, business cycle upswings, proxied by the contractionary benefit measures, increase women's employment, both from home and at the workplace, at the extensive margin, while reducing slightly the overall hours worked by men at the intensive margin.

Table 2 Results of estimation of the impact of expansionary Extended Benefit programs

Outcome: probability of working a positive number of hours					
	work overall	at workplace	from home	elsewhere	commute
1) Analysis sample					
Means year before	0.509	0.432	0.103	0.097	0.397
UI benefits expansion	0.0315 (0.0238)	0.0220 (0.0228)	0.0143 (0.0163)	0.00547 (0.0138)	0.0221 (0.0248)
Observations	21,638	21,638	21,638	21,638	21,638
R squared	0.375	0.364	0.109	0.093	0.319
2) Women					
Means year before	0.452	0.38	0.096	0.0872	0.344
UI benefits expansion	0.0633* (0.0322)	0.0470 (0.0299)	0.0190 (0.0200)	−0.0202 (0.0154)	0.0820*** (0.0286)
Observations	12,255	12,255	12,255	12,255	12,255
R squared	0.376	0.372	0.116	0.114	0.328
3) Men					
Means year before	0.569	0.488	0.11	0.108	0.453
UI benefits expansion	−0.00409 (0.0225)	0.000183 (0.0239)	0.00327 (0.0292)	0.0277 (0.0254)	−0.0443 (0.0270)
Observations	9,359	9,359	9,359	9,359	9,359
R squared	0.388	0.379	0.147	0.126	0.336

Outcome: minutes worked per day (including only individuals with positive hours of work)					
	work overall	at workplace	from home	elsewhere	commute
4) Analysis sample					
Means year before	468.17	381.11	37.69	19.16	30.20
UI benefits expansion	6.049 (18.38)	17.17 (12.00)	12.76 (14.04)	5.875 (4.801)	4.590* (2.721)
Observations	8,874	8,874	8,874	8,874	8,874
R squared	0.180	0.200	0.077	0.077	0.117
5) Women					
Means year before	437.10	357.53	37.07	16.78	25.71
UI benefits expansion	15.34 (14.37)	−1.047 (14.92)	4.705 (10.61)	5.679 (5.827)	6.007 (3.811)
Observations	4,441	4,441	4,441	4,441	4,441
R squared	0.217	0.235	0.144	0.088	0.147
6) Men					
Means year before	499.10	404.59	38.30	21.54	34.67
UI benefits expansion	11.18 (26.96)	−16.13 (20.31)	19.58 (20.10)	2.725 (7.569)	5.004 (5.876)
Observations	4,390	4,390	4,390	4,390	4,390
R squared	0.180	0.218	0.150	0.134	0.134

All models include a quadratic function of the days elapsed since the start of the EB and its interactions with the dummy for the start of the EB program from the right and the left of the cut-off, as well as controls for gender, race and ethnicity, marital status, number and age of kids, education, a quadratic in age, total household income in brackets, home ownership, a dummy for living in a hotel or mobilome or boarding/rooming house, weekend diary dummy, year and fixed effects for state, metropolitan area, (four-digit) industry and month of the year when the diary was filled in. The bandwidth is 365 days. Standard errors, in parentheses, are robust and clustered at the level of both the running variable and the state

***$p<0.01$, **$p<0.05$, *$p<0.10$

ATUS weights are applied

Table 3 Results of estimation of the impact of contractionary Extended Benefit programs

Outcome: probability of working a positive number of hours

	work overall	at workplace	from home	elsewhere	commute
1) Analysis sample					
Means year before	0.49	0.415	0.104	0.083	0.392
Dummy EB end	0.0465** (0.0212)	0.0303* (0.0179)	0.0254* (0.0130)	−0.00368 (0.0118)	0.00934 (0.0196)
observations	27,376	27,376	27,376	27,376	27,376
R squared	0.368	0.349	0.108	0.076	0.311
2) Women					
Means year before	0.436	0.362	0.09	0.075	0.342
Dummy EB end	0.0850*** (0.0275)	0.0687*** (0.0199)	0.0485*** (0.0168)	0.0138 (0.0141)	0.0573** (0.0253)
observations	15,301	15,301	15,301	15,301	15,301
R squared	0.377	0.360	0.120	0.090	0.328
3) Men					
Means year before	0.549	0.471	0.11	0.092	0.446
Dummy EB end	0.0154 (0.0308)	−0.000567 (0.0258)	0.000875 (0.0193)	−0.000567 (0.0258)	−0.0275 (0.0217)
observations	12,056	12,056	12,056	12,056	12,056
R squared	0.376	0.360	0.142	0.360	0.322

Outcome: minutes worked per day (including only individuals with positive hours of work)

	work overall	at workplace	from home	elsewhere	commute
4) Analysis sample					
Means year before	469.03	377.79	36.84	21.58	32.82
Dummy EB end	−29.87** (12.39)	−30.89** (13.38)	10.20 (11.98)	−3.664 (6.257)	−5.520 (3.369)
observations	11,146	11,146	11,146	11,146	11,146
R squared	0.178	0.189	0.100	0.060	0.091
5) Women					
Means year before	445.55	358.50	38.16	21.44	27.45
Dummy EB end	−14.67 (17.84)	−24.08 (15.56)	20.11 (16.58)	−3.682 (10.42)	−7.018** (2.816)
observations	5,517	5,517	5,517	5,517	5,517
R squared	0.203	0.221	0.141	0.221	0.110
6 Men					
Means year before	492.60	397.15	35.51	21.73	38.20
Dummy EB end	−37.97** (14.31)	−28.60 (18.18)	0.181 (14.17)	−5.696 (8.401)	−3.855 (4.579)
observations	5595	5595	5595	5595	5595
R squared	0.189	0.207	0.140	0.107	0.113

All models include a quadratic function of the days elapsed since the end of the EB and its interactions with the dummy for the end of the EB program from the right and the left of the cut-off, as well as controls for gender, race and ethnicity, marital status, number and age of kids, education, a quadratic in age, total household income in brackets, home ownership, a dummy for living in a hotel or mobilome or boarding/rooming house, weekend diary dummy, year, and fixed effects for state, metropolitan area, (four-digit) industry and month of the year when the diary was filled in. The bandwidth is 365 days. Standard errors, in parentheses, are robust and clustered at the level of both the running variable and the state

***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

ATUS weights are applied

4.1 Robustness checks

The findings are generally robust to narrowing the bandwidth to 180 days (see Tables D and E in the online Appendix), although some of the estimates become less precise. In particular, the effects of state EB expansions lose statistical significance. The robustness of the effects of EB expansions and contractions to several other checks, is illustrated for women in Tables 4 and 5, and for men in Tables 6 and 7. The main findings hold when dropping socio-demographics and other controls from the model (see specifications A, B, and C), as well as when additionally including occupational fixed effects (see specification D) or not clustering the standard errors at the level of the running variable, but only at the state level (see specification E). Moreover, our findings are robust to including controls for the duration of state unemployment benefits, allowing for both the regular and the total duration of state unemployment benefit in each month (see specification F).[5] Finally, our conclusions are robust to dropping observations for days close to the cut-off, or dropping states one by one (see Tables F and G, respectively, in the Online Appendix).[6]

4.2 Heterogeneity of findings for other subgroups of the population

We also estimate the models for other subgroups of the population, such as ethnic and racial minorities and Whites (see online Appendix, Tables M and N, respectively, for the impact of EB expansion/contraction); by age, distinguishing people aged fifty and above or below fifty (see online Appendix Tables I and J, respectively, for the impact of EB expansion/contraction); and by education, separating out individuals with college education from individuals with less than college (see online Appendix Tables K and L, respectively, for the impact of EB expansion/contraction).

We find that Blacks and other racial and ethnic minorities (considered altogether) increase employment (by over 8 percentage points) in response to both EB contractions and expansions (see Tables M and N in the online Appendix). These increases correspond to increases in work done from the workplace (which goes up by about 8 percentage points) and commuting (which increases by 8 to 9 percentage points) while work performed from home and elsewhere drops slightly with EB cuts (both effects are only significant at the ten percent level). In contrast, we find generally small responses to EB cuts or expansions by Whites, except for a significant increase (5 percentage points) in hours worked from home in response to contractionary benefit programs.

Considering age groups (see online Appendix Tables I and J, respectively, for the impact of EB start/end), we find that individuals aged 50 and above respond strongly

[5] The data for the latter exercise comes from Robert Valletta (see Valletta, 2014 for more details) and covers the period 2000-2017. We matched this data to our analysis data spanning 2003-2019, and, therefore, we do not include data for 2018 and 2019 in specification F of Tables 4 and 5.

[6] For the sake of conciseness, we present (in Tables F and G) only the estimates of the impact of the ending of state EB programs on the probability of working. There we see that only dropping residents of California makes estimates lose significance (see Table G). Therefore, we also checked the results of estimations for all outcomes for women, both at the extensive and the intensive margin, by dropping residents of California. We find that our main conclusions hold when dropping Californians (see Table H in the online Appendix).

Table 4 Results of estimation for women of the impact of expansionary Extended Benefit programs. Robustness checks

Outcome: probability of working a positive number of hours					
	Work overall	At workplace	From home	Elsewhere	Commute
A) Controlling only for weekend dummy & fixed effect for month, year and state					
UI expansion	0.0574* (0.0314)	0.0397 (0.0293)	0.0258 (0.0219)	−0.0324** (0.0147)	0.0808** (0.0306)
B) Controlling only for weekend dummy & fixed effect for unemployment rate, month, year and state					
UI expansion	0.0560* (0.0328)	0.0367 (0.0311)	0.0266 (0.0218)	−0.0304** (0.0140)	0.0768** (0.0326)
C) Controlling only for weekend dummy & fixed effect for (4-digit) industry fixed effects, unemployment rate, month, year and state					
UI expansion	0.0600* (0.0345)	0.0444 (0.0321)	0.0201 (0.0201)	−0.0213 (0.0161)	0.0796** (0.0311)
D) Including all controls as in the main model (e.g. as in Table 4**) and also occupation fixed effects**					
UI expansion	0.0609** (0.0289)	0.0448* (0.0250)	0.0154 (0.0176)	−0.0178 (0.0148)	0.0740*** (0.0238)
E) Clustering standard errors at state level but not at the level of the running variable					
UI expansion	0.0633* (0.033)	0.0470 (0.033)	0.0190 (0.020)	−0.0202 (0.016)	0.0820** (0.033)
F) Including additional controls for the regular and total duration of state unemployment benefits					
UI expansion	0.0624* (0.0322)	0.0473 (0.0296)	0.0191 (0.0205)	−0.0205 (0.0165)	3.920* (2.053)
Outcome: minutes worked per day (including only individuals with positive hours of **work)**					
	work overall	**at workplace**	**from home**	**elsewhere**	**commute**
G) Controlling only for weekend dummy & fixed effect for month, year and state					
UI expansion	12.47 (15.34)	−4.174 (15.27)	6.038 (12.16)	5.310 (6.450)	5.298 (3.861)
H) Controlling only for weekend dummy & fixed effect for unemployment rate, month, year and state					
Dummy EB start	11.44 (15.82)	−6.354 (15.33)	6.293 (12.38)	6.313 (6.536)	5.190 (3.885)
I) Controlling only for weekend dummy & fixed effect for (4-digit) industry fixed effects, unemployment rate, month, year and state					
UI expansion	11.44 (15.82)	−6.354 (15.33)	6.293 (12.38)	6.313 (6.536)	5.190 (3.885)
J) Including all controls as in the main model (e.g., as in Table 4**) and also occupation fixed effects**					
UI expansion	12.59 (17.38)	−1.032 (17.11)	3.008 (12.45)	6.374 (6.226)	4.243 (3.684)

Table 4 continued

Outcome: probability of working a positive number of hours

	Work overall	At workplace	From home	Elsewhere	Commute
K) Clustering standard errors at state level but not at the level of the running variable					
UI expansion	14.15 (15.49)	−2.140 (16.55)	4.588 (8.695)	6.281 (6.224)	5.419 (3.486)
L Including additional controls for the regular and total duration of state unemployment benefits					
UI expansion	15.47 (15.74)	−3.419 (16.73)	5.331 (9.015)	8.102 (6.498)	5.460 (3.510)

All models include a quadratic function of the days elapsed since the start of the EB and its interactions with the dummy for the start of the EB program from the right and the left of the cut-off. The bandwidth is 365 days. Standard errors, in parentheses, are robust and clustered at the level of both the running variable and the state

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$

The data on the regular and total duration of state unemployment benefits by month used in specification F come from Rob Valletta (see Valletta 2014 for more details). ATUS weights are applied

Table 5 Results of estimation for women of the impact of *contractionary* Extended Benefit programs

Outcome: probability of working a positive number of hours					
	Work overall	At workplace	From home	Elsewhere	Commute
A) Controlling only for weekend dummy & fixed effect for month, year and state					
Dummy EB end	0.0898** (0.0336)	0.0710** (0.0303)	0.0620*** (0.0180)	0.0112 (0.0162)	0.0602* (0.0333)
B) Controlling only for weekend dummy & fixed effect for unemployment rate, month, year and state					
Dummy EB end	0.0902** (0.0338)	0.0714** (0.0306)	0.0621*** (0.0180)	0.0109 (0.0161)	0.0607* (0.0337)
C) Controlling only for weekend dummy & fixed effect for (4-digit) industry fixed effects, unemployment rate, month, year and state					
Dummy EB end	0.0797*** (0.0287)	0.0645*** (0.0219)	0.0500*** (0.0172)	0.00906 (0.0137)	0.0554** (0.0265)
D) Including all controls as in the main model (e.g. as in Table 4**) and also occupation fixed effects**					
Dummy EB end	0.0822*** (0.0258)	0.0745*** (0.0198)	0.0429*** (0.0136)	0.00717 (0.0132)	0.0571** (0.0237)
E) Clustering standard errors at state level but not at the level of the running variable					
Dummy EB end	0.0850*** (0.0260)	0.0687*** (0.0194)	0.0485*** (0.0167)	0.0138 (0.0148)	0.0573** (0.0234)
F) Including additional controls for the regular and total duration of state unemployment benefits					
Dummy EB end	0.0842*** (0.0283)	0.0691*** (0.0209)	0.0475*** (0.0172)	0.241 (4.726)	0.0594** (0.0251)

Outcome: minutes worked per day (including only individuals with positive hours of work)					
	Work overall	At workplace	From home	Elsewhere	Commute
G) Controlling only for weekend dummy & fixed effect for month, year and state					
Dummy EB end	−24.63 (17.30)	−33.51** (15.80)	21.30 (17.32)	−6.012 (10.57)	−6.411** (3.088)
H) Controlling only for weekend dummy & fixed effect for unemployment rate, month, year and state					
Dummy EB end	−24.60 (17.34)	−33.15** (15.97)	21.05 (17.52)	−6.079 (10.64)	−6.424** (3.121)
I) Controlling only for weekend dummy & fixed effect for (4-digit) industry fixed effects, unemployment rate, month, year and state					
Dummy EB end	−24.60* (17.34)	−33.15 (15.97)	21.05 (17.52)	−6.079 (10.64)	−6.424** (3.121)
J) Including all controls as in the main model (e.g. as in Table 4**) and also occupation fixed effects**					

Table 5 continued

Outcome: minutes worked per day (including only individuals with positive hours of work)					
	Work overall	At workplace	From home	Elsewhere	Commute
Dummy EB end	−16.25 (15.34)	−14.26 (14.93)	12.88 (12.73)	−7.354 (10.92)	−7.517** (3.094)
K) Clustering standard errors at state level but not at the level of the running variable					
Dummy EB end	−14.67 (16.62)	−24.08 (14.53)	20.11 (16.51)	−3.682 (10.68)	−7.018** (3.227)
L) Including additional controls for regular and total duration of state unemployment benefits					
Dummy EB end	−11.62 (17.35)	−21.64 (15.24)	18.82 (17.66)	−2.348 (10.45)	−6.457* (3.280)

Robustness checks

All models include a quadratic function of the days elapsed since the end of the EB and its interactions with the dummy for the end of the EB program from the right and the left of the cut-off. The bandwidth is 365 days. Standard errors, in parentheses, are robust and clustered at the level of both the running variable and the state

***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

The data on the regular and total duration of state unemployment benefits by month used in specification F come from Rob Valletta (see Valletta 2014 for more details). ATUS weights are applied

Table 6 Results of estimation for men of the impact of expansionary Extended Benefit programs

Outcome: probability of working a positive number of hours

	Work overall	At workplace	From home	Elsewhere	Commute
A) Controlling only for weekend dummy & fixed effect for month, year and state					
UI expansion	−0.00274 (0.0251)	0.000797 (0.0288)	−5.24e−05 (0.0283)	0.0275 (0.0239)	−0.0428 (0.0309)
B) Controlling only for weekend dummy & fixed effect for unemployment rate, month, year and state					
UI expansion	−0.000740 (0.0251)	0.00143 (0.0288)	0.00144 (0.0281)	0.0279 (0.0243)	−0.0409 (0.0307)
C) Controlling only for weekend dummy & fixed effect for (4-digit) industry fixed effects, unemployment rate, month, year and state					
UI expansion	−0.000740 (0.0251)	0.00143 (0.0288)	0.00144 (0.0281)	0.0279 (0.0243)	−0.0409 (0.0307)
D) Including all controls as in the main model (e.g. as in Table 4**) and also occupation fixed effects**					
UI expansion	−0.00762 (0.0282)	−0.00101 (0.0289)	−0.00614 (0.0265)	0.0276 (0.0274)	−0.0498* (0.0268)
E) Clustering standard errors at state level but not at the level of the running variable					
UI expansion	−0.00507 (0.0238)	−0.000856 (0.0265)	0.00250 (0.0280)	0.0273 (0.0252)	−0.0457 (0.0292)
F) Including additional controls for the regular and total duration of state unemployment benefits					
UI expansion	−0.00767 (0.0255)	−0.00145 (0.0270)	0.00622 (0.0274)	0.0249 (0.0256)	−0.0442 (0.0299)

Outcome: minutes worked per day (including only individuals with positive hours of work)

	Work overall	At workplace	From home	Elsewhere	Commute
G) Controlling only for weekend dummy & fixed effect for month, year and state					
UI expansion	9.789 (26.05)	−17.35 (20.64)	6.038 (12.16)	2.686 ((7.357)	5.031 (3.861)
H) Controlling only for weekend dummy & fixed effect for unemployment rate, month, year and state					
UI expansion	8.090 (25.79)	−18.79 (20.23)	18.90 (23.50)	2.846 (7.448)	5.139 (5.241)
I) Controlling only for weekend dummy & fixed effect for (4-digit) industry fixed effects, unemployment rate, month, year and state					
UI expansion	8.090 (25.79)	−18.79 (20.23)	18.90 (23.50)	2.846 (7.448)	5.139 (5.241)
J) Including all controls as in the main model (e.g., as in Table 4**) and also occupation fixed effects**					

Table 6 continued

Outcome: minutes worked per day (including only individuals with positive hours of work)

	Work overall	At workplace	From home	Elsewhere	Commute
UI expansion	11.79 (30.57)	−19.15 (26.20)	22.38 (25.05)	4.532 (8.694)	4.028 (6.120)
K) Clustering standard errors at state level but not at the level of the running variable					
UI expansion	10.93 (27.02)	−16.22 (20.16)	19.76 (20.00)	2.491 (7.538)	4.902 (5.909)
L) Including additional controls for the regular and total duration of state unemployment benefits					
UI expansion	16.98 (27.67)	−13.82 (21.14)	23.26 ((19.21)	2.775 (7.737)	4.764 (6.234)

Robustness checks

All models include a quadratic function of the days elapsed since the start of the EB and its interactions with the dummy for the start of the EB program from the right and the left of the cut-off. The bandwidth is 365 days. Standard errors, in parentheses, are robust and clustered at the level of both the running variable and the state

***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

The data on the regular and total duration of state unemployment benefits by month used in specification F come from Rob Valletta (see Valletta 2014 for more details). ATUS weights are applied

Table 7 Results of estimation for men of the impact of *contractionary* Extended Benefit programs

Outcome: probability of working a positive number of hours

	Work overall	At workplace	From home	Elsewhere	Commute
A) Controlling only for weekend dummy & fixed effect for month, year and state					
UI contraction	0.0119 (0.0332)	−0.00215 (0.0290)	−0.00708 (0.0188)	−0.0216 (0.0192)	−0.0342 (0.0249)
B) Controlling only for weekend dummy & fixed effect for unemployment rate, month, year and state					
UI contraction	0.0112 (0.0328)	−0.00207 (0.0289)	−0.00726 (0.0188)	−0.0221 (0.0190)	−0.0347 (0.0247)
C) Controlling only for weekend dummy & fixed effect for (4-digit) industry fixed effects, unemployment rate, month, year and state					
UI contraction	0.0112 (0.0328)	−0.00207 (0.0289)	−0.00726 (0.0188)	−0.0221 (0.0190)	−0.0347 (0.0247)
D) Including all controls as in the main model (e.g. as in Table 4**) and also occupation fixed effects**					
UI contraction	0.00137 (0.0277)	−0.0182 (0.0242)	−0.00150 (0.0240)	−0.0276 (0.0234)	−0.0482** (0.0218)
E) Clustering standard errors at state level but not at the level of the running variable					
UI contraction	0.0160 (0.0308)	−0.000110 (0.0267)	−0.000135 (0.0203)	−0.0259 (0.0198)	−0.0281 (0.0221)
F) Including additional controls for the regular and total duration of state unemployment benefits					
UI contraction	0.0184 (0.0313)	0.00361 (0.0268)	−0.000321 (0.0211)	−0.0220 (0.0207)	−0.0265 (0.0226)

Outcome: minutes worked per day (including only individuals with positive hours of work)

	Work overall	At workplace	From home	Elsewhere	Commute
G) Controlling only for weekend dummy & fixed effect for month, year and state					
UI contraction	−40.50*** (18.29)	−26.04 (15.80)	−3.637 (13.75)	−5.988 (8.060)	−4.842 (4.878)
H) Controlling only for weekend dummy & fixed effect for unemployment rate, month, year and state					
UI contraction	−39.72*** (14.34)	−25.10 (18.25)	−3.841 (13.89)	−6.170 (8.257)	−4.616 (4.852)
I) Controlling only for weekend dummy & fixed effect for (4-digit) industry fixed effects, unemployment rate, month, year and state					
UI contraction	−39.72*** (14.34)	−25.10 (18.25)	−3.841 (13.89)	−6.170 (8.257)	−4.616 (4.852)
J) Including all controls as in the main model (e.g. as in Table 4**) and also occupation fixed effects**					

Table 7 continued

Outcome: minutes worked per day (including only individuals with positive hours of work)

	Work overall	At workplace	From home	Elsewhere	Commute
UI contraction	−45.03*** (15.91)	−33.20 (19.88)	0.912 (16.21)	−7.217 (9.993)	−5.531 (5.021)
K Clustering standard errors at state level but not at the level of the running variable					
UI contraction	−38.44** (14.29)	−28.75 (18.11)	−0.0285 (14.21)	−5.761 (8.434)	−3.899 (4.588)
L) Including additional controls for regular and total duration of state unemployment benefits					
UI contraction	−36.71** (14.83)	−26.18 (17.93)	−2.367 (14.38)	−5.254 (8.677)	−2.912 (4.557)

Robustness checks

All models include a quadratic function of the days elapsed since the end of the EB and its interactions with the dummy for the end of the EB program from the right and the left of the cut-off. The bandwidth is 365 days. Standard errors, in parentheses, are robust and clustered at the level of both the running variable and the state

***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

The data on the regular and total duration of state unemployment benefit by month used in specification F come from Rob Valletta (see Valletta 2014 for more details). ATUS weights are applied to benefit cuts by increasing employment (by around 8 percentage points) and hours worked (by 25 min per day, on average). In contrast, individuals younger than 50 do not react significantly to changes in unemployment benefit duration programs.

As for education (see online Appendix Tables K and L, respectively, for the impact of EB start/end), the findings are quite heterogenous, indicating that the college-educated increase employment and commuting in response to state benefit expansions while those without college increase employment and work done from home in reaction to state benefits cuts.

4.3 More outcomes

To better grasp what lies beyond our findings, and thanks to the fact that the ATUS diary also collects separate information on time spent traveling to work, we construct additional measures for the probability of commuting and the time spent commuting to work. We consider as additional outcomes the hours worked at unsociable times: night-time (defined as between 8 pm and 8am), or on a Sunday (Hamermesh and Stancanelli, 2015). We construct a new outcome variable equal to one if individuals did some work both from the workplace and from home, and some of this work was performed at unsocial hours (night-time or on a Sunday), and equal to zero otherwise. We conclude that (see Table 8) EB programs increase commuting by 18% for the average American (this effect is only significant at the ten percent level). In particular, the probability of commuting increases by 6 to 9 percentage points for women and Blacks and other ethnic and racial minorities. This effect is only weakly significant for unemployment benefit expansions but strongly significant for benefit cuts.

In addition, we find a significant increase in night-time work by Blacks and other ethnic and racial minorities in response to both expansions and cuts in unemployment benefit duration programs. Sunday work also increases significantly for women with benefit expansions. All this suggests that vulnerable groups took up more work at hours that may conflict with their family and social life due to business cycle ups and downs. Considering the probability of working on the same day from the workplace, from home, and at unsocial hours, we find a large (80%) but weakly significant (at the ten percent probability level) increase for women in response to EB cuts. This suggests that some of the increase in work done from home by women in response to benefit cuts (see Table 3) reflects women bringing more work home from the workplace, at the end of the working day, rather than an increase in the take-up rate of jobs exclusively performed from home. Considering the probability of doing some work both from the workplace and from home on the diary day (but not whether work was performed at unsocial hours), the estimated coefficient for EB cuts is larger and statistically significant at the 5% level (results available on request).

Finally, we examine earnings, to check whether ups and downs in the business cycle - as captured by, respectively, expansionary and contractionary unemployment insurance measures - affect hourly earnings. To this end, we estimate a Heckman model of earnings, controlling for employment selection, conditional on whether individuals performed some paid work in the ATUS diary interview day. We use the presence of children aged below ten years to identify employment, which works out well. The results of the estimation indicate that economic recovery affects positively

Table 8 Results of estimation of the impact of Extended Benefit programs on *commute and work done at unsocial hours*

		Benefit expansion					From home &
	Commute >0	Commute minutes	Night-time work > 0	Night-time minutes	Sunday work > 0	Sunday minutes	workplace & unsocial hour
1) Analysis sample							**>0**
Means year before	0.432	19.75	0.378	47.67	0.033	11.343	0.044
UI expansion	0.0237 (0.0228)	4.302 (3.571)	0.0151 (0.0207)	7.136 (11.26)	0.0144 (0.0133)	8.432 (10.57)	0.00333 (0.0103)
Observations	21,638	8,874	21,638	8,874	21,638	8,874	21,638
R squared	0.348	0.129	0.281	0.158	0.111	0.282	0.079
2) Women							
Means year before	0.379	15.258	0.307	33.55	0.031	9.77	0.035
UI expansion	0.0609* (0.0336)	2.659 (3.305)	0.0252 (0.0287)	13.09 (9.268)	0.0281** (0.0130)	15.06 (10.19)	0.0123 (0.0175)
Observations	12,255	4,441	12,255	4,441	12,255	4,441	12,255
R squared	0.355	0.174	0.269	0.170	0.109	0.302	0.089
3) Blacks and other racial and ethnic minorities							
Means year before	0.442	19.55	0.39	47.21	0.03	10.94	0.029
UI expansion	0.0750* (0.0373)	0.584 (4.167)	0.0515* (0.0283)	24.33** (11.80)	0.0193 (0.0130)	8.705 (13.41)	0.00876 (0.0136)
Observations	7132	2706	7132	2706	7132	2706	7132
R squared	0.373	0.213	0.311	0.259	0.127	0.328	0.153

		Benefit contraction					From home &
	Commute >0	Commute minutes	Night-time work > 0	Night-time minutes	Sunday work > 0	Sunday minutes	workplace & unsocial hour
4) Analysis sample							**>0**
Means year before	0.421	19.635	0.362	45.58	0.029	9.808	0.045

Table 8 continued

		Benefit contraction					From home &
	Commute >0	Commute minutes	Night-time work > 0	Night-time minutes	Sunday work > 0	Sunday minutes	workplace & unsocial hour
UI expansion	0.0157 (0.0213)	−0.493 (1.465)	0.00820 (0.0171)	3.452 (4.268)	0.00449 (0.0156)	−0.232 (5.200)	0.00145 (0.00987)
Observations	27,376	27,376	27,376	27,376	27,376	27,376	27,376
R squared	0.336	0.188	0.275	0.148	0.105	0.076	0.074
5) Women							
Means year before	0.372	15.322	0.301	32.98	0.026	8.294	0.037
UI expansion	0.0698** (0.0288)	−5.933** (2.216)	0.0403 (0.0274)	−4.791 (16.36)	0.00324 (0.0147)	−5.238 (10.74)	0.0266* (0.0147)
Observations	15,301	5,517	15,301	5,517	15,301	5,517	15,301
R squared	0.348	0.123	0.269	0.153	0.102	0.299	0.084
6) Blacks and other racial and ethnic minorities							
Means year before	0.414	20.33	0.344	48.095	0.028	11.14	0.036
UI expansion	0.0857** (0.0352)	3.579 (5.237)	0.0564* (0.0327)	31.12 (23.54)	0.00612 (0.0190)	−2.683 (15.63)	−0.0198 (0.0120)
Observations	9341	3524	9341	3524	9341	3524	9341
R squared	0.352	0.174	0.287	0.183	0.115	0.314	0.128

All models include a quadratic function of the days elapsed since the start/ end of the EB and its interactions with the dummy for the end of the EB program from the right and the left of the cut-off, as well as controls for gender, race and ethnicity, marital status, number and age of kids, education, a quadratic in age, total household income in brackets, home ownership, a dummy for living in a hotel or mobilome or boarding/rooming house, weekend diary dummy, year and fixed effects for state, metropolitan area, (four-digit) industry and month of the year when the diary was filled in. The bandwidth is 365 days. Standard errors, in parentheses, are robust and clustered at the level of both the running variable and the state

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

ATUS weights are applied

women's hourly earnings, which increase significantly (see Table 9). As earnings are likely to be measured imprecisely, we do not assign too much weight to the size of the estimate, which suggests a very large increase.

5 Conclusions

This study investigates how the business cycle, as captured by the state benefit expansion/contraction measures it triggers, affects Work done from Home. We use over 150,000 daily activity diaries of the American Time Use Survey 2003–2019, along with Local Unemployment statistics and implementation dates of unemployment insurance expansion and contraction programs. During and after the Great Recession, unemployment benefit duration was extended considerably, from the usual 26 weeks, up to 99 weeks, with the timing and generosity of these measures varying substantially across states. While EB expansion and contraction measures are triggered by the state unemployment rate, individuals cannot anticipate the exact implementation date. Therefore, we implement an empirical design inspired by Regression Discontinuity Design, in which the days elapsed between the ATUS interview and the EB expansion/contraction implementation date serve as the running variable.

We find that the Great Recession, as tracked by the large variation in unemployment rates across states, is associated with a substantial drop in overall employment and with an increase in the probability of working from home for women. The causality analysis leads us to conclude that EB contractionary measures (which capture upswings in the business cycle) significantly increased overall employment (by over 4 percentage points, which corresponds to a 9% increase in employment), with work done from home increasing by 24% and work from the workplace by 7%. These findings conceal substantial heterogeneity. In particular, we conclude that EB contractions increased women's employment by 8.5 percentage points, increasing the probability of working from the workplace by 7 percentage points and from home by 5 percentage points. Commuting also increased by 6 percentage points for women. The probability of doing some work both from the workplace and from home, and at unsocial hours (night-time or on a Sunday) almost doubled with EB cuts for women. Moreover, EB expansions (which proxy downswings in the business cycle), significantly increased women's employment (only significant at the ten percent level) and women's commuting. Almost none of these effects are significant for men. This could perhaps be explained by the fact that EB policy measures take place when the recession/recovery is already well underway, and perhaps many men have already lost/resumed their jobs by then. An alternative explanation hinges on women's employment and hours being more responsive to the uncertainty thrown in by business cycle peaks and troughs.

The estimates are robust to several checks, including narrowing the sample-selection bandwidth, as well as dropping covariates, or dropping treated states one by one, or eliminating observations for days close to the cut-off from the estimation sample. In addition, our findings hold when controlling for occupation fixed effects (in addition to several hundred 4-digit industry fixed effects included in our model) or for the duration of state regular and total unemployment benefits.

Table 9 Earnings effects of unemployment benefits expansion and contraction

	Women earnings	Employment		Men earnings	Employment	
UI benefit expansion	199.8 (156.3)	0.115 (0.0755)		18.40 (138.4)	0.0774 (0.104)	
Any child aged > 10 y.		−0.0666** (0.0282)			0.0145 (0.0616)	
athrho			2.782*** (0.277)			−0.0460** (0.0205)
lnsigma			7.616*** (0.160)			7.159*** (0.0522)
observations			12,050			9,154
UI benefit contraction	418.4*** (156.0)	0.260*** (0.0695)		−17.95 (180.3)	−0.0150 (0.0936)	
Any child aged > 10 years		−0.0549*** (0.0172)			−0.0561** (0.0254)	
athrho			3.030*** (0.246)			2.397*** (0.0938)
lnsigma			7.645*** (0.120)			7.560*** (0.0633)
observations			15,003			11,774

The models estimated are Heckman models of earnings, controlling for selection into employment (i.e., positive work hours on the ATUS diary day). The explanatory variables are the same as in the regressions of Tables 2 and 3, for our main model and outcomes, except for children's age dummies, which serve to identify the selection equation. Weights are applied. Standard errors are clustered at the level of the running variable. Clustering at the level of the state, conclusions are robust

By replicating the analysis for Blacks and other ethnic and racial minorities, we conclude that their employment and hours increased significantly in response to business cycle ups and downs. For them, employment increased by over 8 percentage points with either EB expansion or contraction measures. In particular, their night-time work and commuting increased significantly, but not work performed from home.

The evidence gathered indicates that women's employment overall, including work from home, is responsive to business cycle ups and downs, which may also capture economic uncertainty. While recessions destroy mostly men's jobs, women take up jobs with longer commutes in response to business cycle troughs. Women's employment appears to be cyclical, with work from home but also from the workplace and commuting increasing with upswings in the business cycle.

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Author contributions Elena Stancanelli did the empirical analysis while Arie Kapteyn and Elena Stancanelli widely discussed the data, the method, and the results and wrote the text together.

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Compliance with ethical standards

Conflict of interest The authors declare no competing interests.

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