Caregiving and Labor Force Participation: New Evidence from the American Time Use Survey

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[PRELIMINARY AND INCOMPLETE - PLEASE DO NOT CITE OR CIRCULATE]

1 Introduction

The growing need for long-term care is a reality of a rapidly aging population. One fifth of the U.S. population will be 65 and over by 2050, and as approximately one third of adults in this age range report experiencing functional limitations, the number of people requiring long-term care is projected to increase (Hagen, 2013). Much of the demand for long-term care is currently met by informal caregivers, most commonly adult children of the elderly (Weber-Raley and Smith, 2015). The effects of caregiving on informal caregivers, many of whom are also formally employed, is a topic of growing policy interest. While informal care may be an affordable and even preferable alternative to formal care, its implications for the physical and economic wellbeing of caregivers should also be considered. Recent evidence from the US suggests that caregiving may have implications for labor supply on both the intensive and extensive margins, suggesting that caregivers are more likely to leave paid work, transition early into retirement, or experience declines in hours and wages as a result of their caregiving obligations (Fahle and McGarry, 2017; Van Houtven, Coe, and Skira, 2013; Skira, 2015).

Workplace policies such as sick leave and family leave may provide support for individuals juggling work and caregiving opportunities (Maestas, 2017). How well such policies actually work for elder caregivers is not well understood.[1] While in most cases workplace leave policies

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[1] Løken, Lundberg, and Riise (2014) show that after an expansion of subsidies for formal care in Norway in 1998, adult daughters took less sick leave, suggesting that such policies are useful to workers who are also providing informal care.

can be used to provide care for sick relative as well as a new child, such benefits are structured to fit the needs of new parents, who make up 90% of paid leave claimants, and much of the empirical evidence on the impact of paid leave similarly focuses on new parents (Rossin-Slater, Ruhm, and Waldfogel, 2013; Rossin-Slater, 2017).[2] Eldercare may have a different time-use profile than newborn care, requiring differently structured policies. Furthermore, eldercare trajectories are highly heterogeneous, suggesting the need for more flexible policies (National Academy of Sciences 2016).[3]

Thinking about how workplace policies such as sick leave or paid family leave could advantage caregivers requires understanding how caregiving impacts workers in the short-term. Despite a growing literature examining the effects of caregiving on work, the short-term impact of caregiving in the US is not well understood. Existing studies of the relationship between caregiving and work in the US using panel data methods rely on the Health and Retirement study, a nationally representative survey of the US population over 50 (Fahle and McGarry, 2017; Van Houtven, Coe, and Skira, 2013). The HRS is a biennial panel, and measures both caregiving and employment outcomes over two years. While the econometric challenges of identifying the causal effects of caregiving on work can be reasonably addressed using panel data techniques and instrumental variables,[4] a short-term perspective requires a dataset that captures employment outcomes at a high frequency before and after caregiving starts.

In this paper, we consider the short-term impacts of caregiving spells on caregiver outcomes. To do this, we create a high frequency panel dataset that captures employment outcomes before and after caregiving starts. Specifically, we leverage a new data source for eldercare - The American Time Use Survey (ATUS) Eldercare module, which was added to the main survey in 2011. ATUS respondents are a subsample of Current Population Survey (CPS) households and are surveyed two to five months after their final CPS interview, so we are able to link ATUS to the CPS to create an 18-21 month panel with high frequency observations on employment outcomes.[5] We leverage retrospective information about caregiving reported in the eldercare module to position the start of a caregiving spell within the linked panel for those respondents who report starting

[2] Arora and Wolf (2017) finds that nursing home admissions went down in California following the implementation of paid family leave in 2004, suggesting that paid leave increases the supply of informal care.

[3] An additional challenge is defining the family ties that would qualify for elder care. For example, under Family Medical Leave Act, a worker may take protected leave to care for a biological, step, foster, or adoptive parent, but not a parent-in-law.

[4] Van Houtven, Coe, and Skira (2013) describe an instrumental variables approach in detail.

[5] The CPS surveys each sampled household a total of 8 times: 4 consecutive months at a time, with an 8 month break in between. Linking to the ATUS creates a panel with 9 observations per household over approximately 18 months. More details about the data structure can be found in the CPS technical documentation.

caregiving within 24 months of their ATUS interview. This linked longitudinal dataset allows us to observe employment outcomes in the months before and after caregiving starts.

We then exploit panel data methods to examine the short-term effects of starting caregiving on labor supply. We first use a standard individual fixed-effects model and then futher modify the dataset to employ an event study with control group method that exploits the timing of caregiving spells (Fadlon and Nielsen, 2017; Deshpande and Li, 2017). Both approach produce similar average effects. Preliminary results suggest that respondents age 40-65 are 1.3 percentage points less likely to be working in the 6-12 months after caregiving starts, and are nearly 1 percentage point more likely to be absent from work (a 25% increase in absences). There is also a marginally significant one percentage point increase in the likelihood of being out of the labor force after a caregiving spell, but no change in the likelihood of unemployment.

This paper also highlights several advantages of the caregiving information collected by the ATUS eldercare module. Because the ATUS surveys a nationally representative sample, it provides a more complete picture of caregiving than the HRS, which is representative of the US population over 50. Additionally, while the HRS captures eldercare provided to spouses and parents, the ATUS surveys respondents who provide any kind of care, including care to friends, neighbors, and extended family. Finally, the CPS collects information on a rich set of employment outcomes, including absences from work, which allows us to observe changes in absenteeism following a caregiving spell, an outcome that has not been previously studied in the context of caregiving.

2 Data

We leverage the American Time Use Survey, a nationally representative, monthly cross-sectional survey of time use in the United States. Along with the main survey in which respondents fill out a detailed time diary for a randomly selected day of the week, the ATUS also has several topical modules, including, starting in 2011, a module on eldercare. In this module, respondents report if they have provided care to an elderly or disabled person at least once in the last 3 months. If they have, they are then asked to provide further details, including how often they provide care, who they provide care to, and importantly, how long they have been providing care.

2.1 Descriptive Statistics from the Eldercare Module

We first report some descriptive statistic from the eldercare module in Table 1. The ATUS includes just under 65,000 individual observations since 2011. 17% of respondents report having provided some eldercare at least once in the 3 prior months, and 11% report providing such care weekly.[6] Just over half of caregivers have been providing care for more than 36 months. The average caregiver is taking care of 1.4 people. 50% of respondents are caring for their parents, while 7% are caring for a spouse. 18% are caring for another relative (including grandparents, aunts and uncles), and just under 25% are caring for a non-relative.

Table 1: Descriptive Statistics: ATUS Sample caregiving module

	Mean (SD)
Any elder care	0.17
Any weekly care	0.11
Num Adults caring for	1.4 (0.8)
Caregiving duration (months)	
0-5	0.15
6-11	0.07
12	0.10
13-23	0.01
24	0.15
36	0.52
Caring for:	
Spouse	0.07
Parents or in-laws	0.53
Other relative	0.18
Other non relative	0.23

Note: The table presents descriptive statistics for the sample of all individuals age 18+ in the ATUS survey interviewed between 2011 & 2016

Table 2 reports demographic characteristics for the sample of caregivers (Column 1) and compares them to non-caregivers (Column 2). Table 2 also reports the p-value for the difference between the two means (Column 3) as well as descriptive characteristics for the sample split by care recipient: a spouse, a parent, another relative (such as a grandparent or aunt) or a non-relative (Columns 4-7).[7] The average caregiver is just under 52 years old, nearly a year older than the average parental caregiver, who is just over 50 years old. The median caregiver age is 52 (not included in the table). This suggests that nearly half of caregivers are younger than the HRS el-

[6] This compares to approximately 13% of respondents who report providing help of care to another adult during their diary day Mommaerts and Truskinovsky (2017).

[7] In the case of multiple care recipients who fall into more than one category, we code the closest relationship

igibility age cutoff. Caregivers in the ATUS are 60% female, 72% white and 53% married. 38% have a college education or greater. Compared with non caregivers, caregivers are more likely to be female and married, and more likely to be white. They are also more likely to have graduated college (38% of caregivers compared with 34% of non caregivers). This educational gradient is starkest is when comparing those who care for parents, 42% of whom are college graduates.

	Mean (SD)		T-Test	Caring for:			
	Caregivers	Non Caregivers	P-Value	Spouse	Parent	Other Rel	Other Non Rel
rs)	51.65 (15.50)	49.38 (17.33)	0.000	69.14 (10.75)	50.32 (11.24)	41.74 (17.72)	57.46 (16.78)
%)	0.611	0.552	0.000	0.632	0.598	0.632	0.618
)	0.718	0.648	0.000	0.753	0.735	0.670	0.704
)	0.146	0.144	0.514	0.097	0.129	0.194	0.164
)	0.038	0.057	0.000	0.025	0.040	0.039	0.036
(%)	0.098	0.151	0.000	0.125	0.096	0.097	0.096
(%)	0.532	0.497	0.000	0.942	0.585	0.438	0.368
d (%)	0.079	0.100	0.000	0.014	0.044	0.063	0.191
l (%)	0.159	0.149	0.007	0.018	0.171	0.112	0.208
d (%)	0.027	0.029	0.282	0.010	0.025	0.035	0.030
arried (%)	0.203	0.225	0.000	0.015	0.175	0.353	0.203
n HS (%)	0.067	0.114	0.000	0.157	0.045	0.077	0.085
ool (%)	0.439	0.444	0.375	0.458	0.416	0.492	0.446
llege (%)	0.117	0.097	0.000	0.107	0.122	0.114	0.110
Degree (%)	0.226	0.212	0.001	0.167	0.246	0.214	0.207
e (%)	0.150	0.133	0.000	0.111	0.170	0.102	0.151
< 18 in HH (%)	0.312	0.356	0.000	0.045	0.361	0.390	0.215

able presents descriptive statistics for the sample of all individuals age 18+ in the ATUS interviewed between 2011 & 2016. Column 1 presents values for of caregivers (defined as individuals having provided any unpaid care to an elderly or disabled person more than once in the last three months. Column values for the sample of non caregivers. Column 3 presents p-values from a 2 tailed t-test comparing caregivers to non-caregivers.

Table 3 reports employment outcomes for the sample of caregivers and non-caregivers. Overall, caregivers appear to have higher rates of labor force participation than non caregivers, especially when considering parental caregivers. Caregivers are somewhat more likely to be employed than non-caregivers (62.5 % vs 61%), and this appears to be especially true for those providing care to their parents (72% of parental caregivers are employed). Conversely, higher rates of unemployment among caregivers are driven by those caring for elderly other than parents. Approximately 10% of those caring for other relatives or non-relatives report being unemployed, compared to 6% of parent caregivers and 6.5% of non-caregivers. Parent caregivers are also less likely to be out of the labor force (23% of parental caregivers are out of the labor force, compared with nearly 70 % of spousal caregivers, 46% of those caring for non-relatives, and 34% of non-caregivers. Conditional on working, there is no difference in absenteeism rates between caregivers and non caregivers. Approximately 4.6% of parental caregivers report being absent in the last week, compared with 4.1% of non-caregivers.[8]

Table 3: Comparing caregivers and non caregivers: Employment Outcomes

	Mean (SD)		T-Test	Caring for:			
	Caregivers	Non Caregivers	P-Value	Spouse	Parent	Other Rel	Other Non Rel
Working	0.625	0.616	0.065	0.264	0.719	0.657	0.485
Unemployed	0.076	0.065	0.000	0.083	0.062	0.095	0.102
Not in Labor Force	0.323	0.341	0.000	0.712	0.233	0.274	0.460
Absent	0.044	0.041	0.221	0.064	0.046	0.035	0.044

Note: The table presents descriptive statistics for the sample of all individuals age 18+ in the ATUS interviewed between 2011 & 2015. Column 1 presents values for the sample of caregivers (defined as individuals having provided any unpaid care to an elderly or disabled person more than once in the last three months.) Column 2 presents values for the sample of non caregivers. Column 3 presents p-values from a 2 tailed t-test comparing caregivers to non-caregivers.

2.2 Creating a panel with CPS

This section describes how we convert the ATUS eldercare module to a panel dataset by linking it to the Current Population Survey (CPS). Households selected by CPS are interviewed for a total of 8 months, for 4 consecutive months at a time with an 8 month break in between. ATUS respondents are randomly selected from household exiting the CPS rotation every month, and are interviewed 2 to 5 months after their final (8th) CPS interview. Thus each ATUS household is

[8] As neither the CPS or the ATUS collects information on family members living outside the household, we are not able to compare caregivers to potential caregivers - i.e. those who have relatives who may need care.

interviewed for a total of 9 times over a period of 18 to 21 months.[9]

We link ATUS respondents to their CPS household interviews using available individual and household level identifiers. Given the retrospective caregiving information from the eldercare module of the ATUS we identify approximately where in the CPS panel caregiving started, if caregiving began in the last 24 months. Table 1 reports the distribution of caregiving starts for the ATUS respondents. 15% of the sample, or about 1,800 respondents started caregiving within 5 months of their ATUS interview. Another 2,000 (17%) started between 6 and 12 months before their ATUS interview, and another 1,800 between 12 and 24 months. Just over half the sample has been providing care for over 36 month. Those respondents who have started caregiving spells within the last two years are surveyed by the CPS both before and after they started caregiving[10]

Figure 1 demonstrates this approach graphically. Each panel shows the frequency of observations by month relative to the approximate caregiving start month reported in "event time" (i.e. month 0 is the month that caregiving is reported to start, relative to the ATUS interview). For example, respondents who began caregiving 5 months before their time use interview (top left panel) are interviewed by CPS for 4 consecutive months between 13 and 10 months before they started caregiving and between one month before they started caregiving and five months after they started caregiving. Similarly, those respondents who started caregiving 12 months before the time use interview are observed between 6 and 3 months before they started caregiving and 5 to 10 months after they started caregiving. Our empirical strategy stacks these observations on "event time" to obtain a panel dataset with monthly observations for 12 months around a caregiving spell: 12 months before and 12 months after the spell starts.

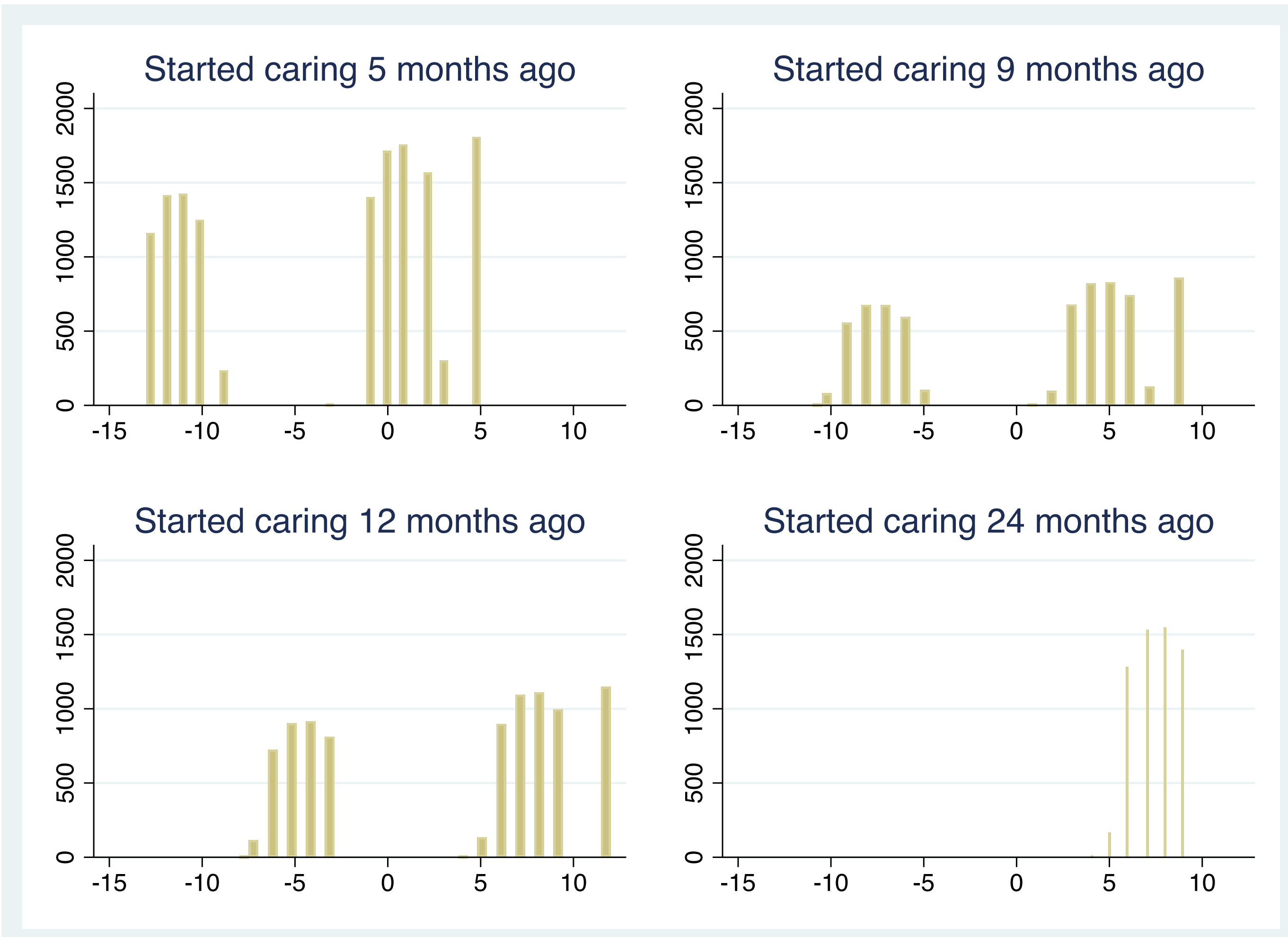
3 Empirical Strategies

Having constructed a longitudinal dataset of monthly employment outcomes around when caregiving starts, we can exploit panel data methods to examine the effects of starting caregiving on labor supply. We first use a standard fixed-effects model employed in other studies of caregiving Van Houtven, Coe, and Skira (2013) and then employ and event study with control group method that exploits the precise timing of caregiving spells Fadlon and Nielsen (2017); Deshpande and Li (2017). Our goal here is not to present well-identified causal estimates of the effects of caregiv-

[9]While the CPS collects information about an entire household, ATUS only asks about a randomly selected individual within the household.

[10]Respondents who started caregiving 24 months (2 years) before their ATUS interview are only observed after the caregiving spell starts.

Figure 1: Distribution of observations relative to when caregiving starts



Note:

ing on labor supply, but to explore the merits and limitations of different identification strategies made possible by this novel data structure. Before describing each method in turn, we first report basic event studies and examine pre-trends.

Figure 2 presents raw, unadjusted monthly means before and after caregiving starts for four employment outcomes: working; absent, unemployed and not in the labor force (NILF). We observe these outcomes for a total of 24 months: approximately 12 months before and for 12 months after caregiving begins. The X-axis denotes "event-time", or time relative to the reported month that caregiving starts, which is normalized to zero. The vertical red line is at event time zero.[11] These event studies reveal several patterns. First, despite some noise due to event-time months with low observations (such as month -2) there is a clear discontinuity around a caregiving spell in all outcomes except for unemployment. Second, there appear to be pre-trends in these raw averages that suggest that suggest an increase employment in the months before caregiving begins. Especially in the care of employment and absences (top two panels), caregivers appear to increase their employment and reduce their absences in the months before caregiving, see a drop when caregiving starts and then gradually return to pre-care levels. While these pre-trends suggests some anticipatory effects, they run counter to the leading identification concern that a relationship between caregiving and employment outcomes is driven by those who start caregiving after they experience a change in employment.

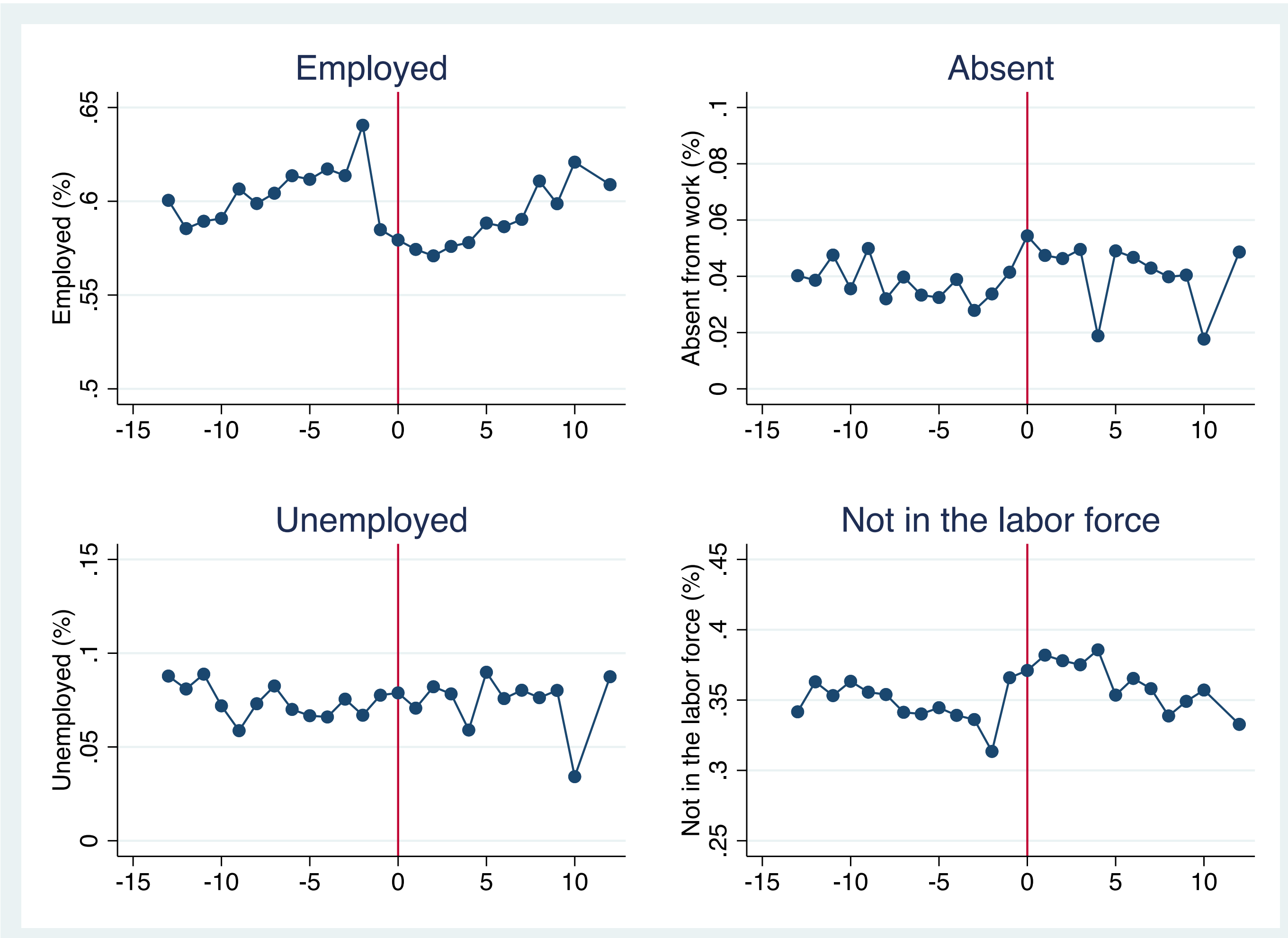
It is important to keep in mind that the upward trends we observe in the raw averages may be driven not by respondent behavior but by compositional changes in the data. Specifically, respondents who have been caring for different lengths of time may also have different levels of labor supply. We examine this possibility graphically in a later subsection. In the regression estimates we present below, these compositional differences are netted out with individual fixed effects.

3.1 Fixed Effects

We present results of our first estimation strategy using individual fixed effects. This approach addresses the possible endogeneity of caregiving by controlling for individual time-invariant characteristics correlated with both labor supply and caregiving that might lead to biased estimates of the effect of caregiving on work. These include cofounders such as weak labor force attachment

[11] Because reported caregiving start times are reported in buckets are are subject to measurement and recall error, we interpret event time around the beginning of a caregiving spell with caution. In the regression estimate, we dummy out month -1, 0 and 1 to account for this.

Figure 2: Panel Event Study



Note:

or a preference for caregiving over employment. All outcomes are binary and we estimate linear probability models of the following form:

$$Y_{it} = \beta PostCare_{it} + \eta_i + \tau_t + \gamma X_{it} + \varepsilon_{it} \quad (1)$$

Where Y_{it} is the employment outcome of interest for individual i at time t. $PostCare_{it}$ is an indicator for if individual i has started caregiving at time t. η_i is an individual fixed effect, and τ_t is a year-month fixed effect. X_{it} is a vector of time varying controls such as age. The coefficient of interest, β captures the change in the outcome variable when an individual begins caregiving averaged over the post period (between 5 and 12 months). The identifying assumption, to interpret β as the causal effect of starting caregiving on work outcomes, is that conditional on time invariant characteristics, and time fixed effects, the caregiving timing is exogenous to employment outcomes.

Table 4: Fixed Effects- Main Results

	(1) Working	(2) Absent	(3) NILF	(4) Unemployed
Caring	-0.0086**	-0.0082**	0.0057	0.0028
	(0.0044)	(0.0032)	(0.0040)	(0.0030)
Unique obs	65747	45797	65747	65747
depvar mean	0.608	0.039	0.353	0.0388

Note: The sample consists of all individuals age 18+ in the merged CPS - ATUS panel interviewed between 2010 & 2016. All columns report results from equation 1. The dependent variable in Column 1 is a binary indicator for if the respondent is employed. The dependent variable in Column 2 is a binary variable for if the respondent is absent from work in the week prior to the interview. The dependent variable in Column 3 is an binary indicator if the respondent is out of the labor force. The dependent variable in Column 4 is a binary indicator for if the respondent is unemployed. The independent variable is an indicator for if the respondent has started providing care for and elderly person. All columns additionally control for year and month of interview fixed effects. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4 reports the results from Equation 1 for the full ATUS sample on four self-reported employment outcomes: employed, absent from work on any day in the week prior to the interview, not in the labor force, and unemployed. Caregivers experience a 0.86 percentage point decrease in the likelihood of working after starting a caregiving spell, from a mean employment rate of 61 percent (Column 1). There is also a 0.82 percentage point increase in the likelihood of being absent following a caregiving spell, or an increase of 25% from a mean absence rate of 4%. This is consistent with an interpretation that caregiving gets in the way of working even for those caregivers who remain employed. Finally, in Columns (3) and (4), we see no changes in the likelihood of leaving the labor force or experiencing unemployment after the onset of caregiving.

We next look at heterogeneity by subgroup of the effect of caregiving on work in Table 5. Panel 1 restricts the sample to respondents age 40 - 70, as the subgroup most likely to be at risk for needing to provide elder care.[12] We see larger treatment effects for this more targeted subgroup. Respondents in this age range experience a 1.3 percentage point decrease in the likelihood of working in the 12 months after a caregiving spell starts, from a mean of 65.2 percent, and a 1 percentage point increase in the likelihood of being absent. They also experience is also a marginally significant 1 percentage point increase in the likelihood of being out of the labor force.

Panels 2 and 3 compare outcomes for men and women. We see a larger effect of caregiving on employment for women (1 percentage point and marginally significant, compared to an insignificant 0.67 percentage points for men), but both groups experience similar increases in absenteeism after they start caregiving. In the final two panels of Table 5 we compare the effects of employment on caregiving outcomes by caregiver educational status. We split the sample by high school graduation. As reported in Table 2, just over 50 percent of caregivers have a high school or lower education (this figure drops to 46% among those caring for aging parents). We find large differences in short-term employment outcomes by educational attainment. Higher educated respondents are 1.7 percentage points less likely to be working following a caregiving spell, and 1.2 percentage points more likely to be absent from work. They are also 0.8 percentage points more likely to report being unemployed following the start of a caregiving spell.[13] Conversely, we see no changes in employment outcomes caregivers with low levels of educational attainment, who also have lower rates of employment (72% of the high educated group is employed, compared with 51% of the low educated group.)

3.2 Event Study with Control Group

A limitation of the fixed effects approach is that it cannot account for time varying confounders, such as a change in employment status or expectation about work that would lead to a change in caregiving status.[14] One way to empirically address these concerns is to use an instrument for caregiving, such as the availability of other caregivers, or sudden changes in parental health outcomes Van Houtven, Coe, and Skira (2013). In this case, we have limited information about family

[12] The interquartile range for caregivers in the full ATUS sample is 41-63 years old.

[13] The pattern is virtually unchanged if we split the sample by by college attainment, with the effects concentrated among college graduates.

[14] For example, Mommaerts & Truskinovsky (2017) show that informal caregiving increases during economic downturns.

Table 5: Fixed Effects- Heterogeneity

	(1) Working	(2) Absent	(3) NILF	(4) Unemployed
		Panel 1: Age 40-70		
Caring	-0.0129**	-0.0093**	0.0095*	0.0033
	(0.0055)	(0.0037)	(0.0052)	(0.0039)
Unique obs	37410	27102	37410	37410
depvar mean	0.653	0.041	0.310	0.0370
		Panel 2: Men		
Caring	-0.0067	-0.0083*	0.0065	0.0003
	(0.0067)	(0.0045)	(0.0059)	(0.0053)
Unique obs	28817	22121	28817	28817
depvar mean	0.688	0.032	0.271	0.0418
		Panel 3: Women		
Caring	-0.0098*	-0.0084**	0.0060	0.0038
	(0.0057)	(0.0044)	(0.0053)	(0.0037)
Unique obs	36930	23676	36930	36930
depvar mean	0.546	0.0471	0.417	0.0365
		Panel 4: More than HS		
Caring	-0.0168***	0.0119***	0.0089	0.0080**
	(0.0059)	(0.0042)	(0.0056)	(0.0039)
Unique obs	29539	23550	29539	29539
depvar mean	0.722	0.042	0.248	0.0291
		Panel 5: HS or less		
Caring	-0.0005	0.0028	0.0030	-0.0025
	(0.0064)	(0.0048)	(0.0058)	(0.0046)
Unique obs	36208	22247	36208	36208
depvar mean	0.512	0.036	0.441	0.0470

Note: The sample consists of all individuals age 18+ in the merged CPS - ATUS panel interviewed between 2010 & 2016. All columns report results from equation 1. The dependent variable in Column 1 is a binary indicator for if the respondent is employed. The dependent variable in Column 2 is a binary variable for if the respondent is absent from work in the week prior to the interview. The dependent variable in Column 3 is an binary indicator if the respondent is out of the labor force. The dependent variable in Column 4 is a binary indicator for if the respondent is unemployed. The independent variable is an indicator for if the respondent has started providing care for and elderly person. All columns additionally control for year and month of interview fixed effects. Robust standard errors are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

member who live in the same household, and no information about family members outside the household. Another concern is that caregivers have ex ante information about caregiving need, and may start modifying their labor supply behavior in anticipation of that need.

In the ideal set-up, we could identify counterfactual individuals who resemble our respondents both in the evolution of their employment outcomes as well as in their ex ante expectations about caregiving, but who do not start providing care (i.e., they remain untreated). Following Fadlon and Nielsen (2017) and Deshpande and Li (2017), we create such a counterfactual by comparing respondents who experience a caregiving event to those who will begin caregiving several months in the future. This method allows us to exploit the emphtiming of caregiving spells. The identifying assumption in the set up is that, among those who anticipate that they will be caregivers soon, the precise timing of when the caregiving spell starts is as good as randomly assigned.

3.2.1 Sample design

This approach requires a new dataset, which we construct in the following way, based on the approach in Fadlon and Nielsen (2017) and Deshpande and Li (2017). We select the sample of individuals who experience a caregiving "shock" (start caregiving) between 2009 & 2016, for whom we have some amount of pre and post information (depending on when they start caregiving relative to when they enter the CPS rotation). We construct the data as follows: For each calendar year *year*, we take the subset of households who begin caregiving in some month m that year and designate them as the treatment group. Then everybody who started caregiving after that calendar year ($year + \epsilon$), is assigned to the control group. We then redefine time with respect to the shock t: for the treatment group, t is just the month relative to when they started caregiving. Three months before they begin caregiving corresponds to t = -3, 2 months after they start caregiving corresponds to $t = 2$, etc. For the control group, we define a placebo shock δ months before they actually experience the shock. For the control group, t is time from placebo shock, which by definition is δ months before their actual shock. We repeat this procedure for each calendar year separately, and then append all the datasets together. For those who start caregiving in 2009, their controls start caregiving in 2010-2016. for those who start in 2010, their controls start caregiving in 2011-2016.[15]

One limitation with this approach, as described in detail in Fadlon and Nielsen (2017), is

[15] A household doesn't serve as its own control, however households do appear in the sample multiple times as controls.

that we can only measure dynamic causal effects $\delta - 1$ periods (months, in our case) post-shock. Unique to our context, where we have a short panel is that the choice of δ also limits the pre-period that we are able to observe. We select $\delta = 7$ to split the available periods in half: we observe 6 months of pre period and 6 months of post period.

3.3 Visual results

Figure 3 graphs the employment outcomes for the treatment and control groups. The X-axis denotes time relative to the reported month that caregiving starts, normalized to zero. The treatment group is mapped in black and the control group is in grey. For the treatment group, the caregiving shock applies at time 0, while the control group experiences a placebo "shock" at this point, and the real shock at month 7. We also adjust outcomes for length of caregiving spell, to address the compositional concerns raised in the previous section.

These panels reveal that treatment and control groups exhibit approximately parallel trends in likelihood of working, being out of the labor force and being unemployed prior to time 0, after which trends start to diverge somewhat. The treatment group outcomes reported at month -2 are very noisy given that that month has very few observations. Absences (top right panel) appear to fall somewhat *before* caregiving starts, suggesting that there may still be an anticipatory effect. The likelihood of being employed (top left panel) begins trending downwards precisely in the month that caregiving starts, and appears to be nearly 2 percentage points lower for the treatment group than the control group by month 4. While somewhat noisier, both absences and labor force participation seem to follow a similar pattern, while unemployment does not exhibit changes after caregiving starts.

3.4 Regression Results

We report the corresponding average treatment effect of caregiving on the first 6 months of employment outcomes using a straightforward difference in differences model:

$$Y_{it} = \alpha_i + \beta post_{it} + \gamma treat_i \times post_{it} + \delta X_{it} + \varepsilon_{it} \tag{2}$$

Where Y_{it} is an outcome for individual i at time t, *treat* is an indicator for if the household belongs to the treatment group, and *post* is an indicator for the post shock period. α_i is an individual fixed effect, and X_{it} is a vector of time varying individual characteristics (age). We report the

Figure 3: Even Study with Comparison Group

Note:

parameter γ, which is the average effect of starting caregiving on employment outcomes.

Table 6 reports the results of Equation 2 on the four main outcomes that we analyze. We present results for the full sample in Panel 1, and for the subset of respondents age 40-70 in Panel 2. The results in this table look similar to the fixed effects results in Table 5, but are more precisely estimated. For the full sample, employment drops by nearly 1 percentage points in the 6 months after a caregiving spell starts, and the likelihood of being absent from work increases by 1.2 percentage points. For the subsample of those age 40 - 70 employment falls by 1.5 percentage points following the start of a caregiving spell, or a 2.3% decrease from an average rate of 65.6%. The likelihood of being absent from work increases by 1.7 percentage points for this group, or a nearly 50% increase from a baseline of 3.7 percent. We also see, as suggested in 3 a large increase in the likelihood of being out of the labor force: 0.87 percentage points for the full sample and 1.5 percentage points for the subsample of those age 40-70, suggesting that those who exit out of employment in the six months after starting caregiving transition out of the labor force, rather than into unemployment.

Table 6: Event Study with control group: Regression Results

	(1) Employed	(2) Absent	(3) Not in Labor Force	(4) Unemployed
		Panel 1: Full Sample		
Post2XTreat	-0.0091***	0.0116***	0.0087***	0.0004
	(0.0029)	(0.0033)	(0.0028)	(0.0021)
Unique Obs	67332	40221	67332	67332
depvar mean	0.597	0.0394	0.357	0.0453
		Panel 2: Age 40-70		
Post2XTreat	-0.0152***	0.0173***	0.0153***	-0.0001
	(0.0036)	(0.0042)	(0.0035)	(0.0028)
Unique Obs	42703	27993	42703	42703
depvar mean	0.656	0.0371	0.303	0.0419

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

4 Conclusion

In this paper, we present evidence on caregiving and labor supply from a new data source: the American Time Use Survey eldercare module. We present a strategy for linking the ATUS to the

CPS to create a short panel that allows us to observe employment outcomes in the months before and after a reported caregiving spell starts. We exploit this longitudinal data and employ two different empirical strategies: individual fixed effects and and event study with a control group.

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