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Caregiving and Labor Force Participation: New Evidence from the Survey of Income and Program Participation

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Abstract

A large share of the growing demand for care is met informally by relatives. Many family caregivers also work, and the empirical evidence suggests that burden of caregiving interferes with employment. Although it is understood that caregiving ultimately results in lower labor force attachment, the dynamic employment trajectories around the start of a caregiving spell are not well understood. We use retrospective caregiving reports from the Survey of Income and Program Participation (SIPP) linked to administrative records to create a high-frequency panel dataset and estimate the dynamic relationship between work and caregiving for new caregivers. We find that the probability of employment declines by approximately 2 percentage points immediately following the start of caregiving and this decline is sustained for at least two years. The decrease in employment is accompanied by a drop in (unconditional) earnings, and is driven largely by exit from the labor force, rather than by transitions into unemployment. We find evidence that female caregivers return to the labor force approximately two years after the start of a caregiving spell, and this return is characterized by lower hours and higher likelihood of self-employment. Labor force exit among male caregivers appears to be permanent. Finally, we find increases in Social Security Disability Insurance (DI) claiming among all caregivers following the start of a caregiving spell.

JEL Classification: I12, J14, J22, J26

1 Introduction

The growing need for long-term care is a reality of a rapidly aging population. One in five Americans will be age 65 or older by 2030, 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 significantly (Hagen, 2013). Much of the demand for long-term care is currently met by informal (unpaid) caregivers, most commonly family members (Weber-Raley and Smith, 2015) and the impacts of caregiving on family 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 negative effects on the physical and economic well-being of caregivers has been well documented. Informal caregiving for family members has negative consequences for caregiver physical and emotional health (Coe and Van Houtven, 2009). The opportunity cost of unpaid family care has been estimated at as much as $5 billion in terms of lost wages alone (Chari et al., 2015). Recent evidence from the US suggests that caregiving affects labor supply on both the intensive and extensive margins: caregivers are more likely than non-caregivers to stop working, exit the labor force, or work at reduced hours and wages as a result of their family obligations (Fahle and McGarry, 2017; Van Houtven et al., 2013; Skira, 2015; Ettner, 1996).

Although it is known that caregiving results in lower labor force attachment, less attention has been paid to how rapidly the adverse employment impacts arise once individuals begin providing care, or what employment trajectories look like around the start of caregiving.[1] Understanding the dynamic impact of caregiving is critical to evaluating how employment policies, such as sick leave, family leave, and caregiver tax credits, might help individuals with family caregiving obligations to sustain employment. Many employers and some states offer paid family leave benefits, and the U.S. government requires most employers to provide unpaid family leave through the Family and Medical Leave Act (FMLA). In general, family leave can be used to provide care for a sick or ailing relative as well as a new child, but family leave benefits are structured to meet the needs of new parents, and new parents make up the majority of leave claimants for both paid and unpaid leave (Bedard and Rossin-Slater, 2016).[2] Meanwhile, caregiving to adults may have a different time-use profile than newborn care, requiring intermittent absences of a few hours, rather than a single absence of several weeks (Maestas, 2017). Furthermore, eldercare trajectories are highly heterogeneous, suggesting the need for a more flexible approach to caregiving leave policy (National Academy of Sciences 2016).[3]

[1] Skira (2015) is the only paper that we are aware of that takes a dynamic perspective in the US context, Schmitz and Westphal (2017) studies the dynamics of employment after caregiving in the German context.

[2] In the first 10 years of California's paid family leave legislation (2004-2014), new parents made up 90% of all PFL claims (California has a separate paid leave program for own medical leave). Much of the empirical evidence on the effectiveness of paid leave similarly focuses on new parents, e.g. Rossin-Slater et al. (2013); Rossin-Slater (2017). However, one study found 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 (Arora and Wolf, 2017).

[3] An additional challenge is defining the family ties that would qualify for elder care. For example, under

In this paper, we create a high-frequency panel dataset to estimate the dynamic relationship between work and caregiving for new caregivers.[4] Specifically, we leverage a relatively underutilized source for information about family caregiving - the Survey of Income and Program Participation (SIPP). The SIPP is a nationally representative survey following households for up to six years with interviews every four months. Along with a core interview that collects earnings and employment information, the SIPP includes a range of topical modules, including a series of questions about informal caregiving. Using this module, we can identify respondents who are family caregivers, and, importantly, determine when they started providing informal care. We use the 1996-2008 panels of the SIPP, and respondents to their Social Security Administration administrative record We leverage retrospective information about unpaid caregiving to adults reported in the topical module to position the start of a caregiving spell within a panel for those respondents who report starting caregiving within 24 months of the informal care module (approximately two-thirds of the way into the SIPP panel), allowing us to track labor force outcomes for up to 10 years before and seven years after the start of a caregiving spell.

We then use an event study approach to examine the dynamic effects of caregiving on range of labor supply related outcomes found both in the administrative and survey data. In the administrative data we study annual outcomes including employment and earnings and receipt of retirement or disability benefits. In the survey data we focus on monthly outcomes (aggregated by wave) and also study hours worked, non participation and unemployment, which we can observe for up to six waves (two years) before and 11 waves (four years) after the start of a caregiving spell. We employ several approaches to exploit variation in the timing of caregiving spells among caregivers to control for the presence of time-varying heterogeneity in our estimates Specifically, we include controls for linear pre-trends (motivated by visual evidence from non parametric event study results) and we use the labor supply of future caregivers to estimate the counterfactual labor supply of recent caregivers (Fadlon and Nielsen, 2017; Deshpande and Li, 2017).

Our results suggest that the probability of employment declines by approximately two percentage points immediately following the start of caregiving and this decline is sustained for at least two years. The decrease in employment is accompanied by a drop in (unconditional) earnings, and is driven largely by exit from the labor force, rather than by transitions into unemployment. We find suggestive evidence of transitions into self-employment for some subgroups of caregivers, as well as increases in Social Security Disability Insurance (DI) claiming. Finally, we document pre-trends and dynamic effects *before* the start of measured caregiving spells and we find evidence of significant heterogeneity in these dynamics across key subgroups of caregivers.

This paper makes several contributions. First we describe the informal care module in the SIPP, a survey of informal caregiving that is not commonly used by economists to look at the effects of caregiving on work.[5] Because the SIPP surveys a nationally representative sample,

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the Family and Medical Leave Act of 1993, a worker may take protected leave to care for a biological, step, foster, or adoptive parent, but not a parent-in-law.

[4]We define new caregivers as those who have been caregiving for two years or less.

[5]He and McHenry (2015) is a notable exception, although their focus is the effect of work on caregiving.

it provides a more complete picture of caregiving than the HRS, which is representative of the US population over 50. Half of all family caregivers were between the ages of 18 and 49 in 2009 (National Alliance for Caregiving and AARP, 2009). Additionally, while the HRS captures eldercare provided to spouses and parents, the SIPP surveys respondents who provide any kind of care, including care to friends, neighbors, and extended relatives. As document, a surprisingly high amount of care is provided to people who are not spouses or parents a trend which is mirrored in national statistics (National Alliance for Caregiving and AARP, 2009; Houser et al., 2015). For example, we find that 20% of caregivers provide care to other relatives.

Next, we leverage the retrospective caregiving information to create a novel panel dataset that allows us to observe dynamic employment outcomes at a high frequency before and after caregiving starts. Existing studies of the relationship between caregiving and work in the US rely primarily on the Health and Retirement Study (HRS), a nationally representative survey of the US population over 50 (Fahle and McGarry, 2017; Van Houtven et al., 2013; Skira, 2015). The HRS is a biennial panel, and measures both caregiving and employment outcomes at two-year intervals. While the econometric challenges of identifying the causal effects of caregiving on work and related outcomes can be reasonably addressed using panel data techniques and instrumental variables, measuring short- and medium-run *dynamic* responses requires a data set that captures employment and caregiving outcomes at a higher frequency.[6] Finally, linking the sample of caregivers to administrative data allows us to examine annual outcomes, extending the SIPP panel, and allowing us to link short-, medium- and long- term employment outcomes for caregivers. To our knowledge, ours is the first study to identify caregivers in administrative data in the US context.

The rest of the paper proceeds as follows: In Section 2, we describe the data construction and provide descriptive statistics for caregivers in the SIPP. Section 3 describes the empirical strategies we employ to identify the effects of caregiving on employment outcomes. We present the results for both strategies in Section 4 and offer some preliminary conclusions in Section 5.

2 Data

We use the 1996, 2001, 2004 and 2008 panels of the Survey of Income and Program Participation (SIPP).[7] Each panel follows a nationally representative sample of U.S. households over two and a half to six consecutive years, with regular interviews at four month intervals (referred to as "waves"). Along with the core longitudinal survey which collects detailed monthly information on demographics, employment, earnings, and program participation, in each wave households respond to topical modules which provide detailed but cross-sectional information on specific topics including informal caregiving.

We identify caregivers from the informal care topical module, which is administered two to three years into the longitudinal panel and asks all respondents the following question:

[6] Van Houtven et al. (2013) describe an instrumental variables approach in detail.

[7] Earlier panels of the SIPP do not ask about informal caregiving.

"There are situations in which people provide regular or unpaid care or assistance to a family member or friend who has a long-term illness or a disability. During the past month, did you provide any such care or assistance to a family member or friend living here or living elsewhere?" Respondents who identify as caregivers on the basis of this question then provide details about who they provide care to, and for how many years they have been providing care (less than one year, one year, two years, etc). Focusing on respondents who have been providing care for two years or less, we leverage this retrospective information to approximately date the start of a caregiving spell within the SIPP panel, allowing us to construct a longitudinal measure of caregiving outcomes for a subset of SIPP respondents, and to observe labor force participation, earnings, and retirement behavior up to two years before and two years after the start of a caregiving spell.

We next link this sample of caregivers to their SSA administrative records and construct a longitudinal panel following caregivers for 10 years before and seven years after the start of their caregiving spell. In order to match SIPP to administrative earnings and beneficiary data, the Census Bureau must receive consent from respondents. The match is based on the respondent's Social Security number (SSN), which is suppressed for research use. In our sample, 81.9% of respondents match to administrative data. Prior to the 2008 panel, respondents had to provide their SSN, so non-matches are due to a combination of non-consent and failure to recall. Starting with the 2008 Panel, the matching process was automated, so non matches are due solely to non-consent. Appendix Table A1 compares demographic characteristics for the full SIPP sample and the sub-sample of new caregivers who do and do not have an administrative match. Respondents without an administrative match are younger, more likely to be Hispanic, and have lower levels of education than the matched sample. Among new caregivers, unmatched respondents are more likely to be caring for a non-relative.

We note two important features of our measure of caregiving. First, this measure is subject to selection bias arising from length-biased sampling: the set of individuals who are observed in a caregiving spell at the time of the informal care topical module (a "stock" sample), will tend to over-represent those engaged in longer spells (Kiefer, 1988). The retrospective inclusion of individuals who have provided any care in the last month mitigates the degree of bias in comparison to a screening question that would have collected information only from individuals actively providing care, but it is larger than if individuals had been asked to provide information about care ever provided. While the latter screener would more accurately characterize caregivers, it would nonetheless not be possible to link monthly labor supply information for spells that occurred beyond the SIPP sample window. We attempt to mitigate some of the bias by including only individuals who have started a caregiving spell within the last two years. The average caregiving spell lasts 4.5 years in most nationally representative estimates, though most estimates of caregiving duration are generated from a similar "stock" sample and will therefore suffer from the same bias (Houser et al., 2015; National Alliance for Caregiving and AARP, 2009). Finally, our sample of caregivers is right-censored: while we observe the reported start of a caregiving spell, we do not observe when it ends.

The second notable feature is that we rely on self-reports to determine caregiver status. Nationally representative surveys that use self-reports of care*givers* often results in significantly higher numbers of caregivers than caregiver estimates that rely on reports from their care recipients (Giovannetti and Wolff, 2010). Among surveys that measure caregiving based on self-reports, caregiver estimates also vary dramatically based on question wording. The SIPP wording is precise in that it asks about care provided for a long-term illness or a disability specifically, and thus generates caregiving prevalence estimates that are on the conservative end of the spectrum: 5% of respondents self-identify as caregivers in the SIPP, compared to 17% of respondents in the American Time Use Survey Eldercare Module.[8] However, there is likely significant heterogeneity in individual latent thresholds for reporting a caregiving spell that cannot be identified from this type of survey question.

2.1 Descriptive Statistics

We report descriptive statistics from the informal care module in Table 1, corresponding to wave 9 for the 2008 panel and wave 7 for the 1996, 2001, and 2004 panels. This cross-section includes over 237,000 individuals age 18 and over.[9] Of these, 12,743 individuals, or 5% of the full sample, report having provided unpaid care in the past month.

Table 1 also reports sample statistics about the details of the caregiving spell. Some 15% of the sample is providing care to a spouse, and 22% to a parent or a parent-in-law. Nearly 20% care for another relative, and a quarter of the sample is caring for a non-relative, or somebody with an unspecified relationship.[10] Nearly one quarter of the sample is caring for a child with a long-term illness or disability, underscoring that the definition of informal care in the SIPP is not limited to the elderly. Because we are focused on caregiving beyond the parent-child relationship, going forward we drop individuals who report providing care only to children from the analysis.[11]

The remaining caregivers in this sample provide care for about 11 hours per week, for on average 1.2 care recipients. Nearly 60% of care is provided to recipients outside the caregiver's household. 41% of caregivers report provide help with Activities of Daily Living (ADLs), and 92% report providing help with Instrumental Activities of Daily Living (IADLs). Over half of caregivers also provide medical help, highlighting that the majority of caregivers are engaged in significant and time intensive caregiving. Finally, Table 1 also reports sample statistics on the caregiving duration. Some 22% of caregivers started providing care within the last year, 12.0% have been providing care for a year and 15.4% have been providing care for two years. Half the sample have been providing care for three years or longer. The distribution of observed care duration is necessarily biased towards longer spells (a well-known sampling bias problem with "stock" sampling), so in our analysis we focus on "new" caregivers, those who have been providing care for two years or less to minimize concerns about length-biased sampling.

We present descriptive statistics for this sample of new caregivers in column 1 of Table

[8]Calculated by author and provided upon request.

[9]The full SIPP sample includes respondents 15 and older.

[10]Percentages do not add up to 1 because individuals can specify up to four care recipients.

[11]We keep respondents providing care both to own children and other adults.

Table 1: Descriptive Statistics: SIPP Informal Care Topical Module

	Mean
Full Sample	(N= 237,385)
Any caregiving	0.05
Caregiver Sample	(N=12,743)
Caring for:	
Spouse	0.15
Parents or in-laws	0.22
Other relative	0.19
Other	0.25
Child	0.24
Caregiver to Adults Sample	(N=10,209)
Hours of care per week	10.9
Num adults caring for	1.2
Care recipient outside household	0.59
Helps with ADLs	0.41
Helps with IADLs	0.92
Helps with medical care	0.51
Sole caregiver	0.48
Started Care:	
Within the past year	23.0
1 year ago	12.0
2 years ago	15.4
3+ years ago	50.0

Notes: Table reports weighted summary statistics for the pooled 1996, 2001, 2004 and 2008 SIPP surveys. Statistics are measured during the Informal Care module.

2, and compare to the sample of long-term caregivers (three or more years) in column 2 and to non-caregivers in column 3. Panel A reports demographic characteristics and employment outcomes from the survey data for the wave in which the topical module was administered, and panel B reports employment outcomes from the linked administrative data, measured in the year that the topical module was administered. Starting with the demographic characteristics in panel A, compared with non-caregivers, caregivers are older, more likely to be female, more likely to be white, and more likely to be married. They are also somewhat more likely to have graduated from college. Comparing new and long-term caregivers, new caregivers are younger, more likely to be female and somewhat less likely to be white, married, and college educated than long-term caregivers, highlighting the potential for selection bias from length biased sampling.

The rest of Table 1 reports sample statistics for the variables that enter as outcomes in our analysis. Staying with the survey data in panel A, overall caregivers are less likely to be employed, but conditional on working are more likely to be self-employed than non-caregivers. They are also more likely to be out of the labor force, and more likely to self-identify as retired than non-caregivers. Caregivers also participate less in the labor market on the intensive margin: they are more likely to work part time, and work fewer hours per week than non-caregivers. However, we do not see evidence of large difference in individual monthly earnings, conditional on working. Caregivers live in households with slightly lower family income than non-caregivers.

Comparing new caregivers to long-term caregivers, we find that new caregivers are more likely to be working than long-term caregivers. If they are not working, they are more likely to report being unemployed and less likely to report being out of the labor force. New caregivers also earn lower monthly wages, conditional on working.

Panel B of Table 1 presents sample statistics for the linked administrative sample. To match the survey data, these outcomes are measured in the year that the informal care topical module was administered. We use data from the Master Earnings File to measure annual employer and self-employment earnings. Employer earnings data derive from IRS Forms W-2, and include wages and tips from all employers. Self-employment earnings data derive from IRS Form Schedule 1040 SE. The earnings variable combines both employer and self-employment earnings, indexed to 2018 dollars. We consider individuals with non-zero, combined earnings as employed in a given year. The self-employment earnings variable includes only the self-employment portion of earnings; individuals with non-zero, self-employment earnings are self-employed in that year.

Employment patterns from administrative records are similar to the survey data. 65% of recent caregivers are employed, compared with 59% of long term caregivers and 71% of non-caregivers. Annual employment measured in the administrative data is higher than monthly employment measured by the survey, pointing to the importance of higher frequency observations to capture within year changes in outcomes. Conversely, rates of self-employment are lower than those reported in the survey data, likely because IRS Form Schedule 1040 SE provides an incomplete picture of self-employment (Abraham et al., 2020). There is no difference in self-employment across these three subgroups. Annual Earnings are lower for caregivers, both overall and conditional on working. Conditional on working, new caregivers

Table 2: Demographic and Employment Characteristics

	Caregivers <3 years (1)	Caregivers 3+ years (2)	Non Caregivers (3)
Panel A: SIPP survey Sample			
Age	50.35	53.18	43.55
Female	0.64	0.62	0.51
White	0.74	0.75	0.70
Black	0.12	0.11	0.11
Hispanic	0.09	0.09	0.13
Married	0.60	0.62	0.52
College Grad	0.24	0.26	0.23
Working	0.55	0.53	0.61
Self-employed (any)	0.10	0.11	0.09
Unemployed	0.05	0.04	0.04
Not in the Labor Force	0.40	0.42	0.34
Retired	0.20	0.23	0.14
Working Part Time	0.40	0.40	0.32
Usual Hours	30.67	32.27	34.83
Total Monthly Earnings (Unconditional)	1734.02	1691.91	2013.00
Total Monthly Earnings (Conditional)	3390.87	3531.40	3522.77
Family Monthly Income	5921.14	5958.20	6433.80
Panel B: Linked Administrative Data Sample			
Employed	0.65	0.59	0.71
Self-employed (any)	0.08	0.08	0.08
Earnings	28,424	26,814	34,503
Earnings (cond.)	43,974	45,304	48,722
Self-emp earnings (cond.)	19,934	24,714	30,512
Receiving OASI	0.24	0.29	0.19
Receiving DI	0.04	0.05	0.04

Notes: Table reports weighted summary statistics for the pooled 1996, 2001, 2004 and 2008 SIPP surveys in Panel A. Panel B reports summary statistics for the linked pooled SIPP-SSA sample. Statistics are measured during the Informal Care module in panel A and in the same year as the informal care module in Panel B. Column 1 reports statistics for the sample of respondents who report starting care in the previous 2 years, and column 2 reports statistics for respondents providing care for 3 or more years. Column 3 reports statistics for non caregivers.

earn just under \$44,000, compared with \$45,300 for long-term caregivers and nearly \$49,000 for non-caregivers. Self-employment earnings follow the same pattern.

We use monthly data from the Master Beneficiary Record (MBR) to identify Old Age and Survivors Insurance (OASI, or retirement) beneficiaries and Disability Insurance (DI) beneficiaries. In this study, OASI beneficiaries include retired workers, as well as dependents and survivors of workers; DI beneficiaries include disabled workers. We consider individuals as receiving OASI or DI benefits in a given calendar year if they receive benefits at least one month during the year. 24% of new caregivers are receiving OASI retirement benefits, compared with 29% of long-term caregivers and only 19% of non-caregivers, likely reflecting the age differences between these groups. There do not appear to be large difference in DI claiming behavior between caregivers and non-caregivers.

These descriptive statistics underscore that caregivers have different employment outcomes than non caregivers, but also hint at the dynamic employment trajectories of family caregivers over time. We now turn to describing the methods we employ in the remainder of the paper to map out these trajectories.

3 Empirical Approach

Given that we observe both labor force and caregiving outcomes over time, we leverage several panel data methods to estimate the relationship between starting a caregiving spell and a range of employment-related outcomes. We estimate both non-parametric and semi-parametric event studies as well as a "stacked" difference-in-differences method that exploits variation in the timing of caregiving spells (Fadlon and Nielsen, 2017; Deshpande and Li, 2017). We present each strategy below before turning to the results in section 4.

3.1 Non-parametric Event Study

We first estimate a non-parametric event study model to visually assess the evolution of employment, earnings and retirement outcomes relative to the reported start of a caregiving spell. Our model takes the following form:

$$y_{i\tau} = \gamma_t + \beta_0 X_{i\tau} + \sum_{\tau} \mu_r D^{\tau} + \varepsilon_{i\tau} \tag{1}$$

Here $Y_{i\tau}$ is the outcome of interest for individual i in event time τ, and γ_t is a calendar time fixed effect. In the survey sample, calendar time corresponds to the calendar year and month of the survey, while in the administrative sample, this corresponds to the calendar year. $X_{i\tau}$ is a vector of individual controls, including a quadratic in age. Our coefficients of interest are the μ_r, which are the coefficients on D^{τ}, the indicators for event time, or time relative to the start of the caregiving spell. These capture the changes in the outcome variable $Y_{i\tau}$ relative to the omitted category. In the survey sample, event time is measured as the survey wave relative to the wave in which caregiving started, and the omitted category is μ_{-3}, which corresponds to 3 waves, or approximately one year before the start of a care spell. In the administrative data, event time is years since the start of the caregiving spell, and we omit μ_{-1} (again, corresponding to roughly one year before the start of a care spell.)

The results from the non-parametric event study allow us to visually observe trends in outcomes in the months and years around the reported start of a caregiving spell, and to identify patterns and pre-trends. We do not interpret the coefficients as causal. A causal interpretation would require the timing of the start of a caregiving spell to be uncorrelated with outcomes, and we suspect this is unlikely to be true in many cases. For example, Mommaerts and Truskinovsky (2020) and He and McHenry (2015) find that changing employment outcomes may precede caregiving for some individuals. It is also likely that individuals time the start of a caregiving spell to coincide with a job transition, such as retirement. Finally, because we rely on retrospective self-reporting about the start of a caregiving spell, it is possible that respondents consider themselves to be a caregiver only once they stop working and start providing care full time, even if they previously performed caregiving duties. Indeed, as we discuss in detail in the next section, we observe pre-trends in all outcomes, which motivate the next two empirical strategies.

3.2 Semi-parametric Event Study

Our next empirical approach is to use a semi-parametric event study to control for linear trends in event-time (Dobkin et al., 2018). This is motivated by a visual inspection of the results from the non-parametric event studies, which suggest that linear models are a good approximation of most of the pre-trends in outcomes. Our parametric models take the following functional form:

$$y_{i\tau} = \gamma_t + \beta_0 X_{i\tau} + \delta r + \sum_{r=0}^{F} \mu_r D^{\tau} + \varepsilon_{i\tau} \tag{2}$$

The key difference between Equation (1) and Equation (2) is the introduction of the term r, a linear pre-trend in event time. This changes the interpretation of the coefficients of interest, which now show the change in outcomes following a care spell relative to any preexisting linear trend δ. As described by Dobkin et al. (2018), to interpret these coefficients as causal requires the assumption that conditional on controls, the timing of the start of a caregiving spell is uncorrelated with any deviations in the outcome from a linear trend in event time. We use this specification to summarize the magnitude of the changes in employment related outcomes following the start of a caregiving spell. In robustness analysis we show results that include individual fixed effects and individual controls.

3.3 Stacked Difference-in-Differences

In our final empirical approach, we use variation in the timing of caregiving spells and construct a control group to estimate counterfactual trends. In an ideal setting, we could identify a control group of individuals who are identical to caregivers (treated respondents) both in the evolution of their employment outcomes and their ex ante expectations about caregiving, but who do not start providing care within the panel (i.e., they remain untreated). We operationalize this ideal by using a "stacked" difference-in-differences method, following Fadlon and Nielsen (2017) and Deshpande and Li (2017). Specifically, we compare respondents who experience a caregiving event to a control group of individuals who will begin caregiving at some time in the future. This method allows us to exploit the *timing* of caregiving spells among people evolving along similar trajectories. Unlike the semi-parametric event study, where we assume a linear pre-trend, in this approach we allow the trends in event-time to be determined by the evolution of outcomes in the control group. We rely only on the administrative sample for this part of the analysis, as the survey sample does not provide a balanced panel with sufficient periods before and after the start of a caregiving spell.

3.3.1 Sample Design

This approach requires a different data structure, which we construct as follows: for each calendar year (or survey wave), we take the subset of individuals who begin caregiving in that year and designate them as the treatment group. Every individual who started caregiving at least δ periods in the future is assigned to the control group. We then redefine event time r with respect to caregiving for the control group: we define a placebo caregiving spell δ years *before* they actually report starting caregiving. For the treatment group, r is unchanged, it is the year they report starting a caregiving spell.

We repeat this procedure for each calendar year and then append all the data sets together.[12] The resulting data set is comprised of the original sample of caregivers, all "matched," in calendar time, to a control group of future caregivers. One limitation of this approach, as described in detail in Fadlon and Nielsen (2017), is that we can only measure dynamic causal effects $\delta - 1$ periods post-shock (i.e. until the control group becomes treated). We set δ as 6 years. Appendix Figure A1 captures this empirical approach, graphing the raw plots of the evolution of outcomes in both the treatment and control groups around event time in the administrative data sample. For most outcomes, the pre-trends in event time are captured reasonably well by the counterfactual trends in the control group.

3.3.2 Estimating Equation

Having linked every caregiver observation in the sample with a control, we estimate the following difference in differences model:

$$y_{i\tau} = \gamma_t + \beta_0 X_{i\tau} + \beta_1 Treat_i + \sum_{\tau} \mu_r D^{\tau} + \sum_{\tau} \eta_r (Treat_i \times D^{\tau}) + \varepsilon_{i\tau} \quad (3)$$

where $Y_{i\tau}$ is an outcome for individual i at event time τ, $Treat$ is an indicator for if the household belongs to the treatment group, and as before, the D^{τ} are indicators for event time, or time period relative to the start of the caregiving spell. The coefficients of interest,

[12] An observation does not serve as its own control, however households do appear in the sample multiple times as controls.

η_r now represent the dynamic changes in outcomes in the treatment group while controlling for changing outcomes in the control group. For table estimates, which summarize the magnitude and statistical significance of the effects, we estimate a pre-post version of equation (3), replacing the individual event-time indicators with a single indicator for the post period. We dummy out year 0. All observations are weighted using SIPP-provided survey weights and we cluster standard errors at the individual by treatment group level. This approach captures the average effect of starting a caregiving spell while controlling for changes in outcomes among future caregivers. The identifying assumption 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. However, this method does not alleviate the concern that caregiving and labor supply are two outcomes of a joint decision making process, rather than a response to a random shock.

4 Results

4.1 Event Study Results

We first present graphical results from the non-parametric and semi-parametric events studies for our two data samples: the matched administrative sample and the SIPP survey sample.

4.1.1 Administrative data sample

We start by reporting results from the matched administrative sample. Figure 1 shows the evolution of employment, earnings (including self-employment), retirement and DI receipt for 10 years before and seven years after the reported start of a caregiving spell. For each outcome, we plot the μ_rs from the non-parametric event study.

The point estimates and standard errors measure changes relative to the omitted category μ_{-1}, the year before caregiving started. In Table 3, we summarize the magnitude and statistical significance of the estimated effects at different points in time, using both the non-parametric estimates from Equation (1) and well as the semi-parametric estimates from Equation (2).

Notably, although all of the outcomes demonstrate substantive (and statistically significant) pre-caregiving patterns, discontinuities or inflection points are evident in year μ_0 or μ_1 for almost all outcomes. Focusing first on employment, there is a visually apparent drop in the likelihood of being employed in the first year after caregiving starts. In Panel 1 of Table 3 we report the magnitude of this change: in column 1, we show that in the year that caregiving starts (μ_0), the likelihood of being employed falls by 3.5 percentage points. The likelihood of working falls in the first year of caregiving, and then remains between 4 and 5 percentage points below the reference year (μ_{-1}) for the remainder of the observable period. The average effect over seven years is a 4.5 percentage point decrease in the likelihood of working, or a 6.4% drop from the pre-caregiving mean of 73%. The pattern over time suggests that, in aggregate, new caregivers transitions out of employment over a two year period following

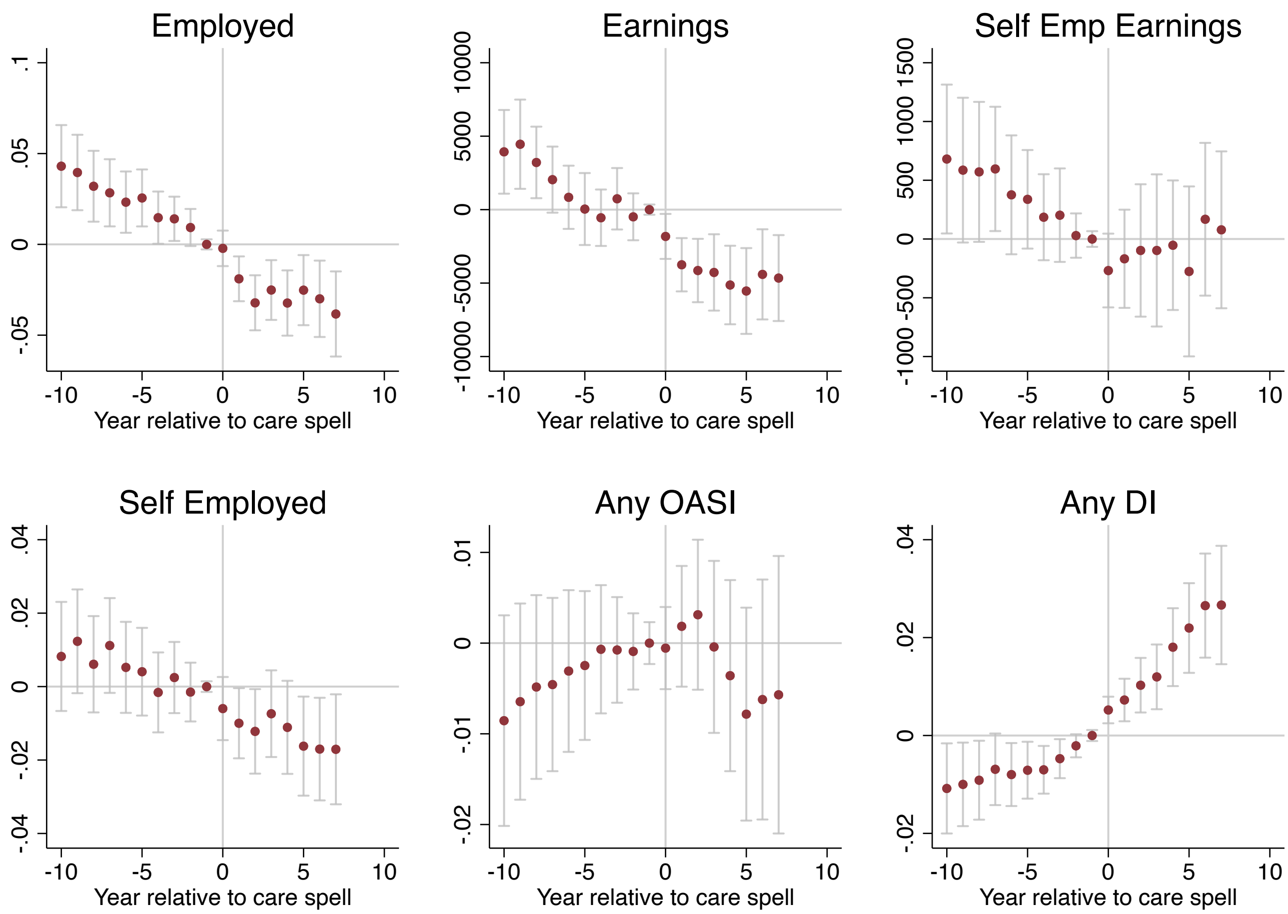

Figure 1: Caregiving and Employment: Administrative Data, Full Sample

Notes: The sample includes all SIPP respondents over 18 who have been providing care for two years or less at the time of the informal care module. Panels display regression coefficients and associated 95% confidence intervals from Equation 1, using the linked SIPP-SSA administrative data. Coefficients for μ_{-1} are normalized to zero. Standard errors clustered at the individual level.

the reported start of a caregiving spell, and do not return to the labor force within our observable time period.

However, these estimates do not take into account the pre-trends that are evident in Figure 1. In Panel 2 of Table 3, we present the results from Equation (2), our preferred specification for this sample, which reflect the changes in outcomes post caregiving relative to a linear pre-trend. As expected, the estimates are attenuated. Specifically, we find a statistically significant decrease in the likelihood of working of 2.2 percentage points in the first year after caregiving starts, but no significant deviations from the trend after. By the sixth year after caregiving, the likelihood of being employed returns to its pre-caregiving trend. In the seven years following the start of a caregiving spell, we find a marginally statistically significant decrease of 1.5 percentage points, or a 2.2% decrease in the likelihood of being employed.

Consistent with this decline in working, we see a gradual decline in unconditional earnings in the decade before the start of a caregiving spell and a discontinuous drop in earnings in the first year after caregiving starts, followed by a return to the pre-caregiving trend. As reported in Column 2 of Table 3, earnings fall by an average of over $4,600 annually (14%) in the first two years following the start of a caregiving spell, relative to the reference year, or by $1,080 (3.5%) relative to a linear pre-trend. By year 6 after the start of a spell, there is no meaningful difference in earnings relative to the trend. We note that a visual inspection of the pre-trend suggests that some discontinuities, in particular earnings fall between 10 and five years before the start of caregiving, but then remain flat for the five years prior to the spell.

Next, we look directly at self-employment and associated self-employment earnings. Self-employment can be a flexible work arrangement that is more compatible with caregiving responsibilities. Self-employment can also be a transitional form of employment for workers exiting the labor force into retirement. However, Figure 1 reveals that self employment, as measured in administrative data, follows roughly the same patterns that employment does. There is a discrete, though imprecise, drop in self-employment earnings in the year that caregiving starts. Table 3 reports the magnitudes of these changes. Although there is a statistically significant decrease of 1.6 percentage points in the likelihood of being self-employed over the post period, once we control for a linear pre-trend, there is no difference in the likelihood of being self-employed following the start of a caregiving spell, and self-employment earnings are positive. Overall, we find no evidence that employed caregivers transition into self-employment as a more flexible arrangement to help manage caregiving responsibilities.

Caregivers leaving the labor market to provide care may compensate for lost earnings by claiming social insurance benefits. In our analysis we focus on two such programs, retirement (OASI) and disability insurance (DI) benefits. Assessing these two outcomes visually in Figure 1, both exhibit a positive, roughly linear trend in the decade before caregiving starts. There is no clear evidence that OASI claiming increases after the start of a caregiving spell.

We see an increase in the likelihood of claiming disability benefits. As reported in column 6 of Table 3 (panel 2), caregivers are 0.9 percentage points more likely to receive DI after

Table 3: Admin Main Results

	Working	Earnings	Self Emp Earnings	Self Emp	Any OASI	Any DI
	(1)	(2)	(3)	(4)	(5)	(6)
Panel 1: Non Parametric Estimates						
Average effect, post period	-0.0449***	-5175.1***	-253.2	-0.0155***	-0.0005	0.0227***
	(0.0095)	(1210.5)	(321.3)	(0.0056)	(0.0056)	(0.0050)
Effect at year 0	-0.0351***	-4140.4***	-330.8	-0.0120***	0.0042	0.0111***
	(0.0070)	(805.9)	(245.2)	(0.0047)	(0.0040)	(0.0031)
Effect at year 1	-0.0486***	-4537.2***	-303.6	-0.0146***	0.0053	0.0142***
	(0.0083)	(974.7)	(302.9)	(0.0053)	(0.0047)	(0.0037)
Effect at year 2	-0.0420***	-4716.5***	-362.3	-0.00996*	0.0021	0.0161***
	(0.0090)	(1190.1)	(353.1)	(0.0057)	(0.0053)	(0.0043)
Effect at year 6	-0.0466***	-5995.3***	-111.4	-0.0193**	-0.0041	0.0298***
	(0.013)	(1703.6)	(400.1)	(0.0075)	(0.0076)	(0.0066)
Average effect, first 2 years	-0.0453***	-4625.6***	-332.6	-0.0123**	0.0037	0.0151***
	(0.0083)	(1055.2)	(322.2)	(0.0051)	(0.0048)	(0.0040)
Panel 2: Controlling for Linear Pre Trends						
Average effect, post period	-0.0145*	-1232.9	257.6	-0.0030	-0.0045	0.0087***
	(0.0080)	(832.4)	(241.7)	(0.0053)	(0.0049)	(0.0031)
Effect at year 0	-0.0129**	-1425.9**	100.3	-0.0043	-0.0001	0.0045**
	(0.0058)	(574.2)	(170.1)	(0.0042)	(0.0033)	(0.0020)
Effect at year 1	-0.0218***	-1272.5*	214.8	-0.0053	0.0001	0.0062**
	(0.0074)	(752.2)	(248.0)	(0.0053)	(0.0043)	(0.0027)
Effect at year 2	-0.0102	-846.4	252.3	0.0010	-0.0041	0.0067**
	(0.0086)	(942.0)	(287.1)	(0.0059)	(0.0053)	(0.0033)
Effect at year 6	0.0012	-171.7	813.5**	-0.0028	-0.0133	0.0156***
	(0.0132)	(1518.5)	(325.4)	(0.0082)	(0.0089)	(0.0058)
Average effect, first 2 years	-0.0165**	-1080.1	231.7	-0.0025	-0.0018	0.0064**
	(0.0075)	(804.9)	(259.0)	(0.0051)	(0.0046)	(0.0029)
Unique Obs	4289	4289	4289	4289	4289	4289
Pre- Care mean	0.73	31797.6	1763.7	0.078	0.147	0.029

Notes: The sample includes all SIPP respondents over 18 who have been providing care for two years or less at the time of the informal care module, and who can be linked to the SSA administrative data. Panel 1 reports results from Equation (1) and panel 2 reports results from Equation (2). Within each panel, the first row reports results for each outcome from a single regression, pooling all post caregiving observations. Rows 2-5 report the results of a single regression with individual indicators for each post caregiving year. Row 5 reports average effects for the first two post caregiving years pooled together. Robust standard errors clustered at the individual level are reported in parentheses. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$)

the start of a caregiving spell, a more than 30% increase over the pre-caregiving mean. This effect appears immediately and increases over time. Six years after the start of a caregiving spell, family caregivers are 1.6 percentage points, or 55% more likely to claim DI as they would have been prior to a caregiving spell. Given that the average waiting period between making an initial claim and receiving benefits is two years, these dynamics suggests these DI claims are initiated both before and after the reported start of a caregiving spell.

As has already been noted, all of our observed outcomes demonstrate substantive and statistically significant pre-trends in the decade before the reported start of a caregiving spell, which can be roughly approximated by a linear trend. There are several possible reasons for these trends. First, our event study analysis could be capturing selection into caregiving based on employment-related outcomes. Alternatively, these could evidence of anticipatory effects: future caregivers who anticipate that they will start caregiving in the future may change their labor force participation ahead of time. Finally, it could be a respondent's latent threshold for self-identifying as a caregiving is higher than the threshold at which caregiving duties interfere with employment. In other words, the average caregiver may not report that they are caregiving until they have already exited the labor force to become a caregiver. Finally, we note that our findings are robust to a number of alternative specifications, including dropping sample weights, including individual fixed effects and individual controls, which we report in Appendix Table A2.

4.1.2 Heterogeneity (Administrative Data Sample)

The average effects presented in the previous section may be masking significant heterogeneity between caregivers in the evolution of employment outcomes around the start of a caregiving spell. For example, older workers may be eligible for social insurance programs such as OASI and DI. Older workers may also be more likely to transition into self employment. Meanwhile, younger workers may have more flexibility to transition between jobs. Women and men may be differentially attached to the labor force, or may have different latent thresholds for reporting caregiving. In Figures 2 & 3, we present visual results of our non-parametric event study model for key sub samples.

In Figure 2 we break the sample into three age groups: younger than 45, 45 to 61 and 62 and older.[13] We focus on these age groups because the interaction of work and caregiving will be different in different life phases. The subgroup age 45 to 61 will have the largest overlap of both caregiving and work responsibility and is most likely to be caring for aging parents. Those aged 62 and older are more likely to be caring for spouses, and may be timing caregiving to coincide with existing retirement plans. Consistent with this assumption, we find that older caregivers (those age 62 or older when they report caregiving) see the largest decreases in employment (5-7 percentage points), and large increases in OASI claiming in the year following the start of a caregiving spell. There is a smaller, but still evident decrease in employment for those aged 45 to 61. There is no detectable change in employment for caregivers younger than 45. All groups experience a fall in earnings, but those age 45-61 see an increase in self-employment earnings. The increase in DI receipt evident in the average

[13] Age groups are calculated as age when caregiving starts, so the panel is balanced over event time

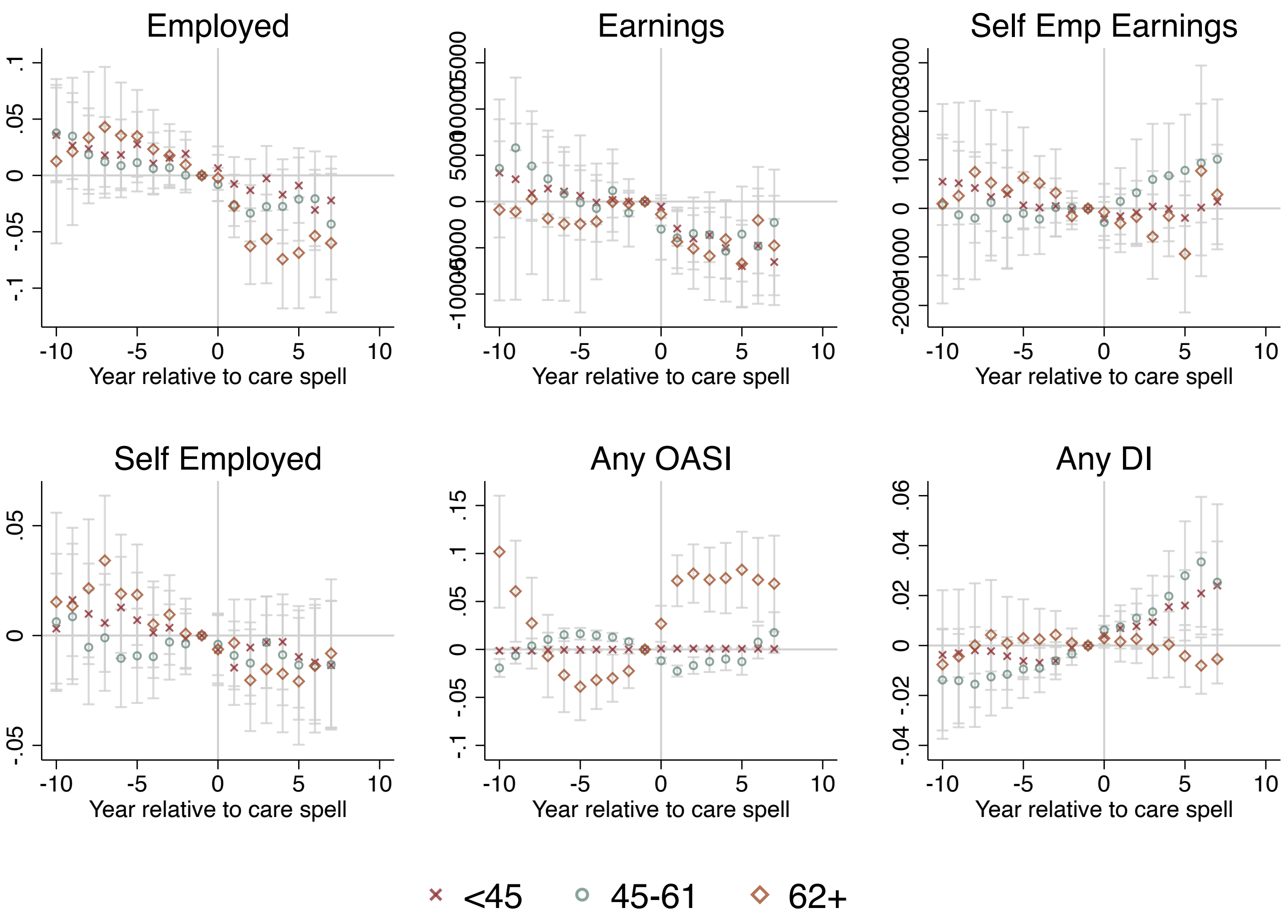

Figure 2: Caregiving and Employment: Administrative Data, by Age

Note: The sample includes all SIPP respondents over 18 who have been providing care for two years or less at the time of the informal care module. Panels display regression coefficients and associated 95% confidence intervals from Equation 1, using the linked SIPP-SSA administrative data. Coefficients for μ_{-1} are normalized to zero. Standard errors clustered at the individual level.

estimates are logically driven by the younger (under 62) age groups.

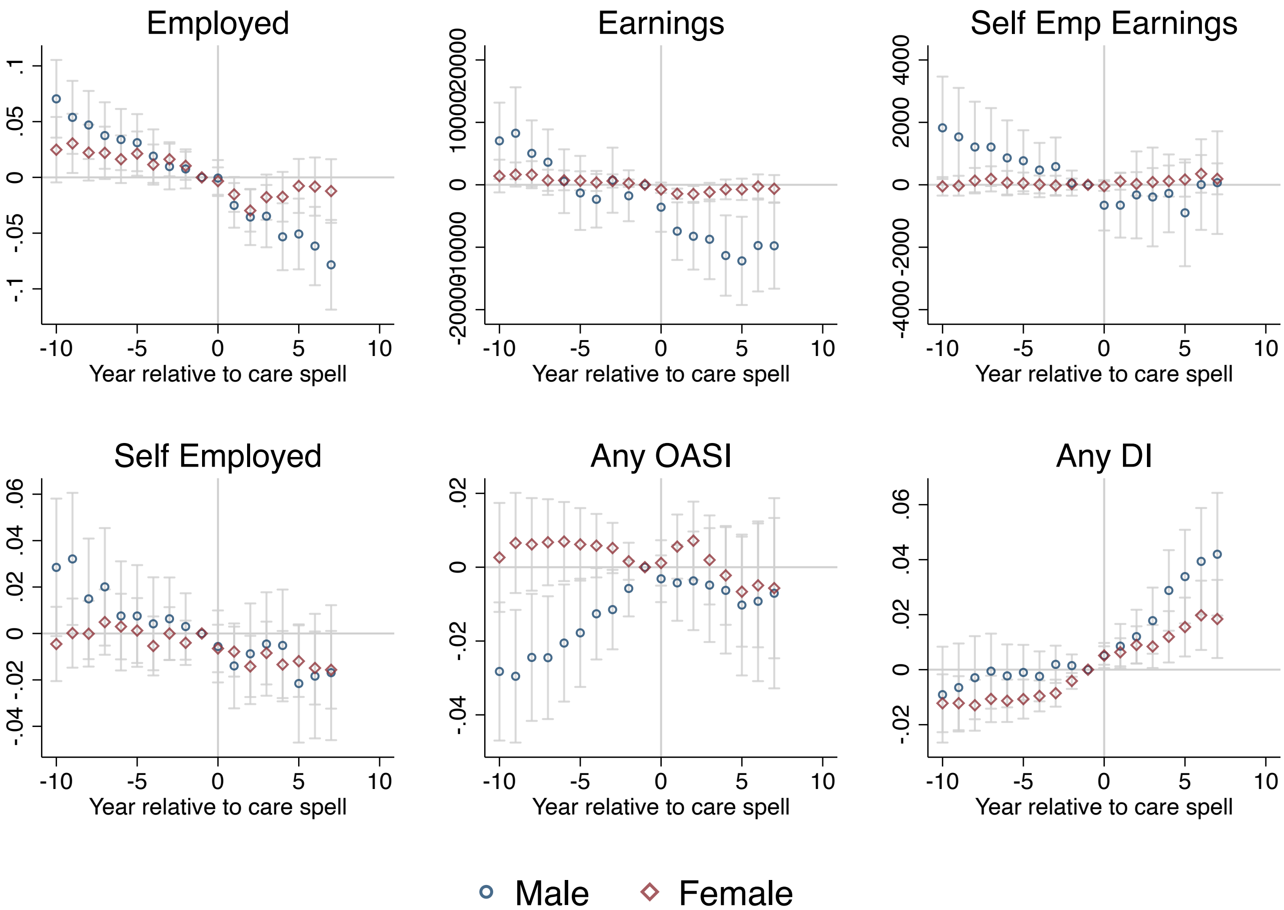

Figure 3: Caregiving and Employment: Administrative Data, by Gender

Note: The sample includes all SIPP respondents over 18 who have been providing care for two years or less at the time of the informal care module. Panels display regression coefficients and associated 95% confidence intervals from Equation 1, using the linked SIPP-SSA administrative data. Coefficients for μ_{-1} are normalized to zero. Standard errors clustered at the individual level.

While women are typically associated with family caregiving responsibilities, nearly 40% of caregivers of adults in the US are men.[14] Existing studies highlight that caregiving responsibilities have a different impact on men's and women's labor force participation, highlighting the need to look at outcomes separately by gender (Van Houtven et al., 2013). In Figure 3, we present results separately for men and women and find that employment patterns around the start of a caregiving spell vary dramatically by gender. Notably, the pre-trends in outcomes in Figure 1 are largely driven by men, and men continue to see decreasing employment and earnings for at least seven years following the start of a caregiving spell.

[14]In the SIPP, men make up over 35% of caregivers.

By contrast, female caregivers experience both less dramatic declines in employment before the start of a care spell and a rapid return to near pre-caregiving rates approximately two years after starting caregiving. The results for men are noticeably noisier, due to the smaller sample size.

A possible reason for the divergent trends could be that men and women have different latent thresholds for self-identifying as caregivers, as noted in the previous section. Existing studies have found that mean and women engage in different caregiving activities (Houser et al., 2015; Van Houtven et al., 2013). Alternatively men and women may have different reasons for entering into caregiving. For example, Mommaerts and Truskinovsky (2020) consider the role of business cycles on the propensity to provide care and find that men are responsive to the opportunity cost of caregiving, while women are not. If men take on caregiving following a job loss while women take on caregiving in response to a need, this may explain some of the differences in trends between genders.

4.1.3 Survey Data Sample

The results in the previous section allow us to examine year-over-year changes in employment outcomes captured by administrative data. Next, we turn to the SIPP survey data to study the changes in related outcomes in a shorter time frame and at a higher frequency. Specifically, we examine the patterns in outcomes across survey waves relative to the start of a caregiving spell. Recall that a survey wave corresponds to four calendar months. We choose to focus on waves rather than months for several reasons. First, the structure of the survey and the limited specificity of the retrospective caregiving information makes it difficult to pinpoint the precise month in which caregiving started, creating some measurement error close to the start of a caregiving spell. Averaging outcomes over four months reduces some of this noise. Second, averaging outcomes over four months reduced some of the issues related to the well know problem of seam bias in the SIPP.[15]

Figure 4 plots the μ_r's from Equation (1) for the survey sample. We present results for six self-reported outcomes: working for pay, self-employed, usual hours worked, unemployment status, labor force non-participation and individual earnings for up to seven waves (28 months) before and 11 waves (44 months) after the approximate start of a caregiving spell. All coefficients and standard errors are plotted relative to μ_{-3}, approximately three waves (12 months) before the wave in which a caregiving spell starts. In the figure, the red vertical lines correspond to one wave before and one wave after the start of a caregiving spell. These eight months capture a transitional period where we cannot be certain of caregiving status. We report estimates in Table 4, and we control for these transitional waves, and start the post period at wave 2, or approximately four months after the start of a caregiving spell. Because we do not observe noticeable pre-trends before the eight-month transitional period indicated by the vertical red lines, our preferred specification for the magnitude and statistical significance of the effects is one without linear pre-trends (Equation 1). However in Table 4 we again present both sets of results.

[15] Seam bias refers to the empirical fact that employment status changes significantly more between survey waves (at the "seam" where to survey waves meet) than within survey waves.

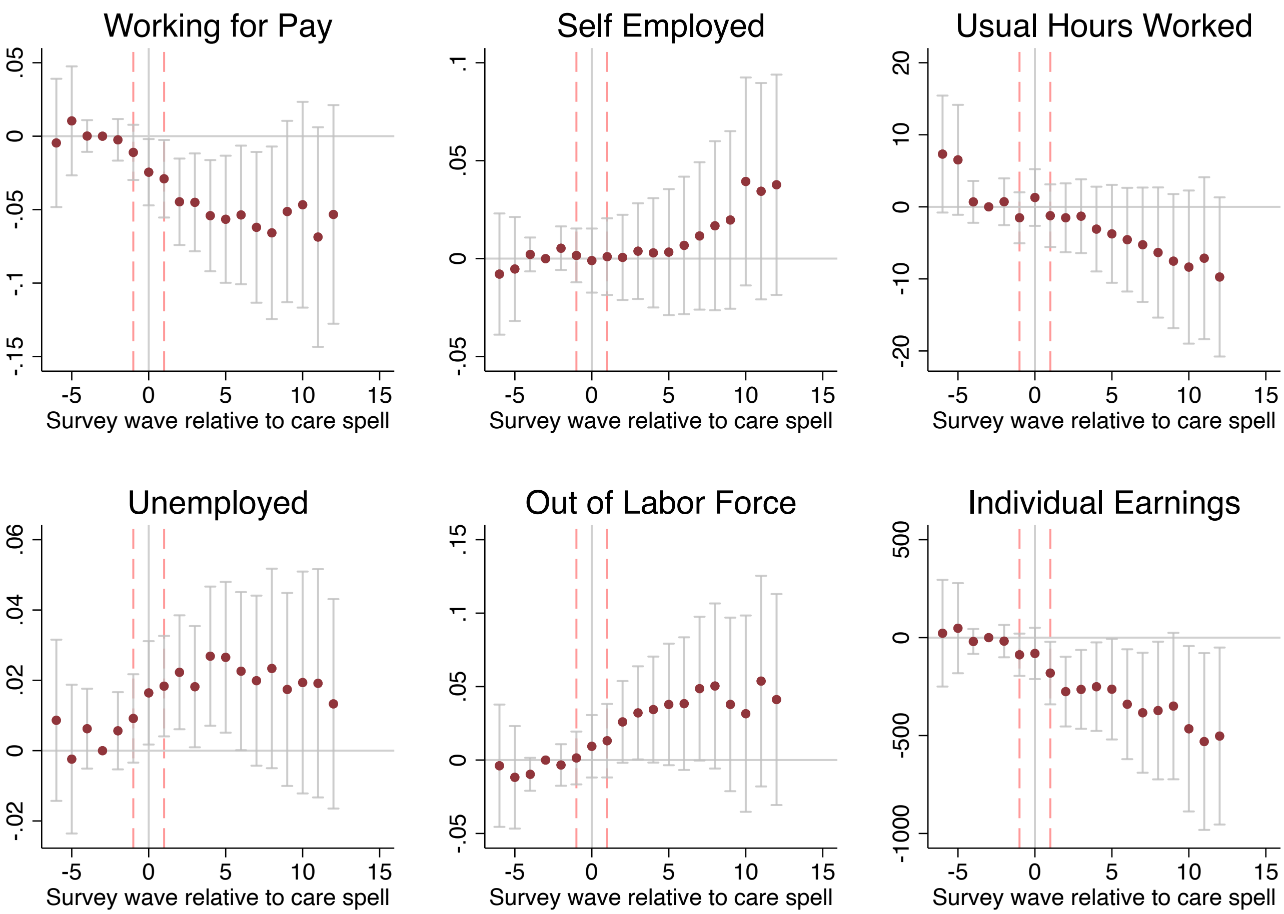

Figure 4: Caregiving and Employment: SIPP Data

Note: The sample includes all SIPP respondents over 18 who have been providing care for two years or less at the time of the informal care module. Panels display regression coefficients and associated 95% confidence intervals from Equation 1, using the linked SIPP-SSA administrative data. Coefficients for μ_{-1} are normalized to zero. Standard errors clustered at the individual level.

The results plotted in Figure 4 correspond roughly to what we observe in the administrative data. The impact of caregiving on employment and earnings is visually apparent immediately. By the second wave after caregiving starts, the likelihood of being employed falls by over 4 percentage points. In wave 6 (approximately 2 years after the start of a caregiving spell, employment is 5.4 percentage points lower than it was in the year before caregiving started. The impact over the entire post period is nearly 5 percentage points, or an 8 percent decrease from the year before caregiving started. In contrast to the administrative sample results, we see no change in the likelihood of being self-employed immediately after the start of a caregiving spell, and self employment appears to increase starting in wave 5 although this increase is not precisely measured. One explanation for the difference between these results and the administrative sample is the definition of self employment, which is self reported here.

This decrease in caregiving is matched by an increase in both unemployment and non-participation (Table 4, columns 4 and 5). In the first wave after the start of a caregiving spell, respondents are 1.8 percentage points more likely to be unemployed and nearly 3 percentage points more likely to be out of the labor force. While the increase in non-participation persist over the entire observable period, the likelihood of being unemployed is significantly attenuated by wave 9. Monthly earnings follow a similar pattern, falling by nearly \$300 per month by wave 2, and \$371 per month by wave 9. On average, earnings are \$274 lower in the post period, a reduction of 14% from the pre-caregiving mean of \$1939.

Finally, we examine the impact of caregiving on self-reported usual hours worked. Caregivers may reduce hours of work either permanently or temporarily to accommodate caregiving responsibilities while also remaining employed. Alternatively, caregivers may leave the labor force temporarily and then return to a part-time position. We see no discrete changes in self-reported (unconditional) usual hours worked around the start of a caregiving spell, although a downward trend is discernible from the event study. In wave 9, there is a marginally significant decrease of approximately nine hours per week, corresponding to over a day less than the pre-caregiving mean of 34 hours per week. In Appendix Table A3, we show that these findings are robust to a number of alternative specifications, including dropping sample weights, including individual fixed effects and individual controls.

4.2 Heterogeneity - Survey Sample

As with the administrative sample, we repeat this analysis for subgroups of respondents. In Figure 5, we split the sample by age, and in Figure 6 we split the sample by gender.

Turning first to Figure 5, in contrast to the annual results, we do not observe noticeable differences in the short run across age groups for most outcomes. The exception is the 45 to 61 age group, who experience an uptick in self-employment approximately one year following the start of a caregiving spell, and simultaneously report lower individual earnings. These patterns suggest that older workers who stop working at the start of a caregiving spell transition into self-employment as a more flexible, but lower paying, form of employment. The fact that we do not observe similar patterns in the administrative data may be due to differences what is captured as self-employment in tax records and what survey respondents

Table 4: SIPP Main Results

	Working	Self Employed	Usual Hours Worked	Unemployed	NILF	Earnings
	(1)	(2)	(3)	(4)	(5)	(6)
Panel 1: Non Parametric Estimates						
Average effect, post period	-0.0818***	-0.0009	-0.410	0.0130	0.0767***	-462.0***
	(0.0206)	(0.0146)	(3.364)	(0.0096)	(0.0197)	(116.5)
Average effect, year 1	-0.0772***	-0.0011	-0.0559	0.0112	0.0728***	-440.6***
	(0.0196)	(0.0139)	(3.206)	(0.0093)	(0.0187)	(110.0)
Average effect, year 2	-0.114***	0.0020	-2.817	0.0260**	0.103***	-609.6***
	(0.0292)	(0.0209)	(4.783)	(0.0132)	(0.0281)	(168.6)
Panel 2: w/individual Fixed Effects						
Average effect, post period	-0.0250	0.0029	2.131	0.0005	0.0220	-109.2
	(0.0162)	(0.0159)	(1.671)	(0.0086)	(0.0155)	(130.3)
Average effect, year 1	-0.0308*	0.0033	1.929	0.0053	0.0257	-97.41
	(0.0170)	(0.0171)	(1.592)	(0.0089)	(0.0165)	(140.8)
Average effect, year 2	-0.0451**	0.0042	1.442	0.0176	0.0348	-68.23
	(0.0215)	(0.0211)	(2.067)	(0.0117)	(0.0212)	(175.0)
Unique obs	4218	4218	584	3064	4218	4218
Pre-caregiving mean	0.597	0.0985	33.94	0.047	0.361	1939.2

Notes: The sample includes all SIPP respondents over 18 who have been providing care for two years or less at the time of the informal care module. Panel 1 reports results from Equation (1) and panel 2 reports results from Equation (2). Within each panel, the first row reports results for each outcome from a single regression, pooling all post caregiving observations. Rows 2-4 report the results of a single regression with individual indicators for each post caregiving wave. Row 5 reports average effects for the first post caregiving year, and row 6 reports results for the second post caregiving year. Robust standard errors clustered at the individual level are reported in parentheses. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$)

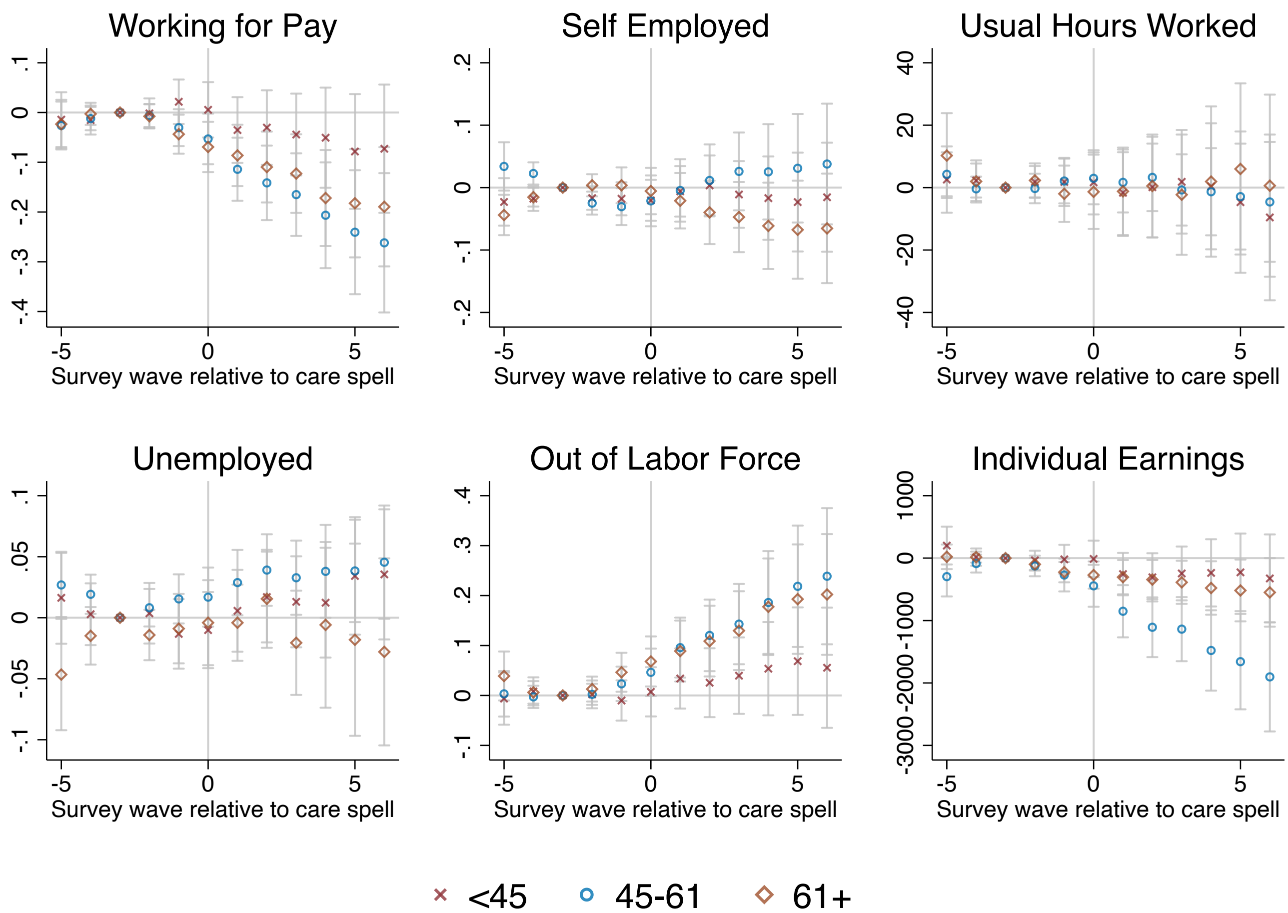

Figure 5: Caregiving and Employment: SIPP Data, by age

Note: The sample includes all SIPP respondents over 18 who have been providing care for two years or less at the time of the informal care module. Panels display regression coefficients and associated 95% confidence intervals from Equation 1. Coefficients for μ_{-3} are normalized to zero. Standard errors clustered at the individual level.

consider as self-employment.

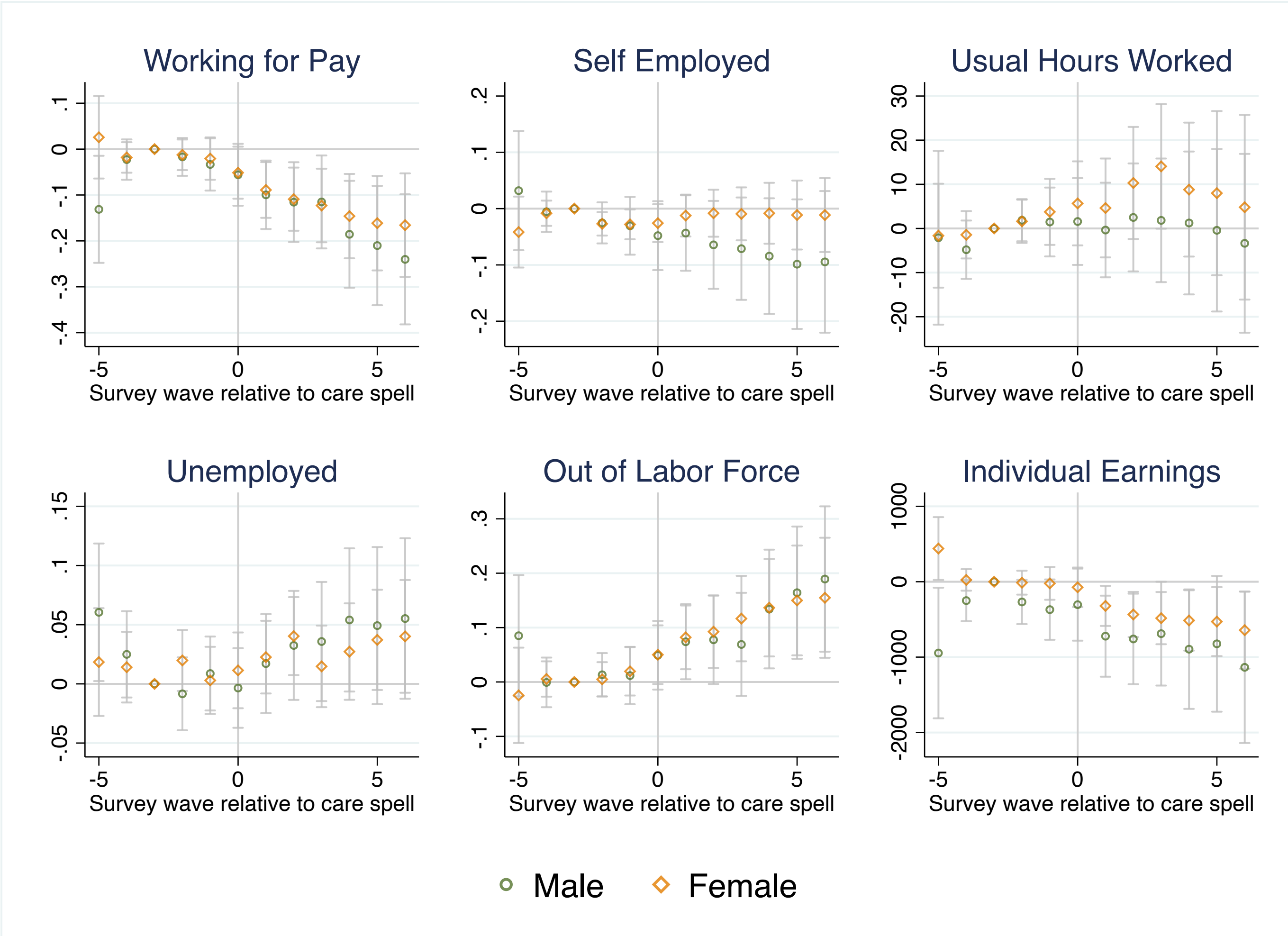

Figure 6: Caregiving and Employment: SIPP Data, by gender

Note: The sample includes all SIPP respondents over 18 who have been providing care for two years or less at the time of the informal care module. Panels display regression coefficients and associated 95% confidence intervals from Equation 1. Coefficients for μ_{-1} are normalized to zero. Standard errors clustered at the individual level.

By contrast, the gender difference we observed in the administrative data are evident in the survey data as well. Specifically, women's employment exhibits no noticeable pre-trends, falls immediately following the reported start of a caregiving spell and then recovers within approximately two years. Women's likelihood of being out of the labor force follows a similar pattern. Women also exhibit a gradual fall in average hours worked. Coupled with the uptick in self-employment approximately two years after the start of a caregiving spell suggests that women who leave employment for caregiving exit the labor market, and take on different (and potentially lower paid) job arrangements when they return. The return to (self-reported) self-employment could be because women wish to combine ongoing care responsibilities with more flexible work arrangements, or because they are unable to find more traditional, employer-based jobs. Women who remain in the labor market (and those who return) are more likely to be working on a part-time basis.

Male caregivers exhibit different trajectories in the short term. Men's employment and earnings falls dramatically and does not recover, consistent with administrative data. Also consistent with administrative data, men's employment appears to fall before the start of a caregiving spell. Men see a corresponding increase in both non-participation and unemployment that is persistent over the entire post period.

4.3 Stacked Difference-in-Differences (Administrative Sample)

Results from our final empirical approach, using the outcomes of future caregivers as a counterfactual trend for current caregivers, are presented visually in Figure 7 and the associate magnitudes and standard errors are presented in Table 5. Because of the revised data structure, we are only able to observe four years prior to the start of a caregiving spell and five years following the start of a caregiving spell. We report estimates for the full five year post period, as well as average effects for years one and two and years three and four. The coefficients we report are the interaction between the treatment indicator and a post indicator. Figure 7 presents the results graphically, and reveals that this approach generally yields estimates that are smaller in magnitude and less precisely estimated.

Starting as before with employment outcomes, we find the results from the stacked difference-in-difference approach are similar to the parametric event study. We see a discrete drop in the likelihood of being employed the year following the start of a caregiving spell, and a return to pre-caregiving levels over the next four years. The likelihood of working decreases by 2.6 percentage points (3.6%) in the first two years after caregiving starts. There is no statistically significant change in earnings, self-employment, or OASI retirement benefit claiming, although the standard errors in these estimates are quite large. Consistent with the event study results, we do see an increase of nearly 1 percentage point in DI claiming after the start of a caregiving spell. However, the visual results in Figure 7 indicate that we cannot reject the existence of a pre-trend in this outcome, even when accounting for counterfactual trends in the control group.

5 Discussion and Conclusion

In this paper, we present evidence on caregiving and labor supply from the Survey of Income and Program Participation linked to administrative earnings records from the Social Security Administration. We leverage the retrospective nature of survey responses in the SIPP to create a longitudinal panel of caregiving outcomes. We exploit this longitudinal data construction by employing several different research designs: non-parametric and semi-parametric event studies and "stacked" difference-in-differences. The latter uses the labor supply of individuals who will become caregivers in the near future as the counterfactual labor supply of individuals who have just started caregiving.

We examine employment and employment-related outcomes for "new" caregivers (those who

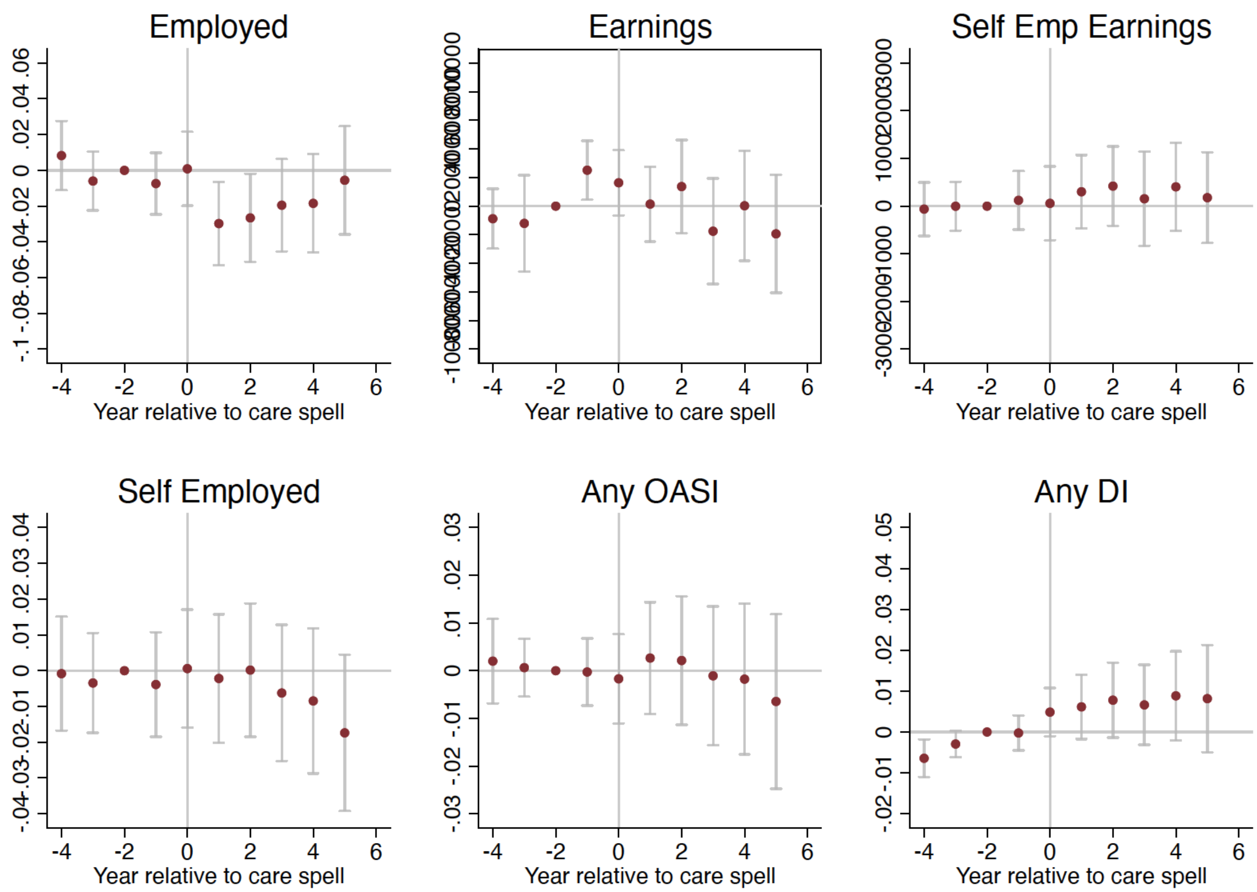

Figure 7: Caregiving and Employment: Stacked Administrative data

Note: The sample includes all SIPP respondents over 18 who have been providing care for two years or less at the time of the informal care module linked to the SSA administrative data. Panels display regression coefficients and associated 95% confidence intervals from Equation 3. Coefficients for μ_{-2} are normalized to zero. Standard errors clustered at the individual level.

Table 5: Stacked Difference in Differences

	Full Sample	Men	Women	Age <40	Age 40-61	Age 62 +
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Employed						
Treat × Post	-0.0209***	-0.0275**	-0.0179*	-0.0087	-0.0271**	0.0065
	(0.0078)	(0.0129)	(0.0098)	(0.0138)	(0.0117)	(0.0204)
Treat × Post (Year 0-2)	-0.0262***	-0.0232*	-0.0284***	-0.0127	-0.0383***	0.00215
	(0.0079)	(0.0130)	(0.0099)	(0.0145)	(0.0115)	(0.0201)
Treat × Post (Year 3-5)	-0.0146	-0.0327**	-0.0055	-0.0033	-0.0124	0.0124
	(0.0093)	(0.0157)	(0.0117)	(0.0167)	(0.0146)	(0.0243)
Mean	0.72	0.77	0.69	0.83	0.79	0.34
Panel B: Self-Employed						
Treat × Post	-0.0021	0.0044	-0.0064	0.0054	0.0011	-0.0028
	(0.0050)	(0.0096)	(0.0057)	(0.0097)	(0.0077)	(0.0118)
Treat × Post (Year 0-2)	-0.000709	0.00817	-0.00642	0.00365	0.00288	0.00387
	(0.00533)	(0.0101)	(0.00616)	(0.0101)	(0.00818)	(0.0116)
Treat × Post (Year 3-5)	-0.00379	-0.000146	-0.00638	0.00790	-0.00128	-0.0118
	(0.00596)	(0.0117)	(0.00667)	(0.0119)	(0.00913)	(0.0141)
Mean	0.08	0.11	0.06	0.07	0.09	0.07
Panel C: Collecting Social Security						
Treat × Post	0.000730	-0.00316	0.00287		-0.00000108	-0.00799
	(0.00374)	(0.00570)	(0.00472)		(0.00612)	(0.0109)
Treat × Post (Year 0-2)	0.00325	-0.000984	0.00500		0.00489	-0.00000786
	(0.00383)	(0.00614)	(0.00473)		(0.00580)	(0.0126)
Treat × Post (Year 3-5)	-0.00231	-0.00587	0.000335		-0.00644	-0.0186*
	(0.00455)	(0.00690)	(0.00586)		(0.00831)	(0.0105)
Mean	0.13	0.17	0.11		0.03	0.69
Panel D:Eligible for SSDI						
Treat × Post	0.00749**	0.00982	0.00658*	0.0116**	0.0131**	-0.00846
	(0.00329)	(0.00630)	(0.00377)	(0.00483)	(0.00553)	(0.00692)
Treat × Post (Year 0-2)	0.00704**	0.00312	0.00948***	0.0118***	0.0137***	-0.0138*
	(0.00311)	(0.00594)	(0.00357)	(0.00431)	(0.00508)	(0.00801)
Treat × Post (Year 3-5)	0.00803*	0.0181**	0.00312	0.0114*	0.0124*	-0.00138
	(0.00416)	(0.00787)	(0.00481)	(0.00669)	(0.00715)	(0.00634)
Mean	0.03	0.04	0.01		0.05	0.02
N	278535	100250	178284		152330	50413
cN	4280	1533	2767		2123	702

Notes: The sample includes all SIPP respondents over 18 who have been providing care for two years or less at the time of the informal care module linked to SSA administrative data. The first row reports results from Equation 3, pooling all post caregiving observations. The next two rows report results from Equation3, start caring within two years of the SIPP survey). We observe annual outcomes for up to 10 years before and seven years after the reported start of a caregiving spell from the administrative data and roughly quarterly outcomes for up to three years before and four years after a the start of a care spell from the survey data.

From our analysis we obtain several key findings. First, we document that the relationship between caregiving and employment-related outcomes is dynamic: We find some evidence of anticipatory effects, as well as changes in outcomes across the post caregiving period. We find that the onset of caregiving leads to a significant–and immediate–reduction in both employment and earnings on average. In the administrative data, we find that the likelihood of working is 4.5 percentage points (6%) lower after the start of a caregiving spell, while annual earnings fall by 16%. Both of the empirical strategies that we employ to address the observed anticipatory effects yield similar results: the likelihood of employment falls by 1.6 percentage points (2%) and earnings fall by $1,400 (4.4%) for two years following the start of a caregiving spell, and then return to the pre-caregiving trend. Although we find no evidence that caregiving spells correspond with immediate transitions into retirement, we find that caregiving is associated with increased DI claiming, suggesting that family caregivers may leverage social insurance to compensate for lost wages associated with caregiving needs. However, we cannot rule out the possibility that receiving disability may induce individuals into caregiving.

The SIPP sample adds a higher frequency, shorter-term perspective. We find similar decreases in employment and earnings which are evident as early as four months after the reported start of a caregiving spell. Exit from employment corresponds to increases in both non-participation and unemployment in the short term. We find evidence of an association between caregiving onset and transitions from employment to unemployment.

Heterogeneity analyses reveal stark differences by gender: we find that male caregivers see dramatic decreases in employment and earnings even before the start of a caregiving spell, and never recover. Female caregivers, by contrast, return to employment within two years of starting a care spell. However, we find evidence that they return to different jobs: women are more likely to report self-employment and lower hours approximately two years after starting a caregiving spell.

While the prior literature has documented a relationship between caregiving activity and employment over a two-year period, our analysis reveals that adverse employment effects are detectable from the very start of the caregiving spell and have a dynamic trajectory. We highlight that this decrease in earnings persists for some subgroups of caregivers and reverses for others. We also find some weak evidence that caregivers transition onto self-employment to balance work and caregiving responsibilities. We also document that caregivers, especially men, may be substituting away from paid employment and into disability.

Our results are roughly in line with the existing literature on caregiving to adults and work in the United States. Looking the the static relationship between caregiving and work, Van Houtven et al. (2013) find no impact on the the likelihood of employment for women, but reductions on hours at the intensive margin. We find that female caregivers do experience reductions on the extensive margin that last for as long as two years. This could be due to labor market frictions suggested by Skira (2015), who studies the dynamic impacts of caregiving to parents and finds that female caregivers are less likely to receive job offers in the two years following a care spell. While we do not find evidence of a wage penalty (looking at unconditional earnings) in the administrative data for female caregivers, we do see evidence of this in self-reported earnings and hours in the survey data. In contrast with Van Houtven et al. (2013) we see no effects on claiming of retirement benefits, though this could be due to measurement differences between self-reported retirement status and administrative records. Our results for male caregivers are also in line with the findings of Van Houtven et al. (2013), who find that men reduce employment by 2.4 percentage points. We find a similar magnitude effect and we show that this grows over time, highlighting the differences in employment trajectories between male and female caregivers.

It is important to note that while we find caregiving depresses employment among new caregivers, our results do not reveal how much of the employment effect is voluntary versus involuntary. Would new caregivers prefer to continue working if their employers could better accommodate them? The fact that adverse labor supply effects arise immediately following the start of caregiving, and appear to persist over the following months (and years), suggests there could be scope for employment policies designed to help working individuals cope with caregiving demands, which are often idiosyncratic and intermittent over a period of several years, and not typically resolved during a single, 12-week spell of continuous leave.

References

Abraham, K. G., B. Hershbein, and S. Houseman (2020). Contract work at older ages. Working Paper 26612, National Bureau of Economic Research.

Arora, K. and D. A. Wolf (2017). Does paid family leave reduce nursing home use? the california experience. *Journal of Policy Analysis and Management*.

Bedard, K. and M. Rossin-Slater (2016). The economic and social impacts of paid family leave in california: Report for the california employment development department. *California Employment Development Department Policy Report*.

Chari, A. V., J. Engberg, K. N. Ray, and A. Mehrotra (2015). The opportunity costs of informal elder-care in the united states: new estimates from the american time use survey. *Health services research 50*(3), 871–882.

Coe, N. B. and C. H. Van Houtven (2009). Caring for mom and neglecting yourself? the health effects of caring for an elderly parent. *Health Economics 18*(9), 991–1010.

Deshpande, M. and Y. Li (2017). Who is screened out? application costs and the targeting of disability programs. Technical report, National Bureau of Economic Research.

Dobkin, C., A. Finkelstein, R. Kluender, and M. J. Notowidigdo (2018). The economic consequences of hospital admissions. *American Economic Review 108*(2), 308–52.

Ettner, S. L. (1996). The opportunity costs of elder care. *Journal of Human Resources*, 189–205.

Fadlon, I. and T. H. Nielsen (2017). Family labor supply responses to severe health shocks. *Unpublished manuscript*.

Fahle, S. P. and K. M. McGarry (2017). Caregiving and work: The relationship between labor market attachment and parental caregiving.

Giovannetti, E. R. and J. L. Wolff (2010). Cross-survey differences in national estimates of numbers of caregivers of disabled older adults. *The Milbank Quarterly 88*(3), 310–349.

Hagen, S. A. (2013). *Rising demand for long-term services and supports for elderly people.* Congressional Budget Office.

He, D. and P. McHenry (2015). Does formal employment reduce informal caregiving? *Health economics*.

Houser, A., W. Fox-Grange, and K. Ujvari (2015). Across the states: Profiles of long-term care services and supports. Technical report, AARP.

Kiefer, N. M. (1988). Economic duration data and hazard functions. *Journal of economic literature 26*(2), 646–679.

Maestas, N. (2017). Expanding access to earned sick leave to support caregiving. *Driving Growth through Women's Economic Participation*, 93.

Mommaerts, C. and Y. Truskinovsky (2020). The cyclicality of informal care. *Journal of Health Economics*, 102306.

National Alliance for Caregiving and AARP (2009). Caregiving in the us 2009.

Rossin-Slater, M. (2017). Maternity and family leave policy. Technical report, National Bureau of Economic Research.

Rossin-Slater, M., C. J. Ruhm, and J. Waldfogel (2013). The effects of california's paid family leave program on mothers' leave-taking and subsequent labor market outcomes. *Journal of Policy Analysis and Management 32*(2), 224–245.

Schmitz, H. and M. Westphal (2017). Informal care and long-term labor market outcomes. *Journal of health economics 56*, 1–18.

Skira, M. M. (2015). Dynamic wage and employment effects of elder parent care. *International Economic Review 56*(1), 63–93.

Van Houtven, C. H., N. B. Coe, and M. M. Skira (2013). The effect of informal care on work and wages. *Journal of Health Economics 32*(1), 240–252.

Weber-Raley, L. and E. Smith (2015). Caregiving in the us 2015. *National Alliance for Caregiving and the AARP Public Policy Institute*.

Appendix

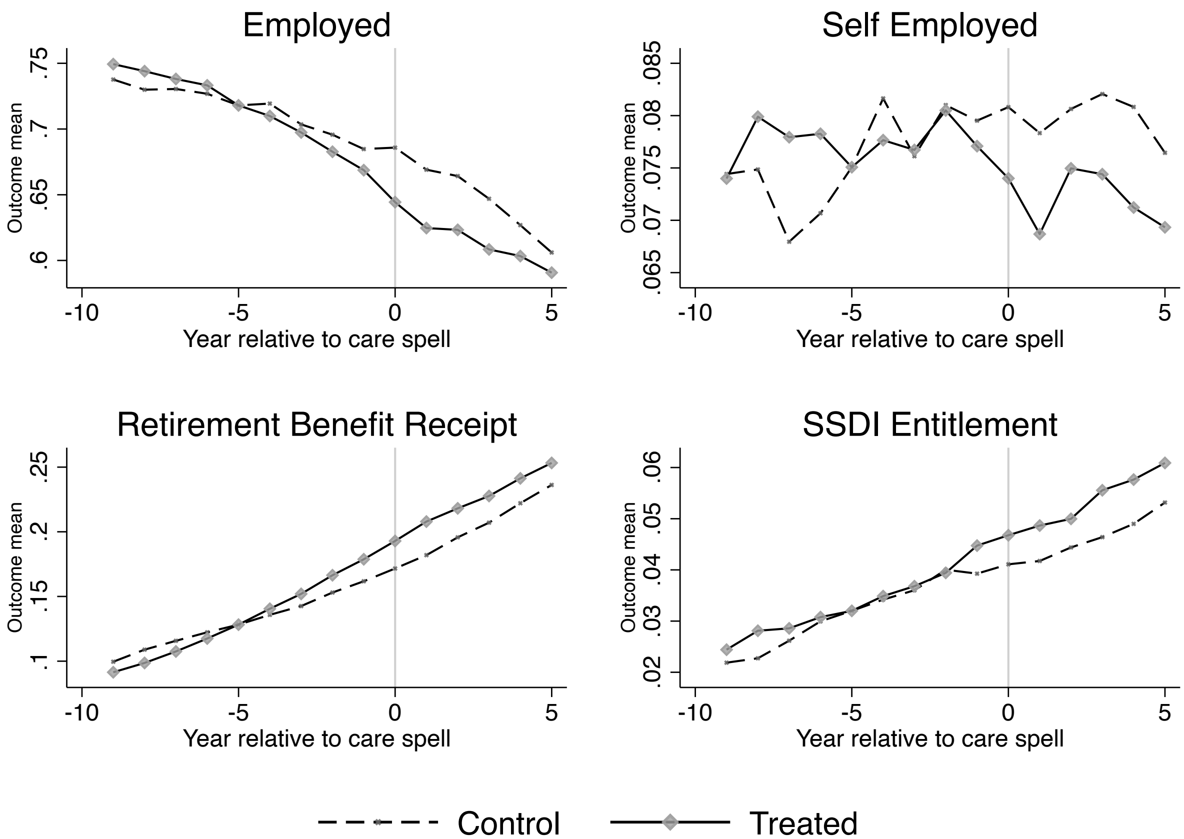

Figure A1: Raw Plots of Employment Outcomes in Treatment and Control Groups

Table A1: Descriptive Statistics: Administrative Match

	Caregiver Sample		Full SIPP	
	No Match	Match	No Match	Match
	(1)	(2)	(3)	(4)
Age	49	52	44.5	47.6
Female	0.62	0.633	0.533	0.537
Education:				
Less than high school	0.164	0.11	0.193	0.138
High school	0.308	0.271	0.32	0.282
Some college	0.291	0.362	0.281	0.331
Bachelor's degree or more	0.237	0.256	0.206	0.249
Race/Ethnicity:				
Non-Hispanic White	0.707	0.767	0.641	0.747
Non-Hispanic Black	0.124	0.103	0.128	0.112
Hispanic	0.11	0.083	0.167	0.086
Caring for:				
Spouse/partner	0.16	0.15		
Parent	0.238	0.282		
Other relative	0.217	0.246		
Other non-relative	0.401	0.347		
Child	0.011	0.015		
N	952	4297	48,600	185,047

Notes: Table reports descriptive statistics measures at year of the caregiving module for pooled 1996, 2001, 2004 and 2008 sample of SIPP caregivers (columns 1& 2) and the full SIPP sample (columns 3 & 4).

Table A2: Administrative Event Study Results: Robustness Checks

	No Trend				Pre-Trend			
	Baseline	No Weights	Individual Fe	Individual Controls	Baseline	No Weights	Individual FE	Individual Controls
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel 1: Employment								
First 2 years	-0.0453***	-0.0464***	-0.0250***	-0.0243***	-0.0165**	-0.0165**	-0.0223***	-0.0230***
	(0.0083)	(0.0078)	(0.0086)	(0.0079)	(0.0075)	(0.0068)	(0.0074)	(0.0075)
Post period	-0.0449***	-0.0437***	-0.0241***	-0.0233***	-0.0145*	-0.0137*	-0.0216***	-0.0221***
	(0.0095)	(0.0089)	(0.0091)	(0.0083)	(0.0079)	(0.0071)	(0.0077)	(0.0078)
Panel 2: Earnings								
First 2 years	-4625.6***	-3836.8***	-885.2	-748.2	-1080.1	-552.5	-1082.1	-1151.2
	(1055.2)	(890.2)	(970.7)	(929.6)	(804.9)	(649.3)	(876.8)	(886.7)
Post period	-5175.1***	-4230.8***	-1026.2	-853.7	-1232.9	-658.8	-1265.7	-1309.3
	(1210.5)	(1025.6)	(1004.9)	(958.4)	(832.4)	(662.0)	(897.1)	(908.6)
Panel 3: Self-Employment Earnings								
First 2 years	-332.6	-395.2	215.5	235.7	231.7	108.1	297.4	288.6
	(322.2)	(341.0)	(257.3)	(263.1)	(259.0)	(282.9)	(262.6)	(266.6)
Post period	-253.2	-295.8	234.2	260.5	257.6	118.5	310.0	309.2
	(321.3)	(337.3)	(243.6)	(249.7)	(241.7)	(262.9)	(251.4)	(254.8)
Panel 4: Self-Employment								
First 2 years	-0.0123**	-0.0117**	-0.0053	-0.0048	-0.0024	-0.003	-0.0036	-0.0040
	(0.0051)	(0.0046)	(0.0050)	(0.0051)	(0.0051)	(0.0044)	(0.0051)	(0.0051)
Post period	-0.0155***	-0.0110**	-0.0061	-0.0052	-0.0030	-0.0023	-0.0043	-0.0043
	(0.0056)	(0.0051)	(0.0051)	(0.0052)	(0.0053)	(0.0046)	(0.0052)	(0.0052)
Panel 1: Any OASI								
First 2 years	0.0037	0.0015	0.0021	0.0021	-0.0018	-0.0056	0.0032	0.0031
	(0.0048)	(0.0047)	(0.0047)	(0.0047)	(0.0046)	(0.0044)	(0.0046)	(0.0046)
Post period	-0.0005	-0.0035	-0.0003	-0.0002	-0.0045	-0.0083*	0.0011	0.0010
	(0.0056)	(0.0053)	(0.0050)	(0.0050)	(0.0050)	(0.0048)	(0.0048)	(0.0048)
Panel 1: Any DI								
First 2 years	0.0151***	0.0139***	0.0084**	0.0067**	0.0064**	0.0038	0.0071**	0.0064**
	(0.0040)	(0.0038)	(0.0035)	(0.0034)	(0.0028)	(0.0025)	(0.0028)	(0.0028)
Post period	0.0227***	0.0200***	0.0106***	0.0086**	0.0087***	0.0056**	0.0089***	0.0082***
	(0.0050)	(0.0048)	(0.0038)	(0.0036)	(0.0031)	(0.0028)	(0.0030)	(0.0030)
Unique Obs	4289	4289	4289	4172	4289	4289	4289	4172

Notes: The sample includes all SIPP respondents over 18 who have been providing care for two years or less at the time of the informal care module and who can be linked to the SSA administrative data. Each cell reports the result from a separate regression using Equation 1. Within each panel, the first row reports pooled effects over the first two years post caregiving, and the second row reports pooled effects for full post caregiving period. Robust standard errors clustered at the individual level are reported in parentheses.(* $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$)

Table A3: Survey Event Study Results: Robustness Checks

	No Trend				Pre-Trend			
	Baseline	No Weights	Individual Fe	Individual Controls	Baseline	No Weights	Individual FE	Individual Controls
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel 1: Employment								
Year 1	-0.0458***	-0.0432***	-0.0260*	-0.0495***	-0.0274**	-0.0272***	-0.0245***	-0.0274***
	(0.0164)	(0.0156)	(0.0138)	(0.0158)	(0.0107)	(0.0095)	(0.0088)	(0.0105)
Year 2	-0.0559**	-0.0545**	-0.0269	-0.0617***	-0.0286**	-0.0307**	-0.0248**	-0.0290**
	(0.0237)	(0.0224)	(0.0194)	(0.0228)	(0.0145)	(0.0131)	(0.0115)	(0.0142)
Panel 2: Self-Employed								
Year 1	0.0026	0.0054	-0.0070	0.0008	-0.0156**	-0.0103	-0.0051	-0.0161**
	(0.0122)	(0.0111)	(0.0125)	(0.0121)	(0.0078)	(0.0067)	(0.0066)	(0.0078)
Year 2	0.0082	0.0098	-0.0090	0.0054	-0.0188*	-0.0136	-0.0062	-0.0196*
	(0.0176)	(0.0160)	(0.0174)	(0.0175)	(0.0107)	(0.0092)	(0.0085)	(0.0106)
Panel 3: Usual Hours Worked								
Year 1	-2.1123	-1.1869	0.1955	-2.4330	1.0411	1.5809	0.5487	0.1472
	(2.3925)	(2.3786)	(1.6828)	(2.3200)	(2.2609)	(2.1100)	(1.8092)	(2.2418)
Year 2	-4.7293	-2.7368	-0.1354	-5.1740	-0.0438	1.3746	0.3905	-1.3404
	(3.4806)	(3.3558)	(2.1973)	(3.3401)	(3.0691)	(2.8178)	(2.3987)	(3.0570)
Panel 4: Unemployed								
Year 1	0.0157**	0.0198**	0.0128	0.0163**	0.0131	0.0142*	0.0138*	0.0134
	(0.0080)	(0.0080)	(0.0079)	(0.0079)	(0.0090)	(0.0085)	(0.0081)	(0.0090)
Year 2	0.0168	0.0197*	0.0125	0.0175	0.0128	0.0115	0.0139	0.0132
	(0.0108)	(0.0105)	(0.0112)	(0.0107)	(0.0125)	(0.0120)	(0.0114)	(0.0124)
Panel 5: Out of the Labor Force								
Year 1	0.0348**	0.0296**	0.0146	0.0392***	0.0159	0.0134	0.0121	0.0160
	(0.0156)	(0.0149)	(0.0133)	(0.0150)	(0.0102)	(0.0091)	(0.0083)	(0.0100)
Year 2	0.0460**	0.0420*	0.0152	0.0525**	0.0179	0.0179	0.0115	0.0182
	(0.0227)	(0.0215)	(0.0188)	(0.0218)	(0.0139)	(0.0126)	(0.0107)	(0.0136)
Panel 6: Individual Earnings								
Year 1	-259.5535***	-248.1604***	-61.6469	-269.8173***	-108.0134*	-110.4614**	-116.3426***	-110.8817**
	(99.8376)	(89.8412)	(88.2336)	(91.8996)	(56.4917)	(48.8763)	(44.8721)	(54.5491)
Year 2	-331.3173**	-319.0929**	-18.2509	-350.6773***	-106.4064	-114.5027*	-98.2606*	-114.7917
	(141.7768)	(126.8986)	(122.3940)	(130.8187)	(77.7558)	(69.1627)	(56.7497)	(73.8345)

Notes: The sample includes all SIPP respondents over 18 who have been providing care for two years or less at the time of the informal care module. Each cell reports the result from a separate regression using Equation 1. Within each panel, the first row reports pooled effects in the first year post caregiving, and the second row reports pooled effects for the second year post caregiving. Robust standard errors clustered at the individual level are reported in parentheses. Within each (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$)

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