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Employment Shocks, Unemployment Insurance, and Caregiving

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Abstract

Working Americans are increasingly taking on various caregiving roles for family members. In light of the COVID-19 pandemic, the impact of job loss and income supports on the labor supply, economic well-being, and caregiving behavior of families with care needs is a pressing policy question. This paper considers caregiving during periods of (involuntary) unemployment and, specifically, the role of unemployment insurance (UI) on caregiving. Although caregiving increases following job separations, more generous UI benefits reduces the likelihood that workers who are laid off provide family care. The effect is the largest for adults between aged 40 and 65, for men, and for unmarried individuals. In the context of a rapidly aging US population, this analysis provides knowledge about how social insurance policies that provide wage replacement support working families with growing long term care needs.

JEL Classification: I12, J14, J22, J26
Keywords: Caregiving, Job loss, Unemployment Insurance, Aging

1 Introduction

The US population is aging rapidly, with the number of Americans aged 65 and older expected to double by 2050. As the elderly are living longer and with more chronic conditions, the demand for long-term, non-acute care is expected to grow apace. A large share of the growing demand for elder care is met informally by relatives, who provide an estimated $470 billion worth of unpaid care annually (Chari et al., 2015). Many family caregivers also work, and there is a large literature showing that the burden of caregiving interferes with employment (Van Houtven et al., 2013; Fahle and McGarry, 2018; Maestas et al., 2021). A number of recent studies investigate the impact of social insurance programs, primarily paid family leave, on employment among family caregivers (Arora and Wolf, 2017; Bartel et al., 2021; Anand et al., 2021).

The present study provides new evidence on the relationship between caregiving and work by considering caregiving during periods of involuntary unemployment as well as the role of Unemployment Insurance (UI) on caregiving following a job separation. A large theoretical and empirical literature considers UI in light of the trade-offs between the moral hazard effect and the consumption smoothing effect. UI has been shown to reduce job search effort and increase jobless spells among recipients (known as the moral hazard effect)(Meyer, 1990; Gruber, 1997). UI has also been shown to reduce consumption changes related to job loss and to reduce the likelihood that households self-insure by substituting consumption spending with home-produced alternatives or by increasing the labor supply of secondary earners (known as the consumption smoothing effect) (Cullen and Gruber, 2000; Guler and Taskin, 2013; Been et al., 2020). Recent studies have shown additional "well-being smoothing" benefits of UI, including reduced mortgage default, improved health outcomes and health insurance rates, and increased investments in higher education (Barr and Turner, 2015; Hsu et al., 2018; Kuka, 2020).

The opportunity cost of providing informal care falls when potential caregivers are not working, and there is evidence that some margin of informal caregivers are sensitive to this cost: people increase time spent caring for family members when they leave work, either voluntarily or involuntarily (Aguiar et al., 2013; Mommaerts and Truskinovsky, 2020). For job losers who receive UI, caregiving may be subject to either the moral hazard effects or the consumption smoothing effects of UI documented in the literature. By reducing the cost of being out of work, UI benefits may further reduce the opportunity cost of caregiving, increasing rates of informal care among recent job losers, which may extend jobless spells or lead to labor force exit. However, by supporting consumption smoothing across job loss related income shocks, more generous UI benefits may reduce the likelihood that family members take on caregiving roles, especially if care is fully or partially purchased formally. Additionally, UI beneficiaries must be available to work while receiving UI, so higher benefits may have no additional impact on caregiving behavior.

Using high frequency longitudinal data on employment outcomes and caregiving from four panels of the Survey of Income and Program Participation (SIPP), I first trace out the caregiving trajectory of workers experiencing a job separation. I show that the caregiving hazard increases significantly in the three month period following a job separation and remains high for nearly two years. Furthermore, there are no significant changes in caregiving prior to a job separation.

Next, matching SIPP respondents to state-level UI policy, I investigate the relationship between UI generosity and family caregiving. Specifically, I leverage plausibly exogenous state-level changes in key parameters that determine individual benefit amount, including eligibility, maximum and minimum benefit cutoffs, maximum duration, and dependent allowances to identify the causal effects of larger benefits on the likelihood that laid off workers will provide informal care. I also link individuals to their spouses and estimate the impact of more generous UI on the caregiving of the spouses of laid off workers.

I find that more generous UI benefits reduce the likelihood that respondents will start providing care following a job separation, suggesting that the consumption smoothing benefits of UI outweigh any moral hazard effects in this context. A one standard deviation increase in UI reduces the likelihood of caregiving by 0.19 percentage points, or 14 percent. These effects are largest among workers aged between 40 and 64, men, and those who are not married. I also find that effects are larger for help with chores and errands, with more muted impacts on help with personal or medical care tasks. Finally, I find weak but suggestive evidence that UI *increases* the likelihood of caregiving by spouses.

This study makes several contributions. First, I show how unemployment insurance contributes to the patchwork of safety net programs available to families to manage the time and financial burdens of family caregiving. While there is a growing body of work addressing how policies such as paid and unpaid family leave impact new parents, very little is understood about how social insurance programs can support workers and families with caregiving needs. The sharp increase in family care needs during the COVID-19 pandemic has underscored both the instability of care arrangements and the potential of such programs to subsidize caregiving spells (Truskinovsky et al., 2021). I provide evidence that safety net programs can help families be more resilient to transitory income shocks and maintain ongoing (formal) care arrangements.

I also describe the timing of caregiving spells and job separations, providing further evidence that some share of caregiving spells start soon after a job loss, and may be driven by resource constraints. Notably, the interaction between labor market fluctuations and the growing need for long-term care may play a role in the increasing trend of non-participation as a channel of labor force exit, especially following the Great Recession (Foote et al., 2019). Establishing short-term employment trajectories of displaced workers who start providing informal care after losing a job highlights how family caregiving obligations may have the potential to turn short-term employment shocks into longer-run decreases in labor force participation, impacting the economic security of future retirees. The evidence that UI *reduces* this hazard suggests a key role for UI in supporting the long-term economic security of families with caregiving needs.

Finally, understanding informal care during periods of unemployment and specifically in the presence of UI sheds light on the nature of caregiving as a time use category. Recent studies have classified this activity as "home production" (Aguiar et al., 2013), while childcare, another form of informal caregiving, has long been understood to be distinct from both home production and leisure (Bianchi, 2000; Kimmel and Connelly, 2007; Guryan et al., 2008). The extent to which time dedicated to eldercare empirically resembles home production, leisure, childcare, or merits its own category remains unclear, and understanding this is important to future work on this growing, and increasingly important, use of time. My finding that UI generosity reduces caregiving supports family caregiving as "home production," but the differences across subgroups suggest that this is not the case for all potential family caregivers.

The rest of the paper is structured as follows. In Section 2, I briefly discuss the Unemployment Insurance program and describe key parameters and sources of variation used in the analysis. Section 3 describes the data construction and sample selection. In Section 4 I describe the timing of caregiving relative to job separations, and in Section 5 I estimate the causal effects of UI on the likelihood of caregiving following a job separation. Section 6 concludes.

2 Unemployment Insurance Details

Unemployment Insurance is a federally-mandated transfer program that provides income replacement to individuals who have lost their jobs for a qualifying reason.The program is administered at the state-level, which gives states significant leeway in setting program parameters, including eligibility, level of income replacement and duration of benefits. Eligibility determines who can claim benefits, and is based on past level of earnings and hours worked, and the type of job loss. Actual benefits are set to 50 percent of pre-unemployment weekly earnings but are capped at a state maximum for high earners, as well as a state minimum. Duration of benefits is the maximum number of weeks eligible workers can claim benefits.

I use two sources of state variation in the generosity of unemployment insurance between 1995 and 2011 to identify the effect of wage replacement on informal caregiving. First, I leverage generosity in the maximum value of the benefit, defined as the product of maximum weekly benefit and maximum duration in weeks. This measure captures the total (undiscounted) present value of the benefit to a laid off worker and varies at the state level as the maximum weekly rates and benefit duration change. Summary statistics for this measure at the state and year level are reported in Table 1. The average maximum benefit between 1995 and 2011 is $8,500. Average benefit duration is 26 weeks, and the average weekly maximum reimbursement is $300.

A state's maximum reimbursement rate may not be the most relevant metric for workers with caregiving responsibilities and does not fully capture the available variation in UI generosity. Along with the maximum weekly benefit amount, states also frequently adjust the minimum UI weekly payment, as well as minimum earnings requirements for eligibility, and fourteen states also provide allowances for dependant children, making replacement rates nonlinear in income (Kuka, 2020). This variation may be the most relevant in the present setting as workers with family caregiving needs may be less attached to the labor force to begin

Table 1: Unemployment Insurance, Descriptive Statistics

	Mean	Median	SD
Max Benefit ($ thousands)	8.5	7.9	3.1
Max Weekly Benefit ($ thousands)	0.32	0.30	0.11
Max Regular Duration	26.1	26.0	0.7
Real Max Benefit (2011 $ thousands)	10.7	10.2	3.2
Average Replacement Rate (% of weekly wage)	0.41	0.41	0.05
State unemployment rate (%)	5.5	5.2	1.8
Average annual wages ($ thousands)	38.3	36.8	10.7

Notes: Table reports summary statistics for key parameters of Unemployment Insurance benefits, as well as the two constructed measures of benefit generosity at the state level for the study time period.

with. To capture these additional sources of variation, I first calculate a replacement rate for each individual in a fixed national sample using individual wages, employment status and characteristics and state UI policy. Then I collapse at the state, year, and number of children cells to generate simulated average replacement rates that vary only by state legislative environments and not by any individual or state demographic characteristics and trends.[1] Along with isolating plausibly exogenous variation in the weekly wage replacement rate, this simulated instrument approach simplifies multiple dimensions of UI policy into a single measure. Descriptive statistics for this measure are reported in Table 1.

Figure 1 presents the state level variation over the study period for both measures. The first row reports the quantiles of the maximum benefit distribution for the first and last year of the analysis. The second row similarly presents the quantiles of the simulated replacement rate for the same period. Figure 1 demonstrates both that there is significant variation in each measure over time, but also that the measures capture different sources of variation. For example, states such as Ohio and Oregon, which are in the top quantile of the maximum benefit distribution in 1995, are not in the top quantile of the average replacement rate distribution in the same year. Oregon remains in the top percentile of the maximum benefits distribution in the study period, but falls from the fourth to the third percentile of the replacement rate distribution.

3 Data and Sample Selection

This study examines the effect of UI generosity on informal caregiving in the Survey of Income and Program Participation (SIPP), a nationally representative, longitudinal household survey conducted by the US Census Bureau. I use four consecutive panels of the SIPP

[1] See Kuka (2020) for a detailed description of how this measure is constructed.

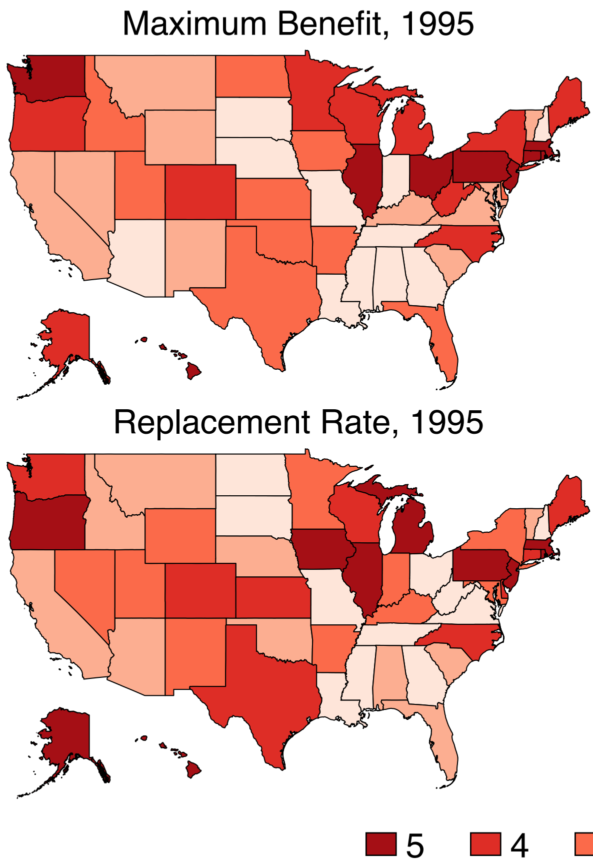

Figure 1: State Unemployment Insurance Benefits by Quantile, 1996-2011

Notes: Each map presents variation in each constructed UI measure by quantile of the distribution in that year.

between 1996 and 2008. Each SIPP panel follows over 40,000 households for up to four years, with regular interviews every four months for a total of up to 14 longitudinal observations per household (14 "waves"). Each interview collects details on individual, family, and household characteristics, as well as employment outcomes and program participation for all adults. The SIPP also incorporates cross-sectional modules on specific topics at specific waves within a panel, including a module on family caregiving.

I rely on the informal care topical module, which is administered once per panel, and includes series of detailed questions about individual caregiving behavior. Each respondent 15 years and older is asked if they provided unpaid care in the previous month to somebody either inside or outside of their household who has a long-term illness or disability. Caregivers are then asked about the details of their caregiving, including frequency, the relationship to the care recipient, and how long they have been providing care.

The first panel of Table 2 reports summary statistics from the cross-sectional caregiving modules for the four SIPP panels. Five percent of the full sample (aged 15 and over) reports having provided informal care in the last month. This is somewhat lower than rates of informal care reported in other nationally representative surveys. By comparison, 17 percent of adults in the American Time Use Survey (ATUS) report providing some care to another adult. A number of factors likely contribute to this difference, including the look-back period (one month in the SIPP compared to three months in the ATUS) and the different time frame.[2] However, the definition of informal care in the SIPP refers to care for somebody with a "long term illness or disability," while the ATUS refers to "a condition of aging," which is less restrictive. As a result of this phrasing, SIPP captures care that is likely more consistent and more intensive.

The rest of Table 2 provides details of the caregiving spell from the sample of caregivers. 15 percent of caregivers in the SIPP are caring for spouses, 22 percent are caring for parents, and 44 percent care for another relative or a non-relative. Almost one quarter of the sample is caring for a disabled child. Because caregiving for children is likely very different in nature to caring for elderly relatives, in particular with its relationship to labor supply, I drop individuals who provide care to children from the analysis.

The remaining caregivers provide on average 12 hours of care per week to one care recipient and 60 percent provide care to somebody outside the household. 41 percent provide help with Activities of Daily Living (ADLs, defined as personal tasks such as bathing, eating and toileting) while 92 percent provide help with Instrumental Activities of Daily Living (IADLs, defined as help with chores, errands and housekeeping). Over half report helping with medical tasks and just under half (48 percent) report being the sole caregiver for the care recipient.

At the bottom of Table 2 I report caregiving duration. Nearly one quarter (23 percent) of caregivers began their caregiving spell within the last year, while over half the sample has been providing care for three or more years.[3] While informal care provision is observed only

[2] The ATUS started in 2003 and only began asking about eldercare in 2011.

[3] The distribution of observed care duration is necessarily biased towards longer spells due to length-biased sampling (Kiefer, 1988).

Table 2: Summary statistics

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 Activities of Daily Living (ADLs)	0.41
Helps with Instrumental Activities of Daily Living (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. All measures are calculated in the informal care modules.

once per SIPP panel (in Wave nine for Panel 2008 and in Wave seven for Panels 1996, 2001 and 2004), the information about retrospective caregiving start time allows me to impute caregiving behavior for respondents in all prior waves of the panel. For example, a respondent who is included in the 2008 Panel is surveyed every four months between 2008 and 2014. They respond to the informal care topical module in Wave nine, which falls in the summer of 2011, and provide a retrospective caregiving report. Those respondents who report starting caregiving in the last year code are coded as providing care in the first half of 2011 and the second half of 2010. Respondents who report starting caregiving one year ago are coded as providing care in the first half of 2010. Respondents who started caregiving two years ago are coded as providing care in 2009, and so on. This approach creates a longitudinal record of approximate caregiving behavior from the respondents' first entry into the SIPP Panel through the informal care wave. In the analysis, I limit the caregiver sample to recent caregivers, who have been providing care for two years or less. I also drop respondents who were out of the labor force for the duration of their participation in the SIPP survey.

Table 3 compares demographic and employment characteristics between this sample of non-caregivers and caregivers. This table includes one observation per individual and all outcomes are measured annually in the same year as the caregiving module. Columns one and two report weighted means for each subgroup, and column three reports the p-value from a simple t-test comparing the two means. In this sample, caregivers are on average five years older than non-caregivers, and are 14 percentage points more likely to be female. They are also more likely to be white, more likely to be Black, and less likely to be Hispanic compared with non-caregivers. They are also more likely to be married, but less likely to have kids under 18 in the household. There is no difference in education level between caregivers and non-caregivers.

Along with retrospective caregiving information, the SIPP collects detailed employment information from each respondent at every interview, providing a monthly snapshot of labor force participation and employment related outcomes including UI receipt. I follow the existing literature in defining unemployment spells as any months where a respondent reports that they were not working at least part of the month, but spent some time looking for work (Hsu et al. (2018); Kuka (2020).[4] I also include a more restrictive definition of an unemployment spell using participants' stated reason for job loss, which only includes separations most likely to qualify for UI insurance (on layoff, employer bankrupt, employer sold business, job was temporary and has ended, or slack work).

Panel two of Table 3 compares descriptive statistics for employment related outcomes between caregivers and non-caregivers. Caregivers in this sample are less likely to be working and more likely to be out of the labor force than non-caregivers. Caregivers are 20 percent more likely to experience a job loss than non-caregivers, and are 25 percent more likely to experience a job loss for UI qualifying reasons. Conditional on experiencing a job loss, unemployment duration is very similar between the two groups. Caregivers are also more likely to receive UI, although when conditioning on receiving UI, both group report a similar monthly payment.

[4] This includes anybody whose employment status is coded as 3 through 7 in SIPP's RMESR variable.

Table 3: Demographic Characteristics

	Non-Caregivers	Caregivers	P-value of difference
Panel 1: Demographic Characteristics			
Age	40.5	45.8	0.000
Female	0.48	0.62	0.000
White Non-Hispanic	0.70	0.72	0.023
Black Non-Hispanic	0.11	0.13	0.023
Hispanic	0.13	0.10	0.000
Married	0.56	0.59	0.000
Any kids under 18 in HH	0.45	0.36	0.000
College degree	0.27	0.26	0.644
Panel 2: Employment and UI Benefits			
Working	0.82	0.77	0.000
Not in Labor Force	0.16	0.21	0.000
Job Loss - any reason	0.05	0.06	0.000
Job Loss - UI qualifying reason	0.03	0.04	0.000
Unemployment duration	25.9	25.9	0.677
Any UI	0.03	0.04	0.000
Monthly UI amount ($)	1083.7	1175.9	0.393

Notes: Table reports weighted summary statistics for the pooled 1996, 2001, 2004 and 2008 SIPP surveys. All measures are calculated in the year of the informal care module and individual respondents appear only once. The first column contains SIPP respondents who did not report provide informal care in the informal care module. The second column contains respondents who reported providing care to another adult (excluding those providing care to own children), and who were providing care for two years or less. Column three reports the p-value from a two way test comparing caregivers to non caregivers.

4 Caregiving and Job Separations

Consistent with the existing literature on the effects of labor market conditions on caregiving outcomes, the descriptive statistics in the previous section suggest that caregivers are more likely to experience job separations than non caregivers, and are more likely to be receiving unemployment insurance. I next take advantage of the longitudinal nature of the SIPP to provide descriptive evidence on the timing of starting caregiving relative to a job separation. Although caregiving questions are only included once per SIPP panel, I leverage the retrospective information collected in the informal care module to approximately date the start of a caregiving spell within the SIPP panel. This allows me to construct a longitudinal measure of caregiving outcomes for a subset of SIPP respondents who started a caregiving spell within two years of the informal care topical module, 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. As this method allows me to approximate the start of a caregiving spell only within a SIPP wave (a period of four consecutive months), in the longitudinal analysis I collapse all outcomes to the individual-wave level.

Figure 2 plots caregiving outcomes for up to five waves (20 months) before and after experiencing a job separation for a sample of SIPP respondents who experience a job separation. The simple event study model includes controls only for calendar time and state fixed effects. The horizontal red line is plotted at event time zero—the wave in which the job separation occurs—and confidence intervals are reported relative to the wave before the separation occurs. I include all reported job separations, though results using a definition of job separations for only qualifying reasons produces similar patterns.

Figure 2 suggests that the likelihood of starting a caregiving spell increases in the first wave (four months) following a job separation and continues to increase for another eight to 12 months. Three waves after a job separation, the likelihood of starting caregiving increases by 0.4 percentage points, or nearly 66 percent, relative to a pre-job separation sample average of 0.6 percent. Prior to a job separation, the likelihood of starting a caregiver spell is flat, suggesting that caregiving roles are not precipitating job separations in this sample. In Figure 3, I limit the sample to respondents who are aged 40–64 when they experience a job separation, because these respondents are most likely to experience both employment and family caregiving pressures at the same time. Although the confidence intervals are wider for this much smaller sample, I find that the likelihood of caregiving increases nearly one percentage point in the 12 months following a caregiving spell. Finally, because the majority (60 percent) of family caregivers are women, Figure 4 plots the results separately by gender, and reveals that most of the increase in caregiving following a job separation is driven by women. Men and women experience similar pre-trends, but the likelihood of caregiving increases significantly for women following a job separation, while staying flat for men.

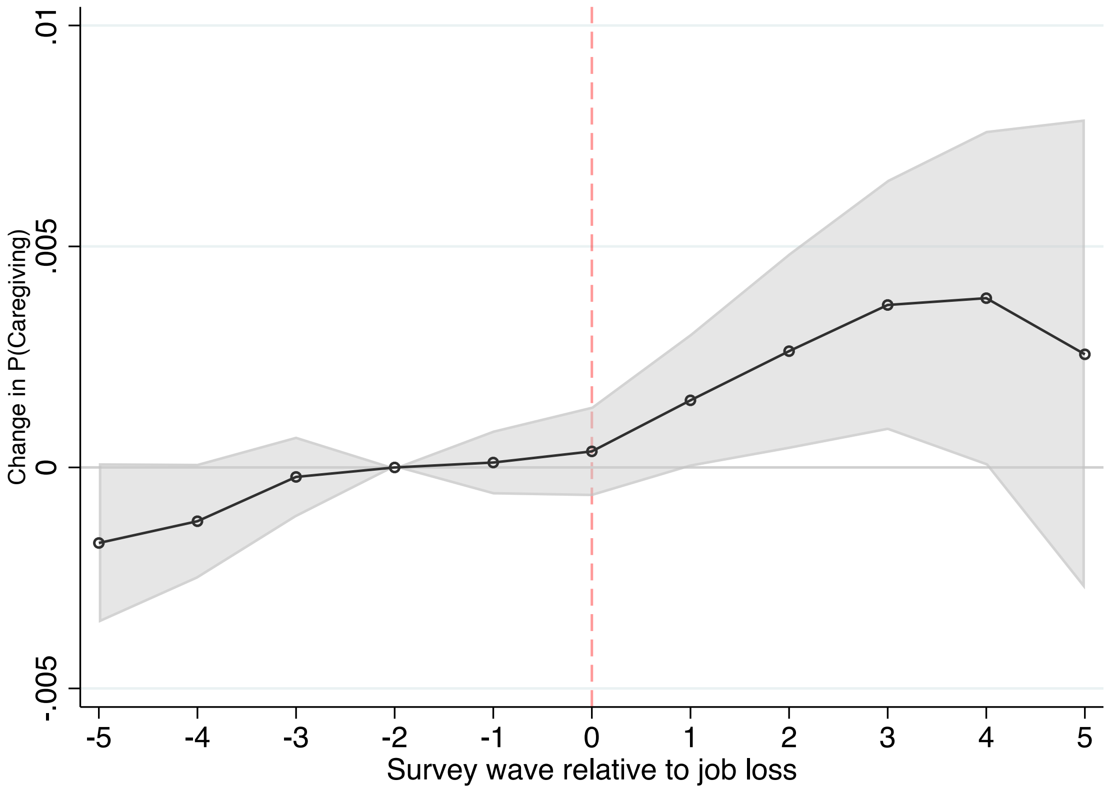

Figure 2: Event Study - Full Sample

Notes: Data are from the 1996–2008 panels of the SIPP. The sample includes all individuals that experience a job separation, five waves (20 months) before and after the wave in which the job separation occurred. The figure reports coefficients and confidence intervals for wave relative to job loss indicators. All regressions include controls as described in Section 4. Standard errors are clustered at the state level.

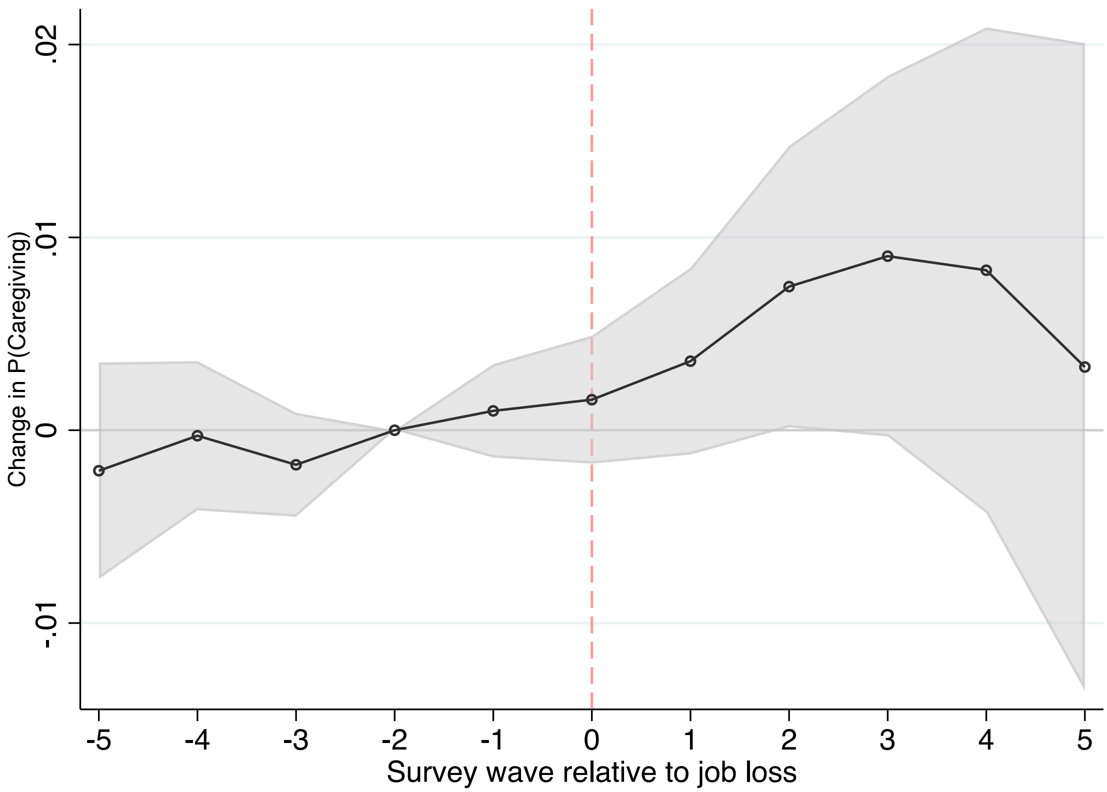

Figure 3: Event Study - Age 40–64

Notes: Data are from the 1996–2008 panels of the SIPP. The sample includes all individuals aged 40–64 that experience a job separation, five waves (20 months) before and after the wave in which the job separation occurred. The figure reports coefficients and confidence intervals for wave relative to job loss indicators. All regressions include controls as described in Section 4. Standard errors are clustered at the state level.

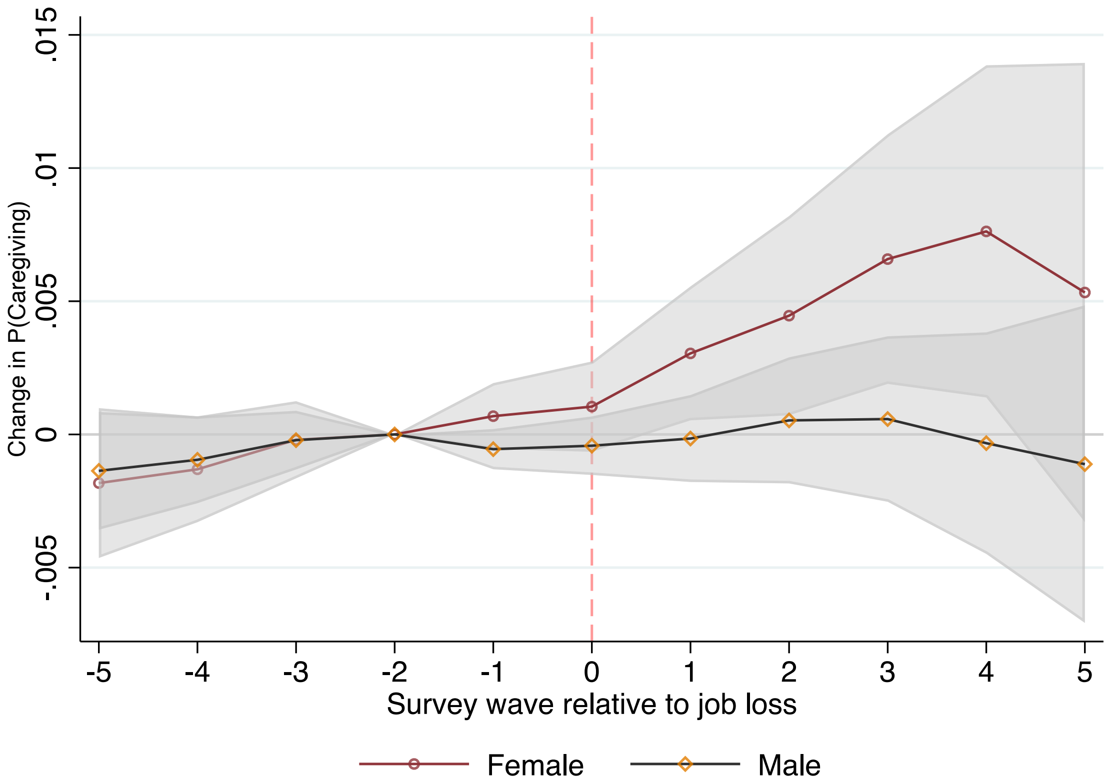

Figure 4: Event Study - Gender

Notes: Data are from the 1996–2008 panels of the SIPP. The sample includes all individuals that experience a job separation, five waves (20 months) before and after the wave in which the job separation occurred. The figure reports coefficients and confidence intervals for wave relative to job loss indicators for models estimated separately by gender. All regressions include controls as described in Section 4. Standard errors are clustered at the state level.

5 Caregiving and Unemployment Insurance

The descriptive analysis in the previous section traces out the change in caregiving "hazard" around the time of a job separation, and suggests that the likelihood of caregiving increases significantly following a job loss. In this section, I consider the role of unemployment insurance in changing the likelihood that an individual experiencing a job loss starts caregiving.

5.1 Empirical Specification

To identify the effects of UI on informal caregiving, I use the SIPP as a repeated cross-section with annual observations of job separations and caregiving outcomes and match to annual state UI policy for the two measures of UI generosity discussed in Section 2 (the maximum benefit and the average replacement rate). I employ two related research designs to leverage exogenous variation in benefit generosity between 1996 and 2011. First, I estimate a simple state and year fixed effects model for the sample experiencing a job separation:

$$Y_{ijtc} = \beta_1 UIGen_{jtc} + \beta_2 X_{ijtc} + Z_{jt} + \alpha_t + S_j + \varepsilon_{ijt} \tag{1}$$

Y_{ijtc} is a binary indicator for if respondent i was a caregiver in state j in year t with number of children c. The vector X includes demographic controls, including age, age-squared, martial status, race and ethnicity, education, and the number of children under 18, while Z_{jt} are controls for time varying state-level factors such as the unemployment rate, age composition, industry mix, and other safety net program generosity, which may be correlated with UI generosity and caregiving outcomes. Finally, this model includes year fixed effects α_t and state fixed effects S_j which capture time-invariant state-level differences and annual shocks that impacts all respondents similarly. The policy variable is measured as either the maximum benefit or the simulated replacement rate described in the previous section. The coefficient of interest, β_1, captures the different impact of UI generosity among unemployed individuals, exploiting variation in UI policy across state, year, and in the case of the simulated replacement rate, also the number of children. The main identifying assumption is that changes in state UI policy are uncorrelated with state level shocks that affect caregiving. Standard errors are clustered at the state level.

Building on this approach, I also estimate a triple difference model using respondents not experiencing a job separation as a comparison group, which takes the following form:

$$\begin{aligned} Y_{ijtc} = \beta_1 UIGen_{jtc} \times JobLoss_{ijtc} + \beta_2 JobLoss_{ijtc} + \beta_3 UIGen_{jtc} + X_{ijtc} + Z_{jt} + \\ \alpha_t \times S_j + \alpha_t \times JobLoss_{ijtc} + S_j \times JobLoss_{ijtc} + \alpha_t \times S_j \times C_c + \varepsilon_{ijt} \end{aligned} \tag{2}$$

This model includes state by year fixed effects $\alpha_t \times S_j$ as well state and year fixed effects for each of the Job Loss and non Job Loss groups. For models which use the simulated replacement rate to capture UI generosity, I also include state by year by number of children fixed effects. The coefficient of interest, β_1, is interpreted as differential effect of a unit increase in UI generosity on caregiving among those experiencing a job separation, relative to those who do not experience a job separation.

The triple difference model allows me to control for state level time varying shocks to caregiving outcomes that may be correlated with changes in UI policy but impact the all groups equally, and to rely on a weaker identification assumption (that changes in UI laws are uncorrelated with state level shocks that affect the unemployed differently from the employed). It also allows me to control for shocks to the supply of *formal* care – a substitute to informal care in some contexts– that are correlated with changes in UI generosity. For example, changes in Medicaid Home and Community Based care funding can change with state economic conditions, or if UI generosity also impacts the employment of direct care workers including nurses and home health aids.

However, the triple difference model also assumes that working individuals are not also "treated" by changes in UI laws. This may happen if, for example, the possibility of higher UI benefits may lead employed individuals to begin caregiving, or if households shuffle caregiving roles for all members in response to UI receipt by an individual (I explore this possibility below). If more generous UI also impacts the caregiving behavior of working individuals, then the estimates obtained from this model will be biased downwards.

5.2 Results

5.2.1 Main results

Table 4 present the main results from Equations 1 and 2 for both measures of UI generosity: the simulated replacement rate and maximum benefit generosity. All models use the most general definition of job separation, as defined in a previous section, but models using more restrictive definitions of layoff produce similar results. The first column of Table 4 simply repeats the event-study model in a static specification with additional controls, reporting the impact of experiencing a job separation on the likelihood of caregiving. Consistent with the dynamic results, I find that individuals experiencing a job layoff are 0.28 percentage points, or 23 percent, more likely to start providing care. Column two of Table 4 reports results from Equation 1, which estimates the impact of changes in UI generosity on caregiving using the sample of workers experiencing a layoff while controlling for state and year fixed effects. A 10 percentage point increase in the replacement rate decreases the likelihood of caregiving by a marginally significant 0.38 percentage points, or 27 percent. The coefficient on maximum benefit generosity, which reports the effect of a \$1,000 increase in the maximum level of UI benefit, is also negative, though not statistically significant.

To interpret and compare the magnitude of these coefficients, it is useful to standardize these measures. The standard deviation of the UI replacement rate is five percentage points in this sample, so a one standard deviation increase in the replacement rate increases the likelihood of caregiving among job losers by 14 percent. For comparison, a standard deviation in the maximum benefit corresponds to \$3,000, so a one standard deviation increase in maximum

Table 4: Effect of UI Generosity on Caregiving

	(1) Full Sample	(2) Job Loss Sample	(3) Full Sample
Job Loss	0.0028***		
	(0.0006)		
Replacement Rate		-0.0382*	
		(0.0214)	
Maximum Benefit		-0.0010	
		(0.0009)	
Replacement Rate X Job Loss			-0.0394**
			(0.0147)
Maximum Benefit X Job Loss			-0.0010
			(0.0006)
Mean Y	0.012	0.014	0.012
Obs	769,274	56,087	769,261
Year Fixed Effects	X	X	
State Fixed Effects	X	X	
State-Year Fixed Effects			X
State-Group Fixed Effects			X
Group-Year Fixed Effects			X
State-Year-Nb. Children Fixed Effects			X

Notes: Data are from the 1996–2008 panels of the Survey of Income and Program Participation (SIPP). Each cell reports the results from a separate regression. The dependant variable in all models in a binary indicator for if the respondent provided informal care to an adult (excluding own children) in that year, excluding caregivers who have been providing care for more than two years. The sample in Columns 1 and 3 include the full SIPP sample, while the sample in Column 2 is restricted to respondents who experienced a job separation. A unit increase in the independent variable maximum benefit corresponds to a $1000 increase, and a unit increase in the variable replacement rate corresponds to a 10 percentage point increase in the weekly replacement rate. All regressions include demographic controls and fixed effects as described at the bottom of the table. Robust standard errors are clustered by state and are shown in parentheses. (* $p < 0.10$, ** $p < 0.05$, ***) benefit decreases the likelihood of caregiving by a similar 0.3 percentage points, or 20 percent (though this coefficient is not statically significant at conventional levels).

Column three of Table 4 reports coefficients of interest from Equation 2 using the two different measures of UI generosity. The results in this column are nearly identical column 2 and are more precisely estimated. The similarity between these two columns given the different sets of controls alleviates some of the identification concerns for each of the empirical approaches. In particular, it suggests that the findings among laid off workers are not driven by state shocks that are correlated with UI generosity, and that there is no attenuation bias in the triple difference model from the partial treatment of the control group. Given the similarity of these results, I present the remainder of the results for the triple difference model only.

5.2.2 Impacts by subgroup

Next, I report the impacts of UI generosity on caregiving among workers who have been laid off by individual characteristics in Table 5. Column one repeats the results for the full sample from Table 4. Column two reports results for the sample aged 40–65, which is the age at which the caregiving hazard is highest for labor force participants who qualify for UI and thus when many are likely to experience conflicting work and caregiving obligations (Fahle and McGarry, 2018). The impact of a more generous replacement rate is much larger (and more precisely estimated) in this sample: a one standard deviation increase in benefit generosity decreases the likelihood of caregiving by 0.5 percentage points, or 33 percent. This is more than twice as large as the effect for the full sample. The coefficient for maximum benefit is also larger, though again not statistically significant. Similarly, a one percentage point increase in the weekly UI wage replacement rate increases the likelihood of caregiving by nearly one percentage point, or 40 percent.

I next split the full sample by gender. While women are assumed to be the default family caregivers, 40 percent of family caregivers are men, and studies show that both genders experience employment disruptions related to caregiving obligations (Van Houtven et al., 2013; Mommaerts and Truskinovsky, 2020; Maestas et al., 2021). The average caregiving rates by gender, reported at the bottom of Table 5, reflects this: 1.5 percent of women in this SIPP sample report providing informal care, compared to 0.8 percent of men. Although they provide less care on average, the coefficients in columns three and four of Table 5 suggest that the impact of the replacement rate on caregiving is concentrated among men: a standard deviation increase in UI generosity decreases the likelihood of caregiving by 0.3 percentage points for men who have experienced a layoff, while the coefficient is much smaller and insignificant for women. Conversely, when UI generosity is measured by the maximum benefit the effects are reversed – essentially null for men but marginally significant and larger for women. This suggests that these two measures are potentially capturing different dimensions of UI which impacts men and women differently.

This differences by gender, and the larger effect on caregiving for men is somewhat surprising, but not inconsistent with existing research. For example, Mommaerts and Truskinovsky (2020) find that men's caregiving behavior is sensitive to the local unemployment rates, suggesting that men respond to the opportunity cost of providing care. Women, on the

Table 5: Effect of UI Generosity on Caregiving- Heterogeneity

	(1) Full Sample	(2) Aged 40–64	(3) Female	(4) Male	(5) Married	(6) Not Married
Repl. Rate X Job Loss	-0.0394**	-0.0987***	-0.0130	-0.0591***	-0.0304	-0.0391*
	(0.0147)	(0.0335)	(0.0287)	(0.0179)	(0.0219)	(0.0217)
Max Ben X Job Loss	-0.0010	-0.0015	-0.0014*	-0.0005	-0.0002	-0.0017**
	(0.0006)	(0.0011)	(0.0007)	(0.0006)	(0.0012)	(0.0007)
Mean Y	0.012	0.015	0.015	0.008	0.012	0.011
Obs	769261	353071	378205	390977	427344	341804

Notes: Data are from the 1996–2008 panels of the Survey of Income and Program Participation (SIPP). Each cell reports the results from a separate regression. The dependant variable in all models in a binary indicator for if the respondent provided informal care to an adult (excluding own children) in that year, excluding caregivers who have been providing care for more than two years. The sample in each column is restricted as defined in the column heading. A unit increase in the independent variable maximum benefit corresponds to a \$1000 increase, and a unit increase in the variable replacement rate corresponds to a 10 percentage point increase in the weekly replacement rate. All regressions include demographic controls as well as state by year fixed effects, state by job loss fixed effects and job loss by year fixed effects. Robust standard errors are clustered by state and are shown in parentheses. (* $p < 0.10$, ** $p < 0.05$, ***) other hand, are more likely to respond to care need. Finally, men are also more likely to qualify for and to receive UI.

In the final two columns of Table 5, I split the sample by marital status. There may be differences in caregiving needs between these two groups, but perhaps more importantly, married households may be better able to self insure, consumption smooth, and shuffle around caregiving responsibilities during periods of job loss than single person household. Consistent with this interpretation, both measures of UI generosity appear to have significant negative impacts on the likelihood of caregiving among non married individuals. A one standard deviation increase in the replacement rate reduces the likelihood of caregiving by 0.2 percentage points, while a standard deviation in the maximum generosity reduces caregiving by a somewhat larger 0.5 percentage points. Notably, the coefficient for married households using the replacement rate is similar in magnitude, though not precisely estimated, for the replacement rate measure.

5.2.3 Impacts by caregiving intensity

Different caregiving roles and obligations may be more or less compatible with working and may be differently elastic with respect to changes in employment and income (Van Houtven et al., 2013). In Table 6, I consider the effect of more generous UI benefits on hours of care, as well as care separately classified by help with personal and medical tasks (ADLs) and help with chores and errands (IADLs). Results are presented for the full sample (column one) as well as for the subgroups discussed in the previous section. In panel one, I consider weekly caregiving hours (instead of a binary caregiving variable) for the full sample, coding non-caregivers with zero hours of care. While the binary model presented clear evidence that more generous UI benefits decrease the likelihood of caregiving on the extensive margin, the coefficients in this panel are noisy and switch signs, suggesting that the intensive margin is more complex. Only the coefficient for maximum benefit in the unmarried sample is marginally significant but small.

Panel two uses help with activities of daily living (ADLs) and medical tasks as the outcome. ADLs are personal care tasks such as dressing, transferring in and out of bed, toileting, and eating, which can be extremely time intensive, as well as time sensitive, tasks. They must be done everyday and cannot be deferred, and therefore are less likely to be sensitive to household changes in employment and income. The results presented in Panel 2 largely confirm this: for the full sample and the 40–64 sample, the coefficients of interest are small and statistically insignificant, suggesting that more generous UI benefits do not have a large impact on this type of caregiving. However, men and unmarried individuals both decrease the likelihood of providing help with ADLs in response to more generous UI benefits. A one standard deviation increase in the average replacement rate decreases the likelihood of help with ADLs by 0.17 percentage points among men (a very large 43 percent decrease from an average rate of 0.4), and a very similar 0.5 percentage points among unmarried households.

In panel three I consider help with instrumental activities of daily living (IADLs), which include help with housekeeping, grocery shopping, transportation and medication. These are less time intensive tasks that can be outsourced easily to another family member or to a

Table 6: Effect of UI Generosity on Caregiving Intensity

	(1) Full Sample	(2) Age 40-65	(3) Female	(4) Male	(5) Married	(6) Not Married
	Panel 1: Outcome variable: Caregiving Hours					
RR X Job Loss	0.0680	-0.1451	0.3813	-0.2052	0.2187	0.0168
	(0.2356)	(0.6707)	(0.3493)	(0.2055)	(0.4110)	(0.2699)
MB X Job Loss	-0.0032	0.0034	-0.0023	-0.0037	0.0115	-0.0167*
	(0.0096)	(0.0132)	(0.0144)	(0.0058)	(0.0146)	(0.0099)
Mean Y	0.10472	0.14146	0.13969	0.07091	0.11924	0.08661
	Panel 2: Outcome variable: Help with ADLs					
RR X Job Loss	-0.0145	-0.0090	0.0092	-0.0354***	0.0050	-0.0299***
	(0.0117)	(0.0248)	(0.0244)	(0.0092)	(0.0224)	(0.0110)
MB X Job Loss	-0.0006	-0.0006	-0.0007	-0.0005	0.0001	-0.0013***
	(0.0004)	(0.0010)	(0.0006)	(0.0004)	(0.0006)	(0.0004)
Mean Y	0.00638	0.00811	0.00902	0.00383	0.00693	0.00570
	Panel 3: Outcome variable: Help with IADLs					
RR X Job Loss	-0.0404**	-0.0939***	-0.0106	-0.0641***	-0.0304	-0.0437*
	(0.0162)	(0.0345)	(0.0263)	(0.0163)	(0.0210)	(0.0246)
MB X Job Loss	-0.0012*	-0.0015	-0.0013*	-0.0010	-0.0007	-0.0017**
	(0.0006)	(0.0010)	(0.0007)	(0.0007)	(0.0011)	(0.0006)
Mean Y	0.01032	0.01368	0.01319	0.00755	0.01104	0.00943
Obs	769261	353071	378205	390977	427344	341804

Notes: Data are from the 1996–2008 panels of the Survey of Income and Program Participation (SIPP). Each cell reports the results from a separate regression. The dependant variable in panel 1 is a continuous measure of hours of care to an adult (excluding own children) in that year, excluding caregivers who have been providing care for more than two years, defined as zero for non caregivers. The dependent variable in panel 2 is a binary indicator for if the respondent provided help with medical or personal care and the dependent variable in panel three is a binary indicator for if the respondent provided help with chores and errands. The sample in each column is restricted as defined in the column heading. A unit increase in the independent variable maximum benefit corresponds to a $1000 increase, and a unit increase in the variable replacement rate corresponds to a 10 percentage point increase in the weekly replacement rate. All regressions include demographic controls as well as state by year fixed effects, state by job loss fixed effects and job loss by year fixed effects. Robust standard errors are clustered by state and are shown in parentheses. (* $p < 0.10$, ** $p < 0.05$, ***) formal caregiver and/or can be done at any time. Mommaerts and Truskinovsky (2020) find that help with IADLs is more sensitive to the unemployment rate than other types of care, and the results presented in panel three are consistent with this interpretation. Changes in both UI measures lead to large decreases in the likelihood that recent job losers provide help with IADL tasks in the full sample, as well as among all subgroups except for married individuals.

5.2.4 Impacts on Caregiving by Spouses

Finally, in light of the research finding impacts of UI reciept on outcomes at the household level (and on the labor supply of spouses), I consider the effect of more generous UI benefits for a laid off *spouse* on own caregiving behavior. I present results for the full sample as well as by gender in Table 7. This model uses a similar specification to Equation 2, substituting the job loss status of spouse, additionally controlling for own employment status, and limits the sample to married households. Thus, the treatment group is respondents with a laid off spouse, compared with respondents who's spouse is working, and the outcome variable is own caregiving behavior. Notably, while the results in Table 7 are not precisely estimated, they are not small in magnitude and they are in most cases positive, suggesting that while more generous UI decreases caregiving among laid off individuals, it *increases* the likelihood of caregiving among their spouses. For example, among respondents aged 40–64, a one standard deviation increase in the UI replacement rate may increase the likelihood of caregiving among the spouses of laid off workers by 0.27 percentage points, or nearly 20 percent.

6 Discussion and Conclusions

This paper studies the relationship between job separations and informal caregiving, and examines the causal effect of income support during unemployment spells on family caregiving by leveraging variation in the generosity of Unemployment Insurance across US states and over time. I find that the likelihood of caregiving increases significantly following a job separation. However, more generous UI benefits, defined either as the weekly maximum benefit amount times the maximum number of weeks benefits are provided, or as the weekly wage replacement rate, reduce the likelihood that recently laid off workers provide informal care. A one standard deviation increase in UI generosity, as measured by the weekly replacement rate, reduces the likelihood of caregiving in the affected sample by 0.2 percentage points, or 14 percent. These effects are concentrated among workers aged 40–64, who are most likely to face informal care and work conflicts and among not married (single) households, who may have more difficulty smoothing consumption over unemployment spells. The effects also appear larger for men. I find larger effects for help with chores and errands (IADLs), which may be more elastic than personal and medical care tasks. Finally, I find suggestive evidence that while more generous UI decreases caregiving by laid off workers, it *increases* caregiving by their spouses, though these results are imprecisely estimated.

These finding suggest that some of the increase in caregiving following a job loss is due to financial constraints which are alleviated by income supports in the form of Unemployment

Table 7: Effect of UI Generosity on Caregiving by Spouse

	(1) Full Sample	(2) Aged 40-64	(3) Female	(4) Male
Repl. Rate X Job Loss	0.0160	0.0530	0.0170	0.0175
	(0.0261)	(0.0485)	(0.0370)	(0.0381)
Max Ben X Job Loss	0.0000	0.0006	-0.0008	0.0010
	(0.0012)	(0.0018)	(0.0015)	(0.0013)
Mean Y	0.012	0.014	0.015	0.009
Obs	410364	231273	215369	194829

Notes: Data are from the 1996–2008 panels of the Survey of Income and Program Participation (SIPP). Each cell reports the results from a separate regression. The dependant variable in all models in a binary indicator for if the respondent provided informal care to an adult (excluding own children) in that year, excluding caregivers who have been providing care for more than two years. The sample includes all married households, and is further restricted as described in the column heading. Job loss refers to a spouses's job loss. A unit increase in the independent variable maximum benefit corresponds to a \$1,000 increase, and a unit increase in the variable replacement rate corresponds to a 10 percentage point increase in the weekly replacement rate. All regressions include demographic controls as well as state by year fixed effects, state by job loss fixed effects and job loss by year fixed effects. Robust standard errors are clustered by state and are shown in parentheses. (* $p < 0.10$, ** $p < 0.05$, ***) Insurance. It also suggests that married households are better able to smooth care-related consumption across income shocks. Finally, while these impacts are contemporaneous, they may have medium- and long-term implications. If caring for family members is an absorbing state, short-term employment shocks have the potential to turn into longer-run decreases in labor force participation, impacting the economic security of future SSA beneficiaries. This study finds that unemployment insurance may reduce this likelihood through reducing the need of laid of workers to become family caregivers.

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