The Impact of Paid Family Leave on Families with Health Shocks*

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Abstract

This paper analyzes the impact of paid family leave (PFL) policies in California, New Jersey, and New York on the labor market and mental health outcomes of individuals whose spouses or children experience health shocks. We use data from the 1996-2019 restricted-use version of the Medical Expenditure Panel Survey (MEPS), which provides state of residence and the precise timing of hospitalizations and surgeries, our health shock measures. We use difference-in-difference and event-study models to compare the differences in post-health-shock labor market and mental health outcomes between spouses and parents before and after PFL implementation relative to analogous differences in states with no change in PFL access. We find that PFL access leads to a 7.0 percentage point decline in the likelihood that the (healthy) wives of individuals with medical conditions or limitations who experience a hospitalization or surgery report "leaving a job to care for home or family" in the post-health-shock rounds. Impacts of PFL access on women's mental health outcomes and on men whose spouses have health shocks are more mixed, and we find no effects on parents of children with health shocks. Lastly, we show that improvements in job continuity are concentrated among caregivers with 12 or fewer years of education, suggesting that government-provided PFL might reduce disparities in leave access.

Keywords: paid family leave, family health shocks, mental health

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1 Introduction

The COVID-19 pandemic has amplified the challenges of work-family balance for millions of workers, fueling public discussions about the lack of a federal paid family leave (PFL) policy in the United States. Like other forms of social insurance—such as health insurance and disability insurance—PFL can insulate a family from the negative consequences of a health event. Yet while PFL refers to paid time off for workers who have two types of caregiving responsibilities—new parents and caregivers of ill or temporarily disabled family members—there is much more consensus among Americans across the political spectrum in favor of paid leave for the former group than the latter.[1] The costs and benefits of paid caregiving leave for individuals who are *not* new parents are under debate among politicians, academics, and policy experts as well. For example, a 2018 report commissioned by a collaboration between the American Enterprise Institute and the Brookings Institution indicates that while the group of paid leave experts endorses paid parental leave, the "most contentious discussions centered on caregiving leave" (Mathur et al., 2018).[2] One major reason for this lack of agreement stems from the imbalance in empirical evidence for the two types of leave. Unlike the volumes of studies documenting the effects of paid parental leave on workers and their children (see Olivetti and Petrongolo, 2017; Rossin-Slater, 2018; Rossin-Slater and Uniat, 2019; Rossin-Slater and Stearns, 2020 for some overviews), the research on paid leave for households who experience non-childbirth-related health shocks is very limited (Waldfogel and Liebman, 2019).

This paper contributes to filling this gap by studying the impact of the implementation of PFL policies in California, New Jersey, and New York on the labor market and mental health outcomes of individuals whose spouses and children experience health shocks.[3] We use data from the restricted-use version of the Medical Expenditure Panel Survey (MEPS) over years 1996–2019, which allows us to observe individuals' states of residence, employment status, and the precise timing of the health shocks of their spouses and children. We study hospitalizations and surgeries (which can occur in emergency room, inpatient, or outpatient settings) as our measures of health

[1] See, for example, the polls discussed here: `https://www.newamerica.org/better-life-lab/blog/polling-summary-paid-family-and-medical-leave-is-one-of-the-most-popular-planks-in-the-build-back-better-`

[2] With regard to politics, the 2016 presidential election was the first to feature paid leave proposals from both Democratic and Republican candidates. However, while the proposals of the Democratic candidates included caregiving leave, those of the Republican candidates were limited to parental leave.

[3] As of 2022, ten states and Washington, D.C., have implemented or passed PFL legislation. Four of these occurred during our time period of analysis: CA (2004), NJ (2009), RI (2014), and NY (2018). We drop Rhode Island from our analysis due to very small sample sizes from this state in our data.

shocks. Additionally, to focus our attention on households who may be in particular need of caregiving leave, we study individuals who are employed at the beginning of the panel and whose spouses report having medical conditions or physical or cognitive limitations.[4] We use difference-in-difference (DD) and event-study models to compare the differences in post-health-shock labor market and mental health outcomes between spouses and parents surveyed before and after PFL implementation relative to the analogous differences among those in states that did not experience a change in PFL availability over the analysis time period.[5] Our regressions include controls for individual and family characteristics, as well as state and year fixed effects.[6]

Our results indicate that access to PFL has large and significant impacts on employment continuity of women whose spouses have medical conditions or limitations and experience a health shock. Specifically, we find that the (healthy) wives in these households, who are all employed at the beginning of the panel, are 7.0 percentage points less likely to report "leaving a job to care for home or family" in the post-shock rounds of the data. This represents a substantial effect size when evaluated at the sample mean of 2.2 percent. In contrast, we find small and statistically insignificant effects on the extensive margin employment outcomes of men whose wives have medical conditions or limitations and experience a health shock. We do, however, observe a 3.5 hour decrease in the weekly number of hours worked and a $90.3 reduction in the weekly income of the husbands, which is consistent with some leave use (without a change in overall employment). We find no statistically significant (or economically meaningful) impacts on the labor market outcomes of parents of children who experience health shocks. Our results on labor market outcomes are robust to using estimators proposed by Sant'Anna and Zhao (2020), Callaway and Sant'Anna (2021), and Sun and Abraham (2021), which apply to cases with multiple time periods and variation in treatment timing, and relax the standard "parallel trends" assumption.

The effects on the mental health outcomes of spousal and parental caregivers are theoretically ambiguous. On the one hand, if access to PFL increases time spent in caregiving, then we might

[4]When studying parents, we similarly restrict our attention to parents who are employed at the beginning of the panel. However, we do not make a restriction based on children's medical conditions or limitations because of concerns about too small sample sizes. Fewer than 100 households in state-years with access to PFL have children with medical conditions or limitations who also experience a health shock.

[5]For the very few individuals who move states during the course of the panel, we assign them to the first state in which they are observed in the data.

[6]As we discuss in Section 4, because the MEPS panels are relatively short (approximately two years in length), we do not study changes in individual outcomes from before to after the shock, as these analyses are under-powered. Instead, we implement a cross-sectional design that leverages the state-year variation in PFL access, and uses as outcomes individuals' labor market and mental health measures averaged over the post-shock rounds in the panel.

expect a deterioration in mental health due to previously documented associations between caregiving and higher rates of depression, anxiety, and stress (e.g., Schulz and Sherwood, 2008). On the other hand, if PFL lowers the likelihood that a potential caregiver must quit their job in order to take care of their family member, then it may in fact reduce stress and improve financial stability, thereby positively influencing caregiver mental health. That said, our empirical results on mental health outcomes are mixed and inconclusive. While the DD models indicate that women whose spouses have medical conditions or limitations and experience health shocks are substantially less likely to report having poor mental health or to have any mental health-related prescription drug in the post-shock periods when they have access to PFL, the event-study models do not confirm this result. Additional analyses using the Sant'Anna and Zhao (2020), Callaway and Sant'Anna (2021), and Sun and Abraham (2021) estimators suggest that the standard DD models for mental health outcomes may be biased due to variation in treatment timing and potentially heterogeneous treatment effects over time.[7] We similarly do not find any robust evidence of mental health impacts on spousal caregivers who are men, or on parents of children with health shocks.

Heterogeneity analyses suggest that the effects on employment following a spousal health shock are concentrated among individuals with low education levels (12 years or less), and are mostly non-existent among those with higher educational attainment. This finding is consistent with prior research on new mothers, which shows that PFL implementation has the largest impacts on leave use among the least advantaged women, thereby reducing pre-existing socio-economic and racial/ethnic inequities in leave use (Rossin-Slater et al., 2013). Workers with low education levels have very limited access to paid leave from their employers,[8] and are thus likely to benefit the most from government-provided PFL. We also provide suggestive evidence that caregivers whose employers do not offer paid sick leave benefits and who work in firms with 50 or more employees experience larger reductions in self-reported poor mental health and in the use of mental health prescription drugs as a result of access to PFL than their counterparts whose employers offer paid sick leave and are smaller in size; however, these results are subject to the same caveats as those for the overall sample. That said, it seems possible that state-level PFL is particularly valuable for workers whose own employers do not offer these types of benefits, and for those who simultaneously

[7] We have explored estimating the effects of each state's PFL policy separately. The state-specific event-study models (e.g., California vs. other non-PFL states) have yielded null effects on mental health outcomes. Results available upon request.

[8] See: Bureau of Labor Statistics, National Compensation Survey, March 2021, `https://www.bls.gov/ncs/ebs/benefits/2021/home.htm`.

qualify for job protection under the federal Family and Medical Leave Act (FMLA).[9]

Our paper contributes to the large literature on PFL policies, which has to date primarily focused on the outcomes of new parents (mostly, mothers) and their children. Nearly all of the U.S. evidence comes from studies of California's first-in-the-nation PFL program, documenting impacts on maternal and paternal leave-taking and labor market outcomes, as well as child and maternal health (Rossin-Slater et al., 2013; Huang and Yang, 2015; Das and Polachek, 2015; Baum and Ruhm, 2016; Byker, 2016; Lichtman-Sadot and Bell, 2017; Bartel et al., 2018; Bullinger, 2019; Pihl and Basso, 2019; Stanczyk, 2019; Bailey et al., 2019; Bana et al., 2020).[10,11]

To the best of our knowledge, only a handful of recent papers have analyzed caregivers who are not new parents, focusing on outcomes of individuals with family members who have disabilities, chronic health conditions, or are in self-reported poor health.[12] Kang et al. (2019) use data from the Current Population Survey (CPS) to show that the CA PFL policy increases employment among 45 to 64-year-old women with a family member who has a work-limiting disability. Anand et al. (2022) use data from the Survey of Income and Program Participation (SIPP) and show that PFL policies in CA and NJ increase the likelihood that an individual works full-time after the onset of a work-limiting health condition of their spouse.[13] Bartel et al. (Forthcoming) use data from the American Community Survey (ACS) and find that the CA PFL policy increases

[9]Note that only individuals in firms with 50+ employees are eligible for the federal Family and Medical Leave Act (FMLA) policy, which provides unpaid but job-protected leave. Thus, individuals residing in California, which implemented a PFL program without job protection, only qualify for job protection if they are simultaneously eligible for FMLA. See Section 2 for more details.

[10]Related, Stearns (2015) analyzes the impact of the 1978 Pregnancy Discrimination Act, which mandated that the five states with temporary disability insurance systems provide partially paid maternity leave for birthing mothers, on infant health. Rossin (2011) studies the impact of the federal Family and Medical Leave Act of 1993, which provides *unpaid* leave to eligible workers, on infant health.

[11]There is also an extensive literature on parental leave from countries outside the U.S., which have much longer leave provisions. For example, some studies find that paid maternity leave has positive or zero effects on maternal employment after childbirth (Baker and Milligan, 2008; Kluve et al., 2013; Bergemann and Riphahn, 2015; Carneiro et al., 2015; Dahl et al., 2016; Stearns, 2016), while others document negative impacts, especially in the long term (Lalive and Zweimüller, 2009; Lequien, 2012; Schönberg and Ludsteck, 2014; Bičáková and Kalíšková, 2016; Canaan, 2017). Studies that compare across countries suggest that provisions of leave up to one year in length typically increase the likelihood of employment shortly after childbirth, whereas longer leave entitlements can negatively affect women's long-term labor market outcomes (Ruhm, 1998; Blau and Kahn, 2013; Thévenon and Solaz, 2013; Olivetti and Petrongolo, 2017). Studies on fathers' outcomes have largely analyzed so-called "Daddy Month" reforms, which earmark a month (or more) of parental leave to fathers only (see, e.g., Duvander and Johansson, 2012; Ekberg et al., 2013; Duvander and Johansson, 2014, 2015; Avdic and Karimi, 2018; Rege and Solli, 2013; Dahl et al., 2014; Cools et al., 2015; Dahl et al., 2016; Eydal and Gislason, 2008; Schober, 2014; Bünning, 2015; Patnaik, 2019; Farré and González, 2019; Olafsson and Steingrimsdottir, 2020; Andresen and Nix, 2019; Lappegård et al., 2020).

[12]Another relevant study on non-childbirth-related leave is by Arora and Wolf (2018), who examine the impact of California's PFL policy on nursing home use.

[13]Related, Saad-Lessler (2020) also uses data from the SIPP to show that the CA PFL policy increases the likelihood that an unpaid care provider is in the labor force, with the effect being driven by women and those who are more educated.

the employment rate of 45 to 64-year-old individuals with a disabled spouse. Braga et al. (2022) use data from the Health and Retirement Survey (HRS) and find that PFL policies in CA and NJ increase employment and reduce the likelihood of depression among women with either a spouse in poor health or with a parent in poor health who lives within 10 miles.

We build on these path-breaking studies in four ways. First, we use the MEPS data, which allows us to precisely identify the timing of health shocks based on encounters with the healthcare system and to study outcomes measured after an individual's family member experiences a health shock. Our results on women being less likely to leave their jobs to care for others in the post-shock periods of the data are consistent with the earlier evidence of increases in women's employment, and provide more direct support for the conjecture that these broad employment effects are in fact due to increased job continuity afforded by the availability of caregiving leave.

Second, we expand beyond caregivers of adults to study parents of children who experience health shocks. Our estimated null effects on their employment and mental health outcomes are consistent with other survey evidence that indicates that parents of children with healthcare needs experience large barriers to taking paid leave (even when they have access to it).[14]

Third, we analyze caregivers' mental health, examining the effects of PFL access on both self-reported mental health and the use of mental health-related prescription drugs. We thus build on the growing evidence about the mental health impacts of paid leave among new mothers (Bullinger, 2019; Persson and Rossin-Slater, 2019; Bütikofer et al., 2021) by asking whether individuals experience changes in mental health when paid leave enables them to be caregivers for their spouses and older children as well.[15]

[14]In general, there is very limited evidence on the impacts of PFL on parents of children who have health care needs. A few surveys of parents of children with special health care needs in Chicago and Los Angeles indicate that parents who are employed report substantial need for having access to paid leave, but experience a variety of barriers to taking such leave (Chung et al., 2007; Schuster et al., 2008; Chung et al., 2012). Another survey of 585 parents of children with special health care needs who reported taking time off for their child's illness during the prior year indicates that the majority of parents experienced positive effects of taking leave on their own and their child's health, but also had leave-related financial challenges (Schuster et al., 2009).

[15]A few studies have used survey data to analyze associations between taking paid leave for caregiving purposes and measures of economic security, well-being, and mental health (Earle and Heymann, 2011; Goodman and Schneider, 2021). However, other differences between workers who are and are not able to take paid leave make causal inference challenging in these research designs. Gimm and Yang (2016) study the impact of CA PFL on the mental health outcomes of self-reported caregivers in the Health and Retirement Survey, focusing on the Center for Epidemiologic Studies (CESD) depression score as the outcome, and finding no significant effects. However, there are some important limitations in this study as it does not include state fixed effects and does not account for clustering of standard errors to account for serial correlation in observations within individuals and states. Moreover, the study treats 2002 as the first policy year, which is not consistent with the fact that California's policy went into effect in July 2004 (the law was passed in 2002).

Fourth, in addition to the policies in California and New Jersey, we also study New York's PFL policy that went into effect in 2018, thereby delivering evidence that is much more recent and arguably more relevant to other states that have only just implemented or are currently considering implementing their own PFL legislation.

We also build on a long literature documenting the spillover impacts of health shocks on other family members' outcomes, including labor supply, consumption, and health-related behaviors (Altonji et al., 1989; Cochrane, 1991; McClellan, 1998; Wu, 2003; Coile, 2004; García-Gómez et al., 2013; Dalton and LaFave, 2017; Jeon and Pohl, 2017; Dobkin et al., 2018; Bom et al., 2019; Fadlon and Nielsen, 2019; Frimmel et al., 2020; Aouad, 2021; Fadlon and Nielsen, 2021; Adhvaryu et al., 2022). Most relevant to our paper is a recent analysis by Arrieta and Li (2022), who use the MEPS data to show that, following a family member's ED visit, women increase their labor supply while men experience a reduction in wages. Our study suggests that access to PFL may be an important determinant of individuals' labor market responses to their spouses' health shocks. Finally, our paper is relevant to the literature on caregiving and employment (see Bauer and Sousa-Poza, 2015, for a review), in that PFL has the potential to buffer against the adverse effects of caregiving responsibilities on employment and long-term financial well-being.

2 Background

As noted in Section 1, the United States does not have any federal policy providing paid family leave to workers. The federal Family and Medical Leave Act (FMLA) of 1993 provides twelve weeks of *unpaid* job-protected leave for workers caring for a newborn or newly adopted child, an ill family member, or an own serious medical condition.[16] The most recent data suggest that only about 56 percent of private sector workers are eligible for the FMLA (Brown et al., 2020), which only covers those who have worked at least 1,250 hours for an employer with 50 or more employees during the 12 months before the start of the leave.

At the state level, five states—California, Hawaii, New Jersey, New York, and Rhode Island—have had Temporary Disability Insurance (TDI) programs since the 1940s and 1950s, which provide partially paid leave for workers who need time off due to an own temporary disability or illness. Since the Pregnancy Discrimination Act of 1978, these programs have been required to cover birth

[16] Job protection refers to an employee's right to return to the same or equivalent job after taking leave.

mothers who are preparing for and/or recovering from childbirth.

In 2004, California became the first state in the nation to implement a paid family leave program, which initially provided new parents and caregivers of ill family members with six weeks of leave at a 55 percent wage replacement rate (up to a maximum weekly benefit amount, which varies slightly every year).[17] As of 2022, ten additional states and Washington, D.C., have either passed or implemented PFL legislation: New Jersey (in 2009), Rhode Island (in 2014), New York (in 2018), D.C. (in 2020), Washington (in 2020), Massachusetts (in 2021), Connecticut (in 2022), Oregon (will go into effect in 2023), Colorado (will go into effect in 2024), Maryland (will go into effect in 2025), and Delaware (will go into effect in 2026). These policies are all similar in that they have minimal eligibility requirements—and thus near-universal coverage—and provide partially paid leave for at least two categories of caregivers: those with newborn or newly adopted children and those with ill family members. Policies in states without pre-existing TDI programs also offer leaves for workers' own temporary disabilities or illnesses. Most of these programs are funded by employee payroll taxes. The policies vary substantially in terms of other key parameters, including statutory leave duration, the wage replacement rate, the maximum weekly benefit amount, and the presence or lack of job protection.[18]

Since our MEPS data span years 1996–2019, we have pre- and post-law data for households in four states: California, New Jersey, Rhode Island, and New York. However, we drop households residing in Rhode Island because we have too few observations in MEPS, and thus study the impacts of PFL implementation in California, New Jersey, and New York.[19] We focus on studying the (healthy) caregivers rather than individuals who need leave for their own illness because all three of our analysis states had a pre-existing TDI program at the time of PFL implementation. Thus, there was no major policy change in the existence of state-provided paid leave for an own health shock during our analysis time frame.

[17] As of 2022, California's PFL policy provides 8 weeks of leave with 60-70 percent of wages replaced, up to a maximum weekly benefit of $1,540.

[18] See `https://www.abetterbalance.org/resources/paid-family-leave-laws-chart/` for an up-to-date chart with details about all current state PFL policies.

[19] As noted above, at the time of implementation, CA-PFL provided six weeks of leave at a 55 percent wage replacement rate, up to a maximum weekly benefit of $728; NJ-PFL provided six weeks of leave with a 66 percent wage replacement rate, up to a maximum weekly benefit of $524; NY-PFL provided 8 weeks of leave with a 50 percent wage replacement rate, up to a maximum weekly benefit which is equal to 50 percent of New York state's average weekly wage. CA-PFL does not have job protection, while NJ-PFL and NY-PFL do.

3 Data and Sample

We use data from the restricted-use version of the Medical Expenditure Panel Survey (MEPS) from the Agency for Healthcare Research and Quality, which contains state of residence identifiers. Since 1996, the Household Component survey of MEPS has collected detailed information about the demographic and socioeconomic characteristics, medical conditions, and labor market outcomes of every member of a household in five rounds of interviews over a two-year panel. Each survey panel is designed to capture a representative sample of the U.S. population.

MEPS also collects data on each household member's engagement with the health care system in each round of the panel in the Hospital Inpatient Stay, Emergency Room Visit, and Outpatient Visit event files. We use these files to construct our measure of a health shock: an indicator for experiencing either an inpatient visit or a surgery (in an emergency department, inpatient, or outpatient visit setting). We exclude individuals who have visits related to pregnancy, birth, or pre- or post-natal maternity care from our analysis.

To study how having access to PFL might affect a potential caregiver's mental health, we also use the MEPS Prescribed Medications event files. These files contain U.S. Food Drug and Administration National Drug Codes, which we map into Anatomical Therapeutic Chemical (ATC) Level 5 codes, which can be used to identify the conditions that every drug is typically used to treat.[20] We are thus able to measure the utilization of all mental health-related prescription drugs, as well as prescriptions that are used to treat anxiety and depression specifically.

Analysis Samples. We pool all panels of data covering the years 1996 to 2019. We use data on respondents from all states except Rhode Island, which implemented PFL in 2014, but has too few observations to have sufficient statistical power to detect the policy's effects. For the very few individuals who move states during the course of the two-year panel, we assign them to the first state in which they are observed in the data. We limit our analysis to survey respondents who are aged 25 to 64 and are employed and at work or have a job to return to in the first round of the Household Component survey. To focus on potential caregivers (rather than people who may need paid leave for their own health issues), we additionally drop all individuals who experience an *own* emergency department visit, hospitalization, or surgery in any round of the panel.

We study two types of caregivers: spouses and parents of children under the age of 18. When

[20]We use the NDC-ATC5 crosswalk available here: `https://github.com/fabkury/ndc_map`.

studying spousal caregivers, we consider individuals with a spouse who experiences a health shock during the panel (after the round 1 interview and before the round 5 interview) *and* who reports having at least one medical condition or a cognitive or physical limitation in the Household Component survey.[21] By focusing on employed working-age individuals whose spouses have medical conditions or limitations and also experience a health shock, we aim to narrow in on the population who may be most likely to be in need of caregiving leave.

When studying parent caregivers, we restrict our attention to parents of at least one child under age 18 in the household who experiences a health shock during the panel. As noted in footnote 4, we do not limit to families with children who have medical conditions or limitations because there are too few of them to constitute a meaningful analysis sample (see also discussion of Appendix Table A1 below).

For both analysis samples, we collapse the data to a cross-section with one observation per individual. We measure control variables using the first round of each panel and outcomes using post-health-shock rounds as described below. Our main spousal analysis sample consists of 2,739 individuals with spouses who have a condition or limitation and experience a health shock, while our main parental analysis sample consists of 2,828 individuals with children under age 18 who experience a health shock.[22]

Outcomes. We study the impacts of having access to PFL on potential caregivers' labor market and mental health outcomes measured post-health-shock. Specifically, for every outcome, we calculate the average value using all rounds of data starting from the round in which the health shock occurs and onward. For example, if a spousal inpatient stay takes place between the round 2 and round 3 interview dates, then we consider the focal individual's employment and mental health as an average across observations in rounds 3 through 5.

We examine three measures of employment available from the Household Component Survey in every round: (1) an indicator for being employed, (2) an indicator for leaving a job to care for home or family and (3) an indicator for leaving a job for all other reasons. Note that the second

[21] While the Household Component survey has collected information about individuals' cognitive or physical limitations since 1996, it only began collecting information about select medical conditions in 2000. The medical conditions that are collected in year 2018 of the Household Component survey include ADHD, angina, arthritis, asthma, cancer, cholesterol, diabetes, emphysema, heart attack, heart disease, high blood pressure, and stroke. Among the 3,894 individuals in our sample with a spouse who experiences a health shock during the panel, 70.2 percent have a spouse with a medical condition or cognitive or physical limitation. Our results are similar (but less precise) when we use the larger sample without restricting to spouses with a condition or limitation.

[22] Our sample sizes reported in the tables are slightly smaller due to missing values for some outcomes.

and third variables are based on questions that are asked only of those individuals who state that they are not employed in a current round but that they were previously employed. We recode the missing values—which in our sample apply to respondents who are employed in a given round—as zeros. The second outcome allows us to study whether access to PFL enables individuals to remain employed in their jobs instead of leaving for caregiving reasons, while the third one covers a range of other reasons why people may leave their jobs including: "could not find work," "retired," "unable to work because ill/disabled," "going to school," "don't want to work," and "other."[23]

In supplementary analyses, we also examine labor market outcomes on the intensive margin. These include the reported usual hours worked per week at an individual's current main job, as well as the hourly wage (in 2018 dollars) for all individuals who are not self-employed.[24] Using the number of hours worked and the hourly wage, we also calculate the weekly income. We present these three labor market outcomes both conditional and unconditional on being employed in each round. For outcomes that are not conditional on employment, we recode missing values as zeros.

Lastly, as mental health outcomes, we consider both self-reported mental health status and the use of mental health-related prescription drugs. The self-reported mental health outcome is an indicator for reporting poor or very poor mental health (a value of 4 or 5 on a 1–5 scale) in the Household Component survey. This question is asked of all survey respondents. We also construct an indicator for using a prescription drug to treat any mental health condition, as well as an indicator for using a prescription drug to treat anxiety or depression specifically. Finally, we create an aggregate variable for having any mental health issues, which is defined as an indicator that is equal to one if an individual reports having poor or very poor mental health or if an individual uses any mental health-related prescription drug.

Descriptive Statistics. Table 1 presents means of selected characteristics of our main spousal analysis sample. Column (1) uses the entire sample, while columns (2) and (3) split it into individuals residing in state-years with and without PFL availability, respectively. All of the reported variables are measured in the first round of each panel. In this sample, average age is

[23]The categories for these reasons have changed slightly over time in the MEPS survey. The ones listed in the sentence above are from 2018. Prior to 2018, the categories were: "could not find work," "retired," "unable to work because ill/disabled," "on temporary layoff," "maternity/paternity leave," "going to school," "taking care of home or family," wanted some time off," "waiting to start new job," "other," and "wanted some time off." We aggregate them all into a single indicator reflecting individuals leaving jobs for all reasons other than caring for their home or family.

[24]Self-employed individuals do not report an hourly wage. Hourly wages in each panel of the Household Component survey are top-coded.

48.4 years, the average number of children residing in the household is 0.7, and the share male is 52.4 percent. Overall, about 4.6 percent of individuals are non-Hispanic Asian, 12.2 percent are non-Hispanic Black, and 65.1 percent are non-Hispanic white, although there are some important differences in the racial and ethnic composition of the sample between state-years with and without PFL. About half of the sample has 12 years or less of education, while the other half has more than 12 years of education. The bottom panel presents the distribution of medical conditions and limitations among spouses.[25] The most common condition category—affecting 67 percent of spouses—is diabetes, cholesterol, or high blood pressure. About 34.3 percent of spouses have heart or lung conditions, 40.4 percent have arthritis, 16.4 percent have asthma, and 9.6 percent have cancer. In terms of limitations, 45.7 percent of spouses report having a physical limitation, while 15.4 percent report a cognitive limitation.

Table 2 presents the 20 most frequently occurring ICD-9 codes associated with spousal health shocks in our main analysis sample for years 1996 and 2012, when these codes are available.[26] These diagnoses account for about 35.9 percent of all health shocks (i.e., inpatient stays and surgeries in any settings) in the sample. Note that, in our sample, 53.7 percent of spousal health shocks are inpatient visits that also involve surgeries, 34.7 percent are inpatient visits that do not involve surgeries, and 11.6 percent are surgeries in the emergency department or an outpatient setting. The table makes clear that the health shocks we study are quite varied in nature, ranging from heart attacks to pneumonia to joint issues.

Appendix Table A1 presents summary statistics for our sample of parental caregivers, using the same format as Table 1. Compared to spousal caregivers, these individuals are younger (average age is 37.3 years) and have more children (average number of children is 2.2). The bottom half of the table presents rates of medical conditions and limitations recorded in the MEPS data for children this sample. As noted previously, the rates for most conditions are quite low, with the exception of asthma, which 22.2 percent of children in the sample have. Lastly, Appendix Table A2 presents the 20 most frequently occurring ICD-9 codes associated with child health shocks. These account for about 42.8 percent of all health shocks in the sample. Wounds and injuries are fairly common, but the health shocks we study also include infections, respiratory conditions, and appendicitis. In our sample, 41.1 percent of child health shocks are surgeries in the outpatient or

[25] Note that the shares do not add up to 100 percent since a respondent can have more than one condition.

[26] MEPS stopped collecting ICD-code information in the Hospital Inpatient Stay, Emergency Room Visit, and Outpatient Visit event files after 2012.

emergency department setting, 33.8 percent are inpatient stays without surgeries, and 25.1 percent are inpatient stays that involve surgeries.

4 Empirical Design

To measure the effect of access to PFL on the outcomes of individuals whose spouses or children experience health shocks, we leverage the state-year variation in PFL access in difference-in-differences (DD) and event-study models. As noted in Section 3, we collapse our panel data into an individual-level cross-sectional dataset, in which outcomes are measured as averages over observations in post-health-shock rounds. Thus, we build on the prior and concurrent literature examining caregiving leave with similar research designs in other data sets (Kang et al., 2019; Anand et al., 2022; Bartel et al., Forthcoming; Braga et al., 2022), except that we use analysis samples in which all individuals experience spousal or child health shocks during the course of the survey panel, and we measure outcomes in the aftermath of those shocks.[27]

When studying spousal health shocks, we estimate the following DD model:

$$Y_{ist} = \alpha_0 + \alpha_1 PFL_{st} + \gamma' X_i + \delta' S_i + \theta_t + \rho_s + \epsilon_{ist} \tag{1}$$

for individual i residing in state s in calendar year t. Y_{ist} is an outcome of interest, such as the share of post-spousal-health-shock rounds that the individual is employed. PFL_{st} is an indicator set to 1 for state-years in which PFL exists, and 0 otherwise. We control for the following individual and family characteristics measured in the first round of the panel in X_i: indicator for male gender, indicators for race/ethnicity (non-Hispanic Asian, non-Hispanic Black, non-Hispanic white, Hispanic, other), education level (less than 12 years, 12-15 years, 16 years or more), age, and the number of children under age 18 in the household. We additionally include indicators for the type of spousal health shock experienced (inpatient visit or a surgery in any setting) and the type of medical condition or limitation that the spouse reports having in S_i. We include calendar year fixed effects, θ_t, which account for aggregate trends in outcomes and state fixed effects, ρ_s, which

[27] While the panel structure of MEPS would theoretically allow us to also leverage the within-individual variation that has been typically used in studies of family health shocks (e.g., Coile, 2004; Fadlon and Nielsen, 2019; Aouad, 2021; Fadlon and Nielsen, 2021; Arrieta and Li, 2022), we do not incorporate this source of variation in our analysis due to the MEPS panels being relatively short (2 years) and the small sample sizes when we zoom in on the intersection between the within-individual pre-post-health-shock variation and the state-year variation in PFL access in three states.

account for all time-invariant differences between states. We cluster standard errors on the state level. The key coefficient of interest is α_1, which measures the difference between the change in individuals' post-spousal-health-shock outcomes from before to after PFL goes into effect in CA, NJ, and NY and the change over the same time period in states without a change in PFL availability.

We also estimate a corresponding event-study model:

$$Y_{ist} = \beta_0 + \sum_{k=-4, k \neq -1}^{k=4} \pi_k \mathbf{1}[t - PFL^*_{st} = k] + \psi' X_i + \zeta' S_i + \eta_t + \gamma_s + \varepsilon_{ist} \tag{2}$$

for individual i residing in state s in calendar year t. The event-time indicators, $\mathbf{1}[t - PFL^*_{st} = k]$, reflect the year relative to PFL adoption, and are set to 0 in all years for states without PFL during our time frame. All of the other variables are the same as in equation (1).[28]

When studying individuals whose children experience health shocks, we estimate similar specifications, except that the control vector X_i additionally includes the individual's marital status, while S_i controls for indicators for the type of child health shock and child medical condition or limitation (if they have one).

A causal interpretation of our estimates relies on the standard "parallel trends" assumption—that outcomes in treatment and control states would have evolved similarly in the absence of PFL implementation. Our event-study models allow for a visual examination of pre-trends in pre-policy years. Additionally, given the recent burgeoning literature raising concerns about the interpretation of and potential bias in DD and event-study models with staggered treatment timing (e.g., De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Borusyak et al., 2021; Sun and Abraham, 2021; Athey and Imbens, 2022; Roth et al., 2022), we examine the sensitivity of our results to using estimators developed by Sant'Anna and Zhao (2020), Callaway and Sant'Anna (2021), and Sun and Abraham (2021), which account for cases with multiple time periods, variation in treatment timing, and possible violations of the "parallel trends" assumption.

[28]The π coefficients for $k = -4$ and $k = +4$ (i.e., the endpoints) reflect effects in state-years four or more years before and four or more years after PFL adoption, respectively.

5 Results

5.1 Effects on Spouses

Labor Market Outcomes. Table 3 presents results for our main sample of individuals with spouses who have a medical condition or limitation and experience a health shock. Panel A contains estimates for the whole sample, while the other panels consider sub-groups of the following types of spousal caregivers: women (Panel B), men (Panel C), those with up to 12 years of education (Panel D), and those with 13 or more years of education (Panel E).

In the overall sample, we find that access to PFL is associated with a 5.4 percentage point higher likelihood that an individual is employed in the rounds following a spousal health shock. Notably, column (2) indicates that this higher likelihood of employment is driven by a 4.0 percentage point lower likelihood of the individual leaving a job to care for their home or family. There is also a 1.8 percentage point reduction in the likelihood of leaving a job for other reasons, which could reflect that not all individuals who stop working to care for their family report doing so directly in the survey.

Interestingly, Panels B and C document a stark difference in labor market effects between women and men. In fact, it appears that the results in the overall sample are entirely driven by women, who are 7.0 percentage points less likely to leave their job to care for their home or family when they have access to PFL. The magnitude of the effect size is more than triple that of the sample mean. By contrast, we do not see any statistically significant or economically meaningful impacts on the employment of men whose spouses have health shocks.

Panels D and E further show that these impacts are concentrated among workers with up to 12 years of education, and are non-existent for those with more years of education. This finding echoes prior research by Rossin-Slater et al. (2013), who show that the effect of California's PFL policy on leave take-up is larger among new mothers who are less educated, unmarried, and racial minorities than for their more advantaged counterparts. While we do not have direct measures of leave use in the MEPS data, other data show similar disparities in leave access along socio-economic and racial/ethnic lines among caregivers of ill family members (Bartel et al., 2019), and our results suggest that government-provided PFL may reduce these disparities, and further improve employment continuity among disadvantaged groups.

Figures 1 and 2 present the corresponding event-study estimates for the first two labor market outcomes for the overall sample and for our 4 main sub-groups (women, men, and individuals with low and high education levels). While it appears that the overall employment effect may in part reflect a continuation of a pre-trend (Figure 1), we see no indication of a pre-trend for our most directly relevant outcome in the context of PFL: leaving one's job to care for the home or family (Figure 2). For this second outcome, the coefficients on the pre-PFL years are mostly small and statistically insignificant, while there is a clear shift down in the four years following PFL implementation. Consistent with the DD evidence, the effect is pronounced for women and those with low education levels, and non-existent for men and those with high education levels.

While our estimates are large, we do not find them to be implausibly so. Among women in our sample who are employed in the first round of the panel, only 89.7 percent remain employed in post-health-shock rounds (see Column 1 of Table 3), indicating that around 10 percent of wives whose spouses experience health shocks leave their jobs in the post-shock periods. Our estimated 7.0 percentage point decline in the likelihood of women reporting that they left a job to care for home or family when they have PFL access is thus lower than the overall probability of leaving employment in this sample. Further, we note that the lower end of the 95 percent confidence interval is 3.7 percent, which is roughly half the size of the estimated coefficient.

Appendix Table A3 and Appendix Figures A1 and A2 present results from estimating models for our main outcomes using the estimators developed by Callaway and Sant'Anna (2021) and Sant'Anna and Zhao (2020), and Sun and Abraham (2021), respectively. The labor market impacts of PFL are robust to these specifications, and if anything, appear to be larger in magnitude—for instance, the Callaway and Sant'Anna (2021) and Sant'Anna and Zhao (2020) estimator yields a 13.6 percentage point reduction in the likelihood of women caregivers leaving their jobs to care for home/family, while the standard DD estimate yields a 7.0 percentage point effect. Similarly, this estimator yields a 9.4 percentage point effect for caregivers with 12 or fewer years of education, larger than the corresponding coefficient from Table 3. As before, there are no statistically significant effects for men caregivers or for caregivers with 13 or more years of education. The event-study results in Appendix Figures A1 and A2 are quite similar to those in Figures 1 and 2.

Appendix Table A4 presents results using intensive margin labor market outcomes, both conditional and unconditional on employment. Consistent with the extensive margin effect on post-spousal-health-shock employment among women, we see an increase in the unconditional weekly number of hours worked, as well as in hours worked conditional on employment. For men, we observe a 3.5 hour decrease in the weekly number of hours worked and a $90.3 reduction in the weekly income conditional on employment, which perhaps reflects some leave use (without any change in employment).

Lastly, Appendix Figure A3 summarizes our sub-group analyses visually by plotting the PFL coefficients and associated 95% confidence intervals from estimating separate regression models for the four sub-groups just discussed (women, men, and individuals with low and high education levels), along with four additional sub-groups constructed using information on focal individuals' employers in round 1: those whose employers do and do not provide paid sick leave benefits, and those employed in firms who have less than 50 or 50 or more employees. Paid sick leave benefit provision is designed to proxy for whether employers might offer their own PFL benefits (we unfortunately do not have direct information on employer provision of PFL). The split by firm size is designed to capture differences in effects by FMLA eligibility, which would provide job protection for workers taking state-level paid leave. We do not see clear patterns of heterogeneity in labor market impacts of PFL along these margins.

Mental Health Outcomes. Having shown that access to PFL affects the labor market outcomes of individuals in the aftermath of a spousal health shock, we turn to the analysis of mental health. There are several mechanisms by which PFL could influence potential caregivers' mental well-being. If the availability of paid leave induces people to spend more time in caregiving than they otherwise would have, then it is possible that their mental health might worsen due to the stresses and demands of this type of work. Indeed, prior research shows that caregiving is associated with higher rates of depression, anxiety, and stress (e.g., Schulz and Sherwood, 2008), although it is difficult to know whether these correlations are causal. If, however, access to PFL allows individuals to take care of their ill spouses while retaining their jobs, then they may experience improved mental health outcomes due to lower financial burdens and improved self-esteem associated with retaining their identities as workers (Reitzes and Mutran, 2006; Payne and Doyal, 2010). Additionally, the spouse who experiences the health shock themselves might be affected by the availability of PFL for their partner, which might in turn influence their caregiver's well-being.

Columns (4) through (7) of Table 3 present DD results for our four mental health outcomes measured in post-spousal-health-shock rounds. In the overall sample, we find that PFL access is associated with a 4.6 percentage point (36 percent at the sample mean, marginally significant at the 10% level) lower likelihood of individuals either reporting poor mental health or using any mental health-related prescription drugs in rounds after their spouse has a health shock. This overall effect appears to be primarily driven by a reduction in the likelihood of using anti-depressant or anti-anxiety medications.

Panels B and C of Table 3 show that the average effect in the whole sample masks important heterogeneity by gender. Women caregivers have a 7.0 percentage point (44 percent at the sample mean) reduction in the aggregate mental health outcome, and the coefficients for both poor self-reported mental health (column 5) and anti-anxiety and anti-depressant drug use (column 7) are negative and large, with the former being statistically significant. The results are more mixed for men caregivers. We observe a 2.7 percentage point (55 percent at the sample mean) increase in the likelihood of reporting poor mental health alongside a 5.5 percentage point (59 percent at the sample mean) reduction in the probability of using any mental health-related drugs in the rounds following a spousal health shock.

Panels D and E of Table 3 explore heterogeneous impacts on mental health by the caregiver's level of education. We find that caregivers with 12 years or less of education are 6.7 percentage points (54 percent at the sample mean) less likely to report poor mental health or use any mental health prescription drugs, and are 4.8 percentage points (67 percent) less likely to use anti-anxiety or anti-depressant drugs in post-spousal-health-shock rounds. We do not observe any significant mental health impacts on caregivers with higher education levels.

However, while the DD results would suggest to large and significant changes especially in women caregivers' mental health, the event-study estimates are less conclusive. Figure 3 presents the event-study estimates for our aggregate mental health indicator as the outcome, with mostly insignificant coefficients on the individual event-time indicators. Moreover, the results on mental health from using the alternative Callaway and Sant'Anna (2021), Sant'Anna and Zhao (2020), and Sun and Abraham (2021) estimators are similarly inconclusive (see Columns 4 through 7 of Appendix Table A3 and sub-figures (c) of Appendix Figure A1 and A2, respectively). Thus, we encourage caution when interpreting the standard DD estimates for mental health outcomes; it seems likely that those results are affected by bias due to heterogeneous treatment effects over time, and potential violations of the "parallel trends" assumption.

Appendix Table A5 investigates the role of the spouse who experiences a health shock in driving the mental health outcomes of the caregiving spouse. As outcomes, we consider post-health-shock employment, as well as our four measures of mental health. We use our baseline analysis sample in Panel A, and study a sub-sample in which both spouses are employed in round 1 in Panel B. Panels C and D split the sample by caregiver gender. Column (1) shows that PFL access does not affect the ill spouse's own employment, which is consistent with the fact that the policies we study did not introduce new forms of paid leave for own temporary disabilities or illnesses (see Section 2). Interestingly, we do see some evidence that the ill spouse's own mental health is affected, though, in sub-samples in which both spouses are employed (Panel B) and with male caregivers (Panel D). In fact, the mental health impacts on the ill spouses with male caregivers are similar to those just discussed for male caregivers themselves—a higher likelihood of self-reported poor mental health combined with a lower likelihood of using mental health prescription drugs. It is possible that access to PFL in these households increases men's time spent in caregiving, which then translates into these mixed impacts for both spouses' mental health. That said, we again urge caution with these estimates, as they are likely subject to the same issues as those for the caregivers' mental health outcomes.

Sub-figures (c) through (f) of Appendix Figure A3 summarize the heterogeneity analyses for the mental health outcomes. Beyond the patterns by caregiver gender and educational attainment already discussed, we observe some suggestive evidence of differences in effects by whether or not the caregiver's employer offers paid sick leave benefits and firm size. Specifically, it appears that caregivers whose employers do not offer paid sick leave benefits and who work in firms with 50 or more employees experience reductions in self-reported poor mental health and in the use of mental health prescription drugs as a result of access to PFL. This pattern is consistent with state-level PFL being particularly beneficial for workers whose own employers do not offer this benefit, and for those who also simultaneously qualify for job protection under the FMLA. We note, however, that the 95% confidence intervals are overlapping across all sub-groups, making these conclusions mostly suggestive.

5.2 Effects on Parents

Table 4 presents results using our sample of parents of children under age 18 who experience a health shock. In contrast with the results for spousal caregivers, we find no evidence of significant impacts on either the employment or the mental health of parent caregivers. We show results here for the whole sample, but the patterns are similar when we split between mothers and fathers. Similarly, Appendix Table A6 shows no evidence of intensive margin labor market impacts. Our results are similar if we use the Callaway and Sant'Anna (2021) and Sant'Anna and Zhao (2020) estimator (Appendix Table A7).

While our data do not allow us to perfectly understand why parents of children who have health shocks seem unaffected by PFL access, one conjecture is that these families are less likely to use paid leave even if it is available, compared to new parents and spousal caregivers. It is possible that the majority of children's health shocks that we observe a relatively minor and do not require an extended period of leave from work.[29] Alternatively, for the cases in which the shocks are severe, it is possible that availability of PFL does not affect parental decisions regarding changing their labor force status (e.g., if a child has a leukemia diagnosis, perhaps one parent will exit the labor force or work part-time regardless of whether they have PFL access or not).

6 Conclusion

This study examines the impact of paid family leave policies on the labor market and mental health outcomes of working-age adults following spousal and child health shocks unrelated to childbirth. Our analysis is one of only a handful of studies exploring impacts on caregivers who are not new parents, as most of the literature to date has focused on parental leaves following the birth of a child.

We use data from the restricted-use Medical Expenditure Panel Survey (MEPS) covering years 1996–2019, and focus on employed working-age spouses of individuals who have medical conditions or limitations and experience either a surgery or a hospitalization during the course of the panel. Additionally, we study employed working-age parents of children under age 18 who experience a surgery or a hospitalization. We analyze the impacts of PFL access in California, New Jersey, and New York using difference-in-differences and event-study designs.

We find that PFL access supports employment by increasing job continuity for the wives of individuals who have a health shock. To our knowledge, our study is the first to document this mechanism. We find that these women are 7.0 percentage points less likely to "leave a job to care for home or family" in the post-spousal-health-shock rounds of the data. For men, we find no evidence of an extensive margin effect on employment, but we do observe a small decrease in the weekly number of hours worked and their weekly income. We do not find any labor market

[29] See Appendix Table A2 for the most common diagnoses associated with the health shocks we study.

impacts of PFL on parent caregivers.

Our evidence on mental health impacts is much more mixed. While the standard DD models suggest that PFL access leads to a large reduction in the likelihood of reporting having poor mental health or of using a mental health-related prescription drug in the post-health-shock rounds for women and for caregivers with 12 years or less of education—the same sub-groups for which we observe job continuity effects—the event-study and alternative estimators do not support this conjecture. We find mixed and inconclusive evidence on the mental health outcomes of husband caregivers. Similar to the labor market outcomes, we find no evidence of mental health effects on parent caregivers.

Taken together, our results suggest that when spouses with a medical condition or limitation experience a hospitalization or surgery, having PFL access enables (healthy) wives to care for them while retaining their jobs. For husbands in a similar situation, PFL access has no effect on employment (on the extensive margin). The gendered impacts of PFL among spousal caregivers are consistent with the previous literature that has found that women are substantially more likely to engage in caregiving for their ill spouses than men (e.g., Allen, 1994; Boye, 2015; Sharma et al., 2016; Maestas et al., 2020; Cubas et al., 2021). We also find that the effects of PFL access on employment are concentrated among spousal caregivers with low education levels. Thus, our findings suggest that government-provided PFL might reduce pre-existing disparities in leave use and associated outcomes among spousal caregivers.

Despite the robust evidence of improvements in job continuity among women caregivers, the results on mental health outcomes are less clear. Future work should examine the mental health effects of PFL for non-childbirth-related health shocks using other data sources and research designs.

In contrast to our results for spousal caregivers, we find no evidence that PFL access affects the labor market or mental health outcomes of parent caregivers. The lack of impacts of PFL on parent caregivers raises questions about the barriers that these parents may face in using paid leave. Future research should continue to study the needs of working parents whose children experience health shocks and how PFL policies may better serve these families. Finally, while data limitations did not allow us to examine use of PFL to manage parental health issues, around 30 percent of women are caregivers for a parent or parent-in-law at some point during their 50s (Fahle and McGarry, 2022), indicating that this is an important area for future work on paid leave policies.

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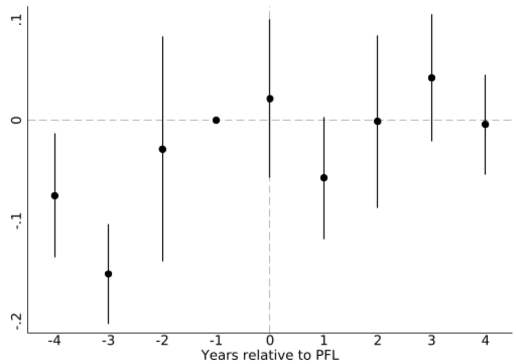
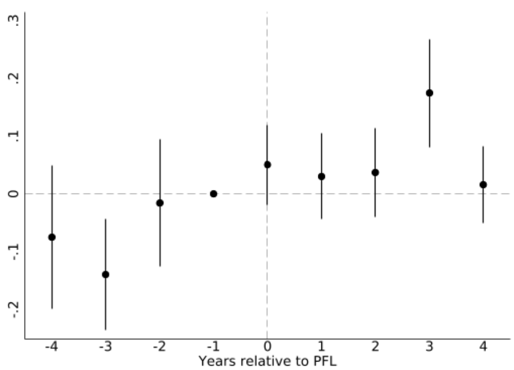
7 Figures

Figure 1: Event-Study Estimates of Effects of PFL on Likelihood of Being Employed Following a Spousal Health Shock

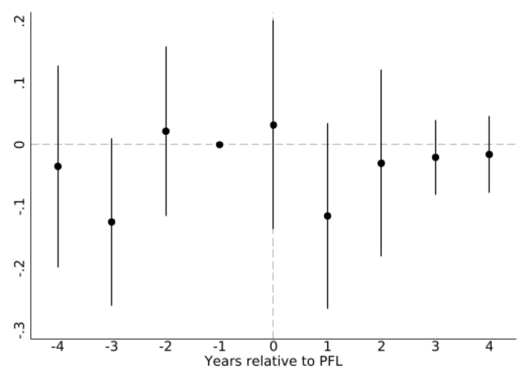
(a) All



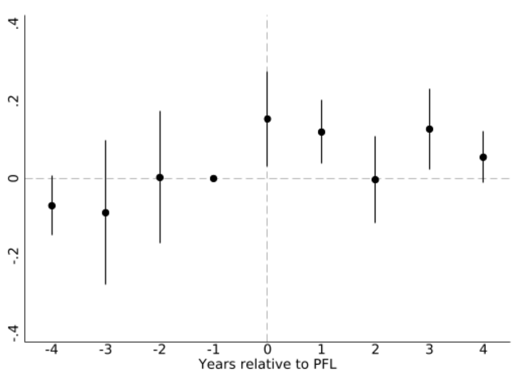
(b) Women Caregivers



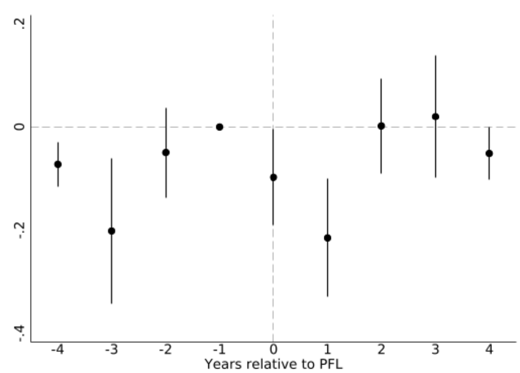
(c) Men Caregivers



(d) Caregivers with 0-12 Yrs of Education



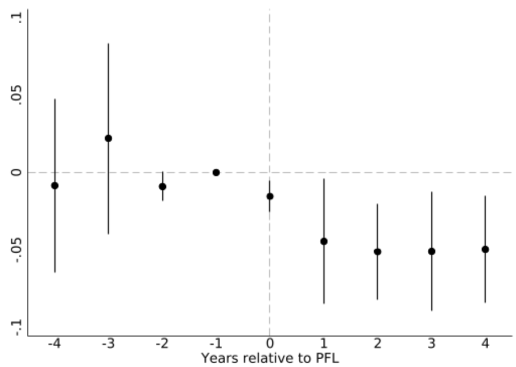
(e) Caregivers with 13+ Yrs of Education



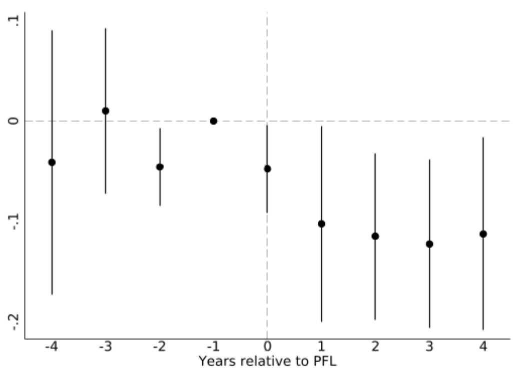
Notes: These figures plot the event-study coefficients and 95% confidence intervals from estimating equation (2), using the entire analysis sample (sub-figure a) and for sub-groups of the following caregivers: women (sub-figure b), men (sub-figure c), those with up to 12 years of education (sub-figure d), and those with 13 or more years of education (sub-figure e). The outcome is an indicator equal to 1 if the individual is employed, and is measured as an average across all post-spousal-health-shock rounds. Spousal health shocks are defined as inpatient visits and surgeries in any setting. All regressions control for state and year fixed effects, and individual characteristics including: indicators for individual gender, race/ethnicity, education level, age and number of children under 18 in the household in the first round of the panel. All regressions also control for indicators for the type of spousal medical condition or limitation and the type of spousal health shock (inpatient stay or surgery). Robust standard errors are clustered on the state level. See notes under Table 1 for additional information about the analysis sample.

Figure 2: Event-Study Estimates of Effects of PFL on Likelihood of Leaving Job to Care for Home or Family Following a Spousal Health Shock

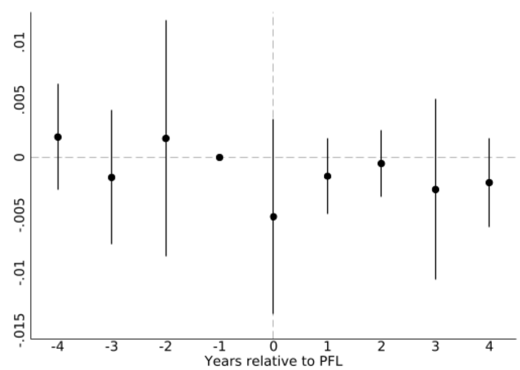
(a) All



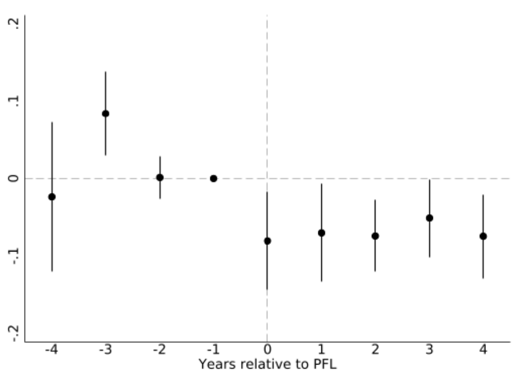
(b) Women Caregivers



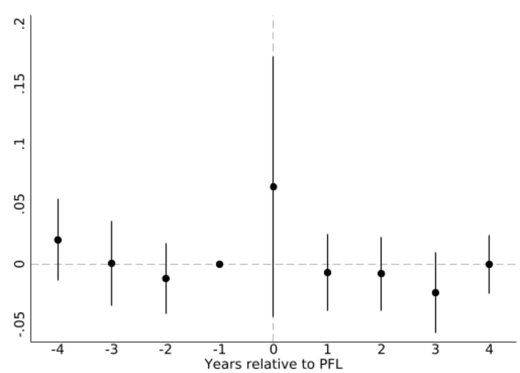
(c) Men Caregivers



(d) Caregivers with 0-12 Yrs of Education



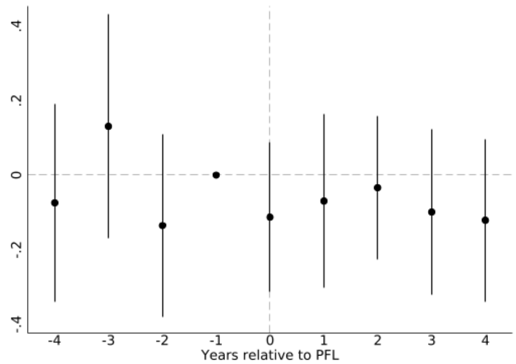
(e) Caregivers with 13+ Yrs of Education



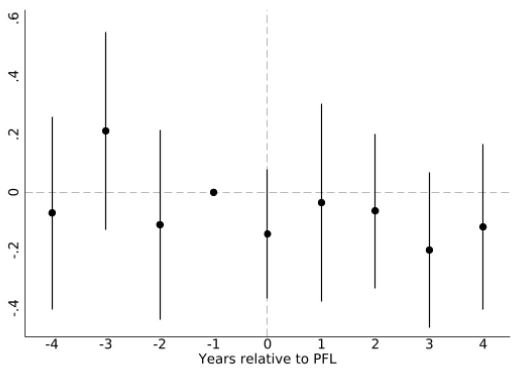
Notes: These figures plot the event-study coefficients and 95% confidence intervals from estimating equation (2), using the entire analysis sample (sub-figure a) and for sub-groups of the following caregivers: women (sub-figure b), men (sub-figure c), those with up to 12 years of education (sub-figure d), and those with 13 or more years of education (sub-figure e). The outcome is an indicator equal to 1 if the individual has left their job to care for their home or family, and is measured as an average across all post-spousal-health-shock rounds. Spousal health shocks are defined as inpatient visits and surgeries in any setting. All regressions control for state and year fixed effects, and individual characteristics including: indicators for individual gender, race/ethnicity, education level, age and number of children under 18 in the household in the first round of the panel. All regressions also control for indicators for the type of spousal medical condition or limitation and the type of spousal health shock (inpatient stay or surgery). Robust standard errors are clustered on the state level. See notes under Table 1 for additional information about the analysis sample.

Figure 3: Event-Study Estimates of Effects of PFL on Likelihood of Reporting Poor Mental Health or Having Any Mental Health Rx Following a Spousal Health Shock

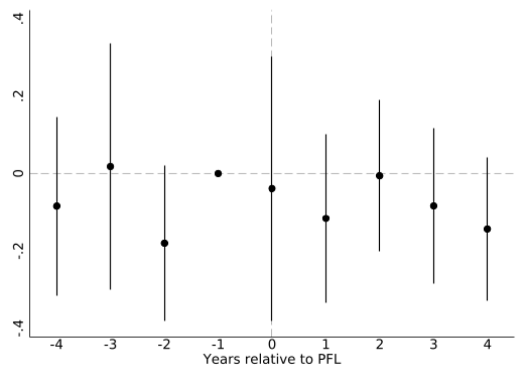
(a) All



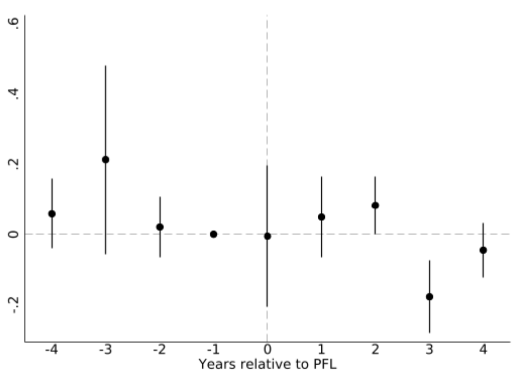
(b) Women Caregivers



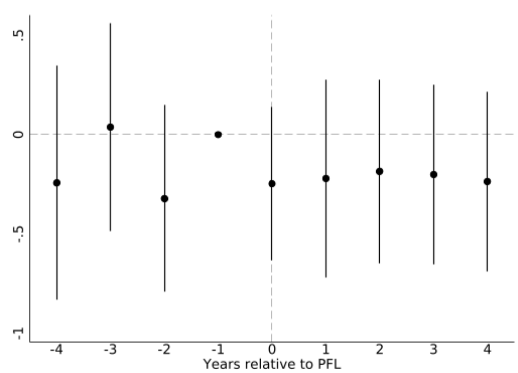
(c) Men Caregivers



(d) Caregivers with 0-12 Yrs of Education



(e) Caregivers with 13+ Yrs of Education



Notes: These figures plot the event-study coefficients and 95% confidence intervals from estimating equation (2), using the entire analysis sample (sub-figure a) and for sub-groups of the following caregivers: women (sub-figure b), men (sub-figure c), those with up to 12 years of education (sub-figure d), and those with 13 or more years of education (sub-figure e). The outcome is an indicator equal to 1 if the individual reports poor mental health or has any mental health prescription drugs, and is measured as an average across all post-spousal-health-shock rounds. Spousal health shocks are defined as inpatient visits and surgeries in any setting. All regressions control for state and year fixed effects, and individual characteristics including: indicators for individual gender, race/ethnicity, education level, age and number of children under 18 in the household in the first round of the panel. All regressions also control for indicators for the type of spousal medical condition or limitation and the type of spousal health shock (inpatient stay or surgery). Robust standard errors are clustered on the state level. See notes under Table 1 for additional information about the analysis sample.

8 Tables

Table 1: Summary Statistics for Individuals with Spouses Who Have Any Condition or Limitation and Experience a Health Shock, MEPS 1996–2019

	(1) All individuals	(2) Individuals with PFL	(3) Individuals without PFL
Average age	48.4	48.2	48.5
Average number of children under 18	0.7	0.9	0.7
Percent male	52.4%	52.3%	52.4%
Percent Hispanic	16.7%	41.8%	14.4%
Percent non-Hispanic Asian	4.6%	15.2%	3.6%
Percent non-Hispanic Black	12.2%	4.6%	12.9%
Percent non-Hispanic White	65.1%	37.1%	67.8%
Percent 0-12 years of education	51.0%	47.3%	51.3%
Percent 13+ years of education	49.0%	52.7%	48.7%
Percent has spouse with diabetes, cholesterol, or high blood pressure	67.0%	75.1%	66.3%
Percent has spouse with heart/lung conditions	34.3%	29.1%	34.7%
Percent spouse with arthritis	40.4%	40.5%	40.4%
Percent spouse with asthma	16.4%	15.6%	16.5%
Percent has spouse with cancer	9.6%	13.9%	9.2%
Percent has spouse with physical limitation	45.7%	43.0%	45.9%
Percent has spouse with cognitive limitation	15.4%	17.7%	15.2%
Observations	2,735	237	2,498

Notes: This table presents the means of key variables for individuals with spouses in the household in the MEPS data covering years 1996–2019. The sample is further limited to individuals aged 25–64 who are employed or have a job in the first round of the panel, who do not experience an emergency department visit, hospital inpatient stay, or surgery of their own during the panel, and who have a spouse with a medical condition or limitation who experiences a health shock (a hospital inpatient stay or surgery in any setting). The sample excludes individuals who reside in the state of Rhode Island. The heart or lung conditions category includes angina, heart attack, heart disease, emphysema, and stroke.

Table 2: Top 20 ICD-9 Codes Associated with Health Shocks Among Spouses Who Have Any Condition or Limitation, MEPS 1996–2012

ICD-9 Code	ICD-9 Code Description	Percent of All Health Shocks	Cumulative Percent of All Health Shocks
486	Pneumonia, organism unspecified	3.25%	3.25%
786	Symptoms involving respiratory system and other chest symptoms	2.36%	5.61%
780	General symptoms	2.25%	7.86%
436	Acute, but ill-defined, cerebrovascular disease	2.18%	10.04%
410	Acute myocardial infarction	2.16%	12.20%
428	Heart failure	2.13%	14.33%
575	Other disorders of gallbladder	2.08%	16.41%
250	Diabetes mellitus	2.04%	18.45%
429	Ill-defined descriptions and complications of heart disease	1.81%	20.26%
414	Other forms of chronic ischemic heart disease	1.79%	22.05%
719	Other and unspecified disorders of joint	1.74%	23.80%
722	Intervertebral disc disorders	1.58%	25.37%
401	Essential hypertension	1.54%	26.91%
427	Cardiac dysrhythmias	1.42%	28.34%
553	Hernia of abdominal cavity	1.36%	29.70%
959	Injury other and unspecified	1.32%	31.02%
366	Cataract	1.27%	32.29%
239	Neoplasms of unspecified nature	1.24%	33.53%
592	Calculus of kidney and ureter	1.19%	34.72%
724	Other and unspecified disorders of back	1.12%	35.85%

Notes: This table presents the 20 most frequently occurring three-digit ICD-9 codes associated with focal individuals' spouses' health shocks (defined as either an inpatient stay or a surgery in any setting), using MEPS data covering years 1996–2012. See notes under Table 1 for additional information about the analysis sample.

Table 3: Effects of PFL on the Employment and Mental Health Outcomes of Individuals Following a Spousal Health Shock

	Employment Outcomes			Mental Health Outcomes			
	(1) Is employed	(2) Left job (care for home/family)	(3) Left job (other reasons)	(4) Reports poor MH or any MH Rx	(5) Reports poor MH	(6) Has MH Rx	(7) Has anx./dep. Rx
Panel A: All Individuals							
PFL	0.0538***	-0.0404***	-0.0183**	-0.0461*	-0.00384	-0.0214	-0.0367**
	[0.0106]	[0.00764]	[0.00896]	[0.0234]	[0.00767]	[0.0224]	[0.0151]
Dep. Var. mean	0.917	0.0113	0.0389	0.127	0.0514	0.129	0.0849
N	2738	2738	2738	2739	2735	2739	2739
Panel B: Women Caregivers							
PFL	0.0872***	-0.0704***	-0.0158	-0.0695**	-0.0285**	-0.00410	-0.0328
	[0.0182]	[0.0171]	[0.0154]	[0.0346]	[0.0141]	[0.0537]	[0.0318]
Dep. Var. mean	0.897	0.0216	0.0449	0.158	0.0545	0.168	0.116
N	1302	1302	1302	1302	1301	1302	1302
Panel C: Men Caregivers							
PFL	-0.00246	-0.00340	-0.0133	-0.0264	0.0268**	-0.0548**	-0.0543***
	[0.0117]	[0.00236]	[0.0183]	[0.0181]	[0.0132]	[0.0265]	[0.0152]
Dep. Var. mean	0.935	0.00203	0.0335	0.0984	0.0485	0.0936	0.0570
N	1436	1436	1436	1437	1434	1437	1437
Panel D: Caregivers with 0-12 Years of Education							
PFL	0.112***	-0.0716***	-0.0361**	-0.0671**	-0.00481	-0.0372	-0.0484**
	[0.0129]	[0.0116]	[0.0145]	[0.0260]	[0.0125]	[0.0376]	[0.0206]
Dep. Var. mean	0.902	0.0115	0.0455	0.125	0.0615	0.117	0.0725
N	1395	1395	1395	1396	1394	1396	1396
Panel E: Caregivers with 13+ Years of Education							
PFL	0.00512	-0.00181	-0.00790	-0.0220	-0.0121	0.00878	-0.0157
	[0.0166]	[0.00994]	[0.00854]	[0.0306]	[0.0106]	[0.0275]	[0.0239]
Dep. Var. mean	0.933	0.0111	0.0320	0.129	0.0408	0.141	0.0979
N	1343	1343	1343	1343	1341	1343	1343

Notes: This table presents the α_1 coefficients and standard errors from estimating equation (1), using the entire analysis sample (Panel A) and for sub-groups of the following caregivers: women (Panel B), men (Panel C), those with up to 12 years of education (Panel D), and those with 13 or more years of education (Panel E). Spousal health shocks are defined as inpatient visits and surgeries in any setting. The analysis sample includes all individuals aged 25–64 with a spouse in the household in all states excluding Rhode Island, observed in years 1996–2019. The sample is further limited to individuals who are employed or have a job in the first round of the panel, who do not experience their own emergency department visit, inpatient visit, or surgery during the panel, and who have a spouse with a medical condition or limitation who experiences a health shock. Each outcome is measured as an average across all post spousal health shock rounds. The outcomes are: (1) an indicator for the individual reporting being employed or having a job, (2) an indicator for the individual leaving a job to care for their home or family, (3) an indicator for the individual leaving a job for any reason except for caring for others, (4) an indicator for the individual reporting poor or very poor mental health (a score of 4 or 5 on a 1-5 scale) or having any mental health prescription drug, (5) an indicator for the individual reporting poor or very poor mental health (a score of 4 or 5 on a 1-5 scale), (6) an indicator for the individual having any mental health prescription drug, and (7) an indicator for the individual having any anti-anxiety or anti-depressant prescription drug. The key independent variable is PFL, which is an indicator set to 1 for observations in CA in 2004 or later, NJ in 2009 or later, and NY in 2018 or later, and 0 otherwise. All regressions control for state and year fixed effects, and individual characteristics including: indicators for individual gender, race/ethnicity, education level, age, and number of children under 18 in the household in the first round of the panel. All regressions also control for indicators for the type of spousal medical condition or limitation and the type of spousal health shock (inpatient stay or surgery). Robust standard errors are clustered on the state level. Significance levels: $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

Table 4: Effects of PFL on the Employment and Mental Health Outcomes of Parents After Their Children Experience Health Shocks

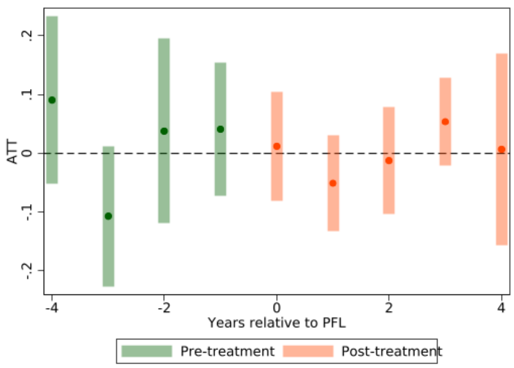
	Employment Outcomes			Mental Health Outcomes			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Is employed	Left job (care for home/family)	Left job (other reasons)	Reports poor MH or any MH Rx	Reports poor MH	Has MH Rx	Has anx./dep. Rx
PFL	0.000803	0.00284	-0.00860	-0.0225	-0.0146	-0.00766	-0.00881
	[0.0156]	[0.00829]	[0.00708]	[0.0149]	[0.0117]	[0.0104]	[0.00758]
Dep. Var. mean	0.931	0.0202	0.0217	0.0789	0.0346	0.0743	0.0497
N	2828	2828	2828	2828	2828	2828	2828

Notes: This table presents the α_1 coefficients and standard errors from estimating equation (1). Child health shocks are defined as inpatient visits and surgeries in any setting. The analysis sample includes all parents aged 25–64 with a child under 18 in the household in all states excluding Rhode Island, observed in years 1996–2019. The sample is further limited to parents who are employed or have a job in the first round of the panel, who do not experience their own emergency department visit, inpatient visit, or surgery during the panel, and who have a child under 18 who experiences a health shock. Each outcome is measured as an average across all post child health shock rounds. The outcomes are: (1) an indicator for the individual reporting being employed or having a job, (2) an indicator for the individual leaving a job to care for their home or family, (3) an indicator for the individual leaving a job for any reason except for caring for others, (4) an indicator for the individual reporting poor or very poor mental health (a score of 4 or 5 on a 1-5 scale) or having any mental health prescription drug, (5) an indicator for the individual reporting poor or very poor mental health (a score of 4 or 5 on a 1-5 scale), (6) an indicator for the individual having any mental health prescription drug, and (7) an indicator for the individual having any anti-anxiety or anti-depressant prescription drug. The key independent variable is PFL, which is an indicator set to 1 for observations in CA in 2004 or later, NJ in 2009 or later, and NY in 2018 or later, and 0 otherwise. All regressions control for state and year fixed effects, and individual characteristics including: indicators for individual gender, race/ethnicity, marital status, education level, age and number of children under 18 in the household in the first round of the panel. All regressions also control for indicators for the type of child health shock (inpatient stay or surgery) and child's medical condition or limitation (if any). Standard errors are clustered on the state level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

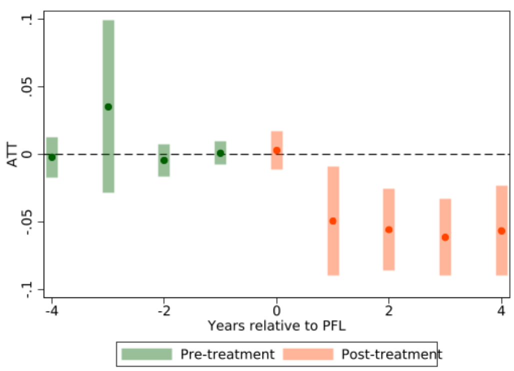
A Appendix Figures

Figure A1: Callaway and Sant'Anna Event-Study Estimates of Effects of PFL Following a Spousal Health Shock

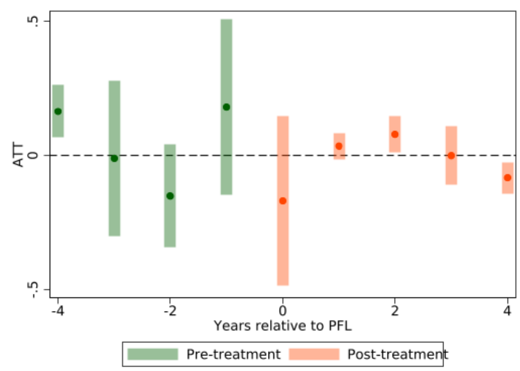
(a) Is Employed



(b) Left Job to Care for Home/Family



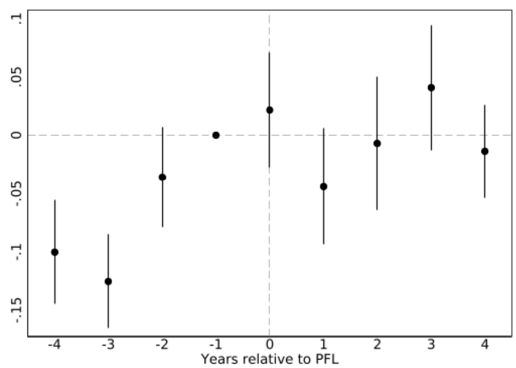
(c) Reports Poor MH or Any MH Rx



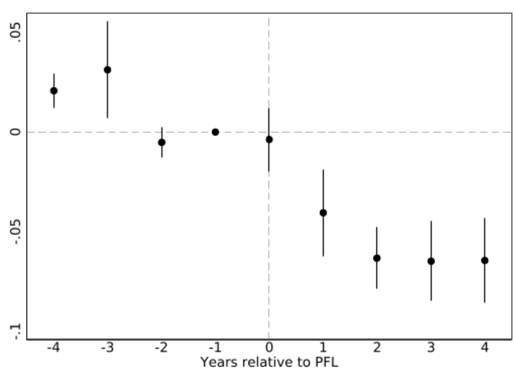
Notes: These figures plot the event-study coefficients and 95% confidence intervals from estimating equation (2) using the estimator proposed by Callaway and Sant'Anna (2021) and Sant'Anna and Zhao (2020). See notes under Figure 1 for additional information about the specifications and notes under Table 1 for details about the sample.

Figure A2: Sun and Abraham Event-Study Estimates of Effects of PFL Following a Spousal Health Shock

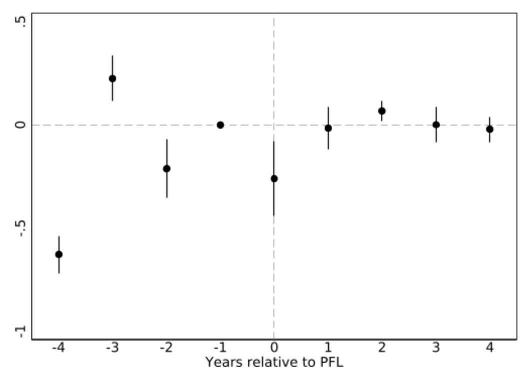
(a) Is Employed



(b) Left Job to Care for Home/Family

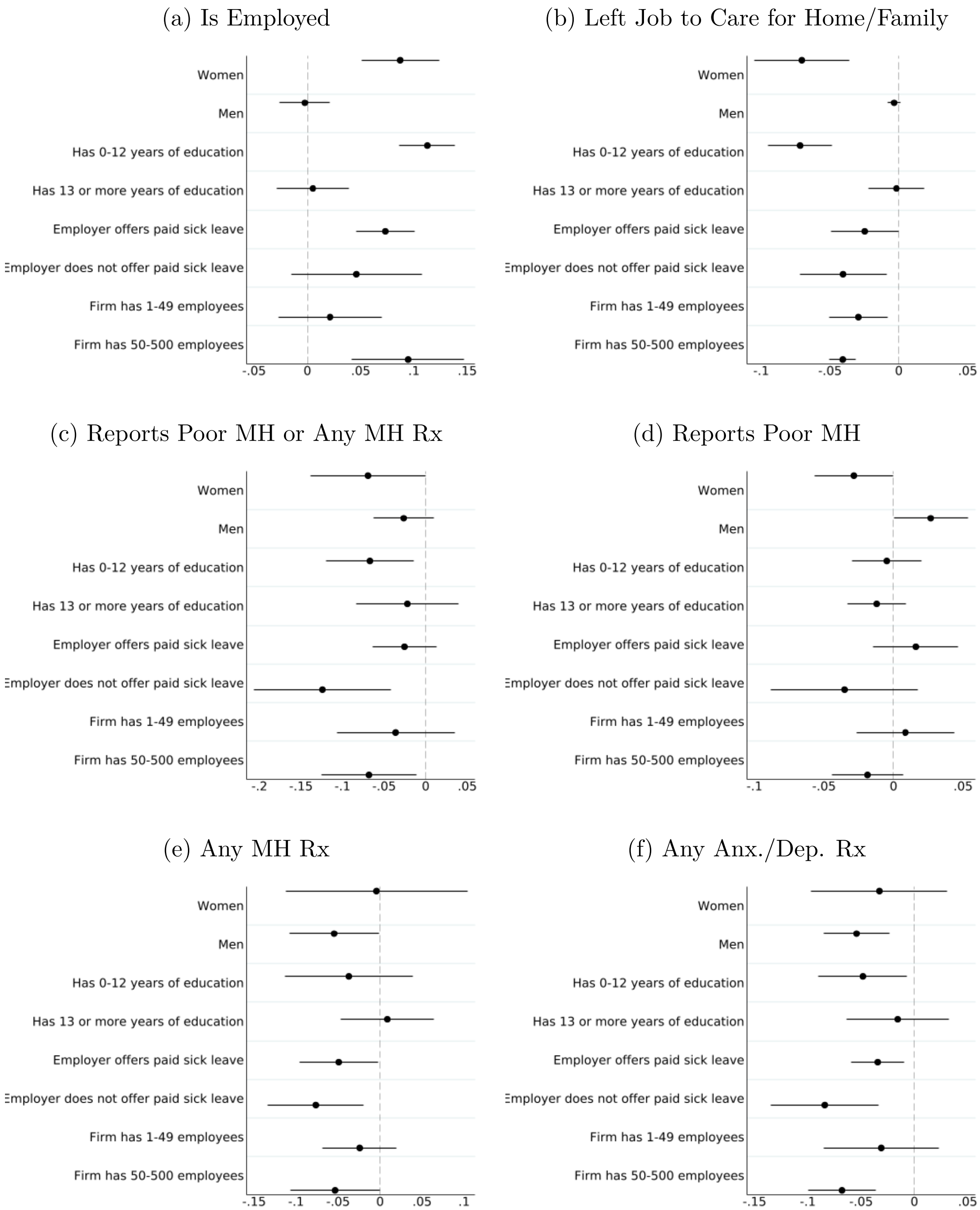


(c) Reports Poor MH or Any MH Rx



Notes: These figures plot the event-study coefficients and 95% confidence intervals from estimating equation (2) using the estimator proposed by Sun and Abraham (2021). See notes under Figure 1 for additional information about the specifications and notes under Table 1 for details about the sample.

Figure A3: Effects of PFL on the Employment and Mental Health Outcomes of Individuals Following a Spousal Health Shock, By Sub-Group



Notes: These figures plot the estimated α_1 coefficients and the associated 95% confidence intervals from equation (1), which is estimated separately for each sub-group described on the vertical axes. Robust standard errors are clustered on the state level. The analysis sample includes all individuals aged 25–64 with a spouse in the household in all states excluding Rhode Island, observed in years 1996–2019. The sample is further limited to individuals who are employed or have a job in the first round of the panel, who do not experience their own emergency department visit, inpatient visit, or surgery during the panel, and who have a spouse with a medical condition or limitation who experiences a health shock. Spousal health shocks are defined as inpatient visits and surgeries in any setting. Each outcome is measured as an average across all post spousal health shock rounds. See notes under Table 3 for additional information about the outcome and control variables. The sub-groups based on employer paid sick leave offering and firm size refer to employers of the caregiving (healthy) spouse, measured in the first round of the panel.

B Appendix Tables

Table A1: Summary Statistics for Parents of Children Who Experience a Health Shock, MEPS 1996–2019

	(1) All parents	(2) Parents with PFL	(3) Parents without PFL
Average age	37.3	38.1	37.3
Average number of children under 18	2.2	2.3	2.2
Percent married	81.2%	79.2%	81.4%
Percent male	56.2%	61.9%	55.7%
Percent Hispanic	28.1%	52.7%	26.0%
Percent non-Hispanic Asian	3.5%	10.2%	2.9%
Percent non-Hispanic Black	12.4%	6.6%	12.9%
Percent non-Hispanic White	54.6%	28.3%	56.9%
Percent 0-12 years of education	48.6%	51.8%	48.3%
Percent 13+ years of education	51.4%	48.2%	51.7%
Percent has child with diabetes, cholesterol, or high blood pressure	0.6%	0.0%	0.7%
Percent has child with heart/lung conditions	0.1%	0.0%	0.1%
Percent has child with asthma	22.2%	32.3%	21.4%
Percent has child with ADHD	6.3%	6.2%	6.3%
Percent has child with physical limitation	1.8%	0.9%	1.9%
Observations	2,828	226	2,602

Notes: This table presents the means of key variables for individuals with spouses in the household in the MEPS data covering years 1996–2019. The sample is further limited to individuals aged 25–64 who are employed or have a job in the first round of the panel, who do not experience an emergency department visit, hospital inpatient stay, or surgery of their own during the panel, and who have a child under 18 who experiences a health shock (a hospital inpatient stay or surgery in any setting). The sample excludes individuals who reside in the state of Rhode Island. The heart or lung conditions category includes angina, heart attack, heart disease, emphysema, and stroke.

Table A2: Top 20 ICD-9 Codes Associated with Health Shocks Among Children, MEPS 1996–2012

ICD-9 Code	ICD-9 Code Description	Percent of All Health Shocks	Cumulative Percent of All Health Shocks
873	Other open wound of head	8.72%	8.72%
959	Injury other and unspecified	3.05%	11.77%
780	General symptoms	2.93%	14.70%
486	Pneumonia, organism unspecified	2.77%	17.47%
541	Appendicitis, unqualified	2.58%	20.06%
493	Asthma	2.43%	22.49%
079	Viral and chlamydial infection in conditions classified elsewhere and of unspecific site	2.27%	24.76%
891	Open wound of knee, leg (except thigh), and ankle	2.18%	26.94%
883	Open wound of finger(s)	2.06%	28.99%
311	Depressive disorder, not elsewhere classified	1.74%	30.74%
882	Open wound of hand except finger(s) alone	1.49%	32.23%
818	Ill-defined fractures of upper limb	1.40%	33.63%
208	Leukemia of unspecified cell type	1.31%	34.94%
276	Disorders of fluid electrolyte and acid-base balance	1.31%	36.25%
382	Suppurative and unspecified otitis media	1.28%	37.53%
008	Intestinal infections due to other organisms	1.21%	38.74%
250	Diabetes mellitus	1.15%	39.89%
786	Symptoms involving respiratory system and other chest symptoms	1.00%	40.89%
490	Bronchitis, not specified as acute or chronic	0.97%	41.86%
892	Open wound of foot except toe(s) alone	0.93%	42.79%

Notes: This table presents the 20 most frequently occurring three-digit ICD-9 codes associated with focal individuals' children's health shocks (defined as either an inpatient stay or a surgery in any setting), using MEPS data covering years 1996–2012. The sample for analysis in this table includes individuals aged 25–64 who are employed or have a job in the first round of the panel, who do not experience an emergency department visit, hospital inpatient stay, or surgery of their own during the panel, and who have a child under 18 who experiences a health shock. The sample excludes individuals who reside in the state of Rhode Island.

Table A3: Callaway and Sant'Anna Estimates of the Effects of PFL on the Employment and Mental Health Outcomes of Individuals Following a Spousal Health Shock

	Employment Outcomes			Mental Health Outcomes			
	(1) Is employed	(2) Left job (care for home/family)	(3) Left job (other reasons)	(4) Reports poor MH or any MH Rx	(5) Reports poor MH	(6) Has MH Rx	(7) Has anx./dep. Rx
Panel A: All Individuals							
PFL	-0.00454	-0.0511***	0.0245*	-0.0113	0.0781***	-0.104***	-0.0808***
	[0.0210]	[0.00994]	[0.0104]	[0.0334]	[0.0215]	[0.0228]	[0.0209]
N	2979	2979	2979	2980	2976	2980	2980
Panel B: Women Caregivers							
PFL	0.0470	-0.136***	0.0453*	0.0563	0.0957*	-0.0202	-0.0291
	[0.0281]	[0.0210]	[0.0203]	[0.0583]	[0.0421]	[0.0526]	[0.0362]
N	1396	1396	1396	1396	1395	1396	1396
Panel C: Men Caregivers							
PFL	-0.0148	-0.0130	-0.00509	-0.0450	0.0716**	-0.151***	-0.110***
	[0.0354]	[0.0198]	[0.0156]	[0.0312]	[0.0258]	[0.0327]	[0.0218]
N	1464	1464	1464	1465	1462	1465	1465
Panel D: Caregivers with 0-12 Years of Education							
PFL	0.0409	-0.0942***	0.0191	-0.0282	0.0956**	-0.141***	-0.115***
	[0.0351]	[0.0125]	[0.0212]	[0.0414]	[0.0362]	[0.0278]	[0.0275]
N	1314	1314	1314	1315	1313	1315	1315
Panel E: Caregivers with 13+ Years of Education							
PFL	-0.0903***	0.0152	0.0350***	0.0748	0.0649**	0.00942	0.0180
	[0.0241]	[0.0103]	[0.0105]	[0.0469]	[0.0233]	[0.0528]	[0.0303]
N	1350	1350	1350	1350	1348	1350	1350

Notes: This table presents results from estimating equation (1) using the estimator proposed by Callaway and Sant'Anna (2021) and Sant'Anna and Zhao (2020), using the entire analysis sample (Panel A) and for subgroups of women caregivers, men caregivers, caregivers up to 12 years of education, and caregivers with 13 or more years of education (Panels B, C, D, and E, respectively). See notes under Table 3 for more details about the sample, outcomes, and control variables. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Effects of PFL on Intensive Margin Labor Market Outcomes of Individuals Following a Spousal Health Shock

	Conditional on employment			Not conditional on employment		
	(1)	(2)	(3)	(4)	(5)	(6)
	Hours worked	Hourly wage	Weekly income	Hours worked	Hourly wage	Weekly income
Panel A: All Individuals						
PFL	-0.906	-1.304*	-44.40	1.286	-0.456	-20.96
	[1.259]	[0.770]	[33.64]	[0.961]	[1.287]	[37.06]
Dep. Var. mean	40.47	23.66	988.8	36.90	19.18	796.8
N	2563	2281	2266	2739	2739	2739
Panel B: Women Caregivers						
PFL	2.074*	-0.759	27.31	4.451***	0.537	55.35
	[1.181]	[0.834]	[65.29]	[1.511]	[0.926]	[35.22]
Dep. Var. mean	36.91	21.25	825.0	32.95	17.13	661.6
N	1199	1081	1074	1302	1302	1302
Panel C: Men Caregivers						
PFL	-3.511**	-1.406	-90.32**	-2.246***	-1.805	-101.4
	[1.581]	[1.166]	[43.65]	[0.783]	[2.017]	[73.37]
Dep. Var. mean	43.60	25.83	1136.4	40.49	21.03	919.3
N	1364	1200	1192	1437	1437	1437
Panel D: Caregivers with 0-12 Years of Education						
PFL	-1.788**	-1.420	-38.11	3.074**	1.391	50.92
	[0.846]	[2.367]	[106.5]	[1.363]	[0.930]	[30.86]
Dep. Var. mean	40.41	17.47	728.2	36.08	14.04	580.4
N	1288	1163	1150	1396	1396	1396
Panel E: Caregivers with 13+ Years of Education						
PFL	1.107	-1.253	-41.82	1.459	-2.108	-60.10
	[1.419]	[2.505]	[72.26]	[2.452]	[3.140]	[84.97]
Dep. Var. mean	40.53	30.10	1257.3	37.75	24.51	1021.7
N	1275	1118	1116	1343	1343	1343

Notes: See notes under Table 3. Each observation represents an individual's average post-spousal-health-shock outcome. The outcomes are: (1) the number of hours worked conditional on employment, (2) hourly wage in 2018 dollars conditional on employment, (3) weekly income in 2018 dollars conditional on employment, (4) the number of hours worked not conditional on employment, (5) hourly wage in 2018 dollars not conditional on employment, and (6) weekly income in 2018 dollars not conditional on employment. Standard errors are clustered on the state level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Effects of PFL on Own Outcomes of Spouses Who Experience Health Shocks

	(1) Is employed	(2) Reports poor MH or any MH Rx	(3) Reports poor MH	(4) Has MH Rx	(5) Has anx./dep. Rx
Panel A: Whole Analysis Sample					
PFL	-0.0133	-0.0381	0.00927	-0.0541	-0.0361
	[0.0337]	[0.0250]	[0.0235]	[0.0476]	[0.0248]
Dep. Var. mean	0.582	0.296	0.135	0.380	0.218
N	2739	2739	2739	2739	2739
Panel B: Both Spouses Employed in Round 1					
PFL	0.0327	-0.106***	-0.0359**	-0.0725	-0.0671***
	[0.0380]	[0.0223]	[0.0163]	[0.0480]	[0.0236]
Dep. Var. mean	0.841	0.230	0.0866	0.332	0.176
N	1743	1743	1743	1743	1743
Panel C: Women Caregivers					
PFL	-0.0106	0.00990	-0.0207	0.0306	0.0238
	[0.0344]	[0.0191]	[0.0277]	[0.0549]	[0.0420]
Dep. Var. mean	0.632	0.249	0.124	0.329	0.165
N	1302	1302	1302	1302	1302
Panel D: Men Caregivers					
PFL	-0.00638	-0.0768	0.0537***	-0.147***	-0.107***
	[0.0540]	[0.0522]	[0.0195]	[0.0406]	[0.0281]
Dep. Var. mean	0.537	0.339	0.146	0.426	0.267
N	1437	1437	1437	1437	1437

Notes: See notes under Table 3. Each observation represents the (sick) spouse's own post-health shock outcome. The outcomes are: (1) an indicator for reporting being employed or having a job, (2) an indicator for reporting poor or very poor mental health or having any mental health prescription drug, (3) an indicator for reporting poor or very poor mental health, (4) an indicator for having any mental health prescription drug, and (5) an indicator for having any anti-anxiety or anti-depressant prescription drug. Standard errors are clustered on the state level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Effects of PFL on the Intensive Margin Labor Market Outcomes of Parents After Children Experience Health Shocks

	Conditional on employment			Not conditional on employment		
	(1) Hours worked	(2) Hourly wage	(3) Weekly income	(4) Hours worked	(5) Hourly wage	(6) Weekly income
PFL	-1.128	0.950	7.407	-0.720	-0.770	-52.36
	[0.755]	[0.939]	[48.00]	[0.658]	[0.699]	[35.92]
Dep. Var. mean	40.74	22.74	957.6	37.68	18.52	774.6
N	2672	2358	2338	2828	2828	2828

Notes: See notes under Table 4. Each observation represents an individual's average post-child-health-shock outcome. The outcomes are: (1) the number of hours worked conditional on employment, (2) hourly wage in 2018 dollars conditional on employment, (3) weekly income in 2018 dollars conditional on employment, (4) the number of hours worked not conditional on employment, (5) hourly wage in 2018 dollars not conditional on employment, and (6) weekly income in 2018 dollars not conditional on employment. Standard errors are clustered on the state level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Callaway and Sant'Anna Estimates of the Effects of PFL on the Employment and Mental Health Outcomes of Parents After Their Children Experience Health Shocks

	Employment Outcomes			Mental Health Outcomes			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Is employed	Left job (care for home/family)	Left job (other reasons)	Reports poor MH or any MH Rx	Reports poor MH	Has MH Rx	Has anx./dep. Rx
PFL	-0.0468	0.0125	0.0168	-0.0363	0.0123	-0.0169	-0.0359
	[0.0240]	[0.0140]	[0.00945]	[0.0281]	[0.0178]	[0.0231]	[0.0194]
N	2928	2928	2928	2928	2928	2928	2928

Notes: This table presents results from estimating equation (1) using the estimator proposed by Callaway and Sant'Anna (2021) and Sant'Anna and Zhao (2020). See notes under Table 4 for more details about the sample, outcomes, and control variables. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.