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 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 their spouses' and children's 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 surveyed before and after PFL implementation relative to the analogous differences among those in states that did not implement PFL over our analysis time period. We find that the (healthy) wives of individuals with medical conditions or limitations who experience a hospitalization or a surgery are 7.0 percentage points less likely to report "leaving a job to care for home or family" in the post-health-shock rounds of the data. These women also experience improved mental health, measured based on both self-reports and the use of mental health-related prescription drugs. We find no consistent impacts on the outcomes of men whose spouses have health shocks, or on parents of children with health shocks.

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. 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 begins to fill 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)

[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-bette`

[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.

as our measures of health shocks. Additionally, to focus our attention on households who may be in particular need of caregiving leave, we use our data to identify 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 2.1 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.

When it comes to mental health, we find that women whose spouses have conditions or limitations and experience health shocks are 7.0 percentage points (44 percent at the sample

[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 3, 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 in our main specifications, 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.

mean) 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 results for men are more mixed, with some evidence of an increase in the likelihood of poor self-reported mental health combined with a decrease in the likelihood of having a mental health-related prescription drug. We do not find mental health impacts of PFL on the parents of children with health shocks.

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).[7,8]

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.[9] 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

[7]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.

[8]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).

[9]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.

(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.[10] Bartel et al. (Forthcoming) use data from the American Community Survey (ACS) and find that the CA PFL policy increases 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).[11]

Third, we analyze caregivers' mental health. In doing so, we contribute to the growing evidence that paid leave improves new mothers' mental health (Bullinger, 2019; Persson and Rossin-Slater, 2019; Bütikofer et al., 2021) by documenting that women experience improvements in mental health when they are caregivers for their spouses as well.[12]

[10]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.

[11]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).

[12]A few studies have used survey data to analyze associations between taking paid leave for caregiving pur-

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 not only be an important driver of individuals' labor market responses to their spouses' health shocks, but it may also influence their mental well-being.

2 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

poses 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).

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.[13] 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 studying spousal caregivers, we consider individuals with a spouse who experiences a health shock in any of rounds two through five in the panel *and* who reports having at least one medical condition or a cognitive or physical limitation in the Household Component survey.[14]

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

[14] 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.

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 in any of rounds two through five in 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.

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.[15]

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 in round 3, 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 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 allows 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

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

including: "could not find work," "retired," "unable to work because ill/disabled," "going to school," "don't want to work," and "other."[16]

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.[17] 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 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 are non-Hispanic Asian, 12.2 percent are non-Hispanic Black, and 65.1 percent are non-Hispanic white, although there are some important

[16] 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.

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

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.[18] 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.[19] These diagnoses account for about 36.6 percent of all health shocks (i.e., inpatient stays and surgeries in any settings) in the sample. Note that, in our sample, 53.6 percent of spousal health shocks are inpatient visits that also involve surgeries, 34.6 percent are inpatient visits that do not involve surgeries, and 11.8 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 to open wounds.[20]

3 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 2, 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 cross-sectional data (Kang

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

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

[20] Appendix Table A1 presents the 20 most frequently occurring ICD-9 codes associated with child health shocks. These account for about 42.7 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 emergency department setting, 33.8 percent are inpatient stays without surgeries, and 25.1 percent are inpatient stays that involve surgeries.

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.[21]

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 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, $\mathbf{1}[t - PFL^*_{st} =$

[21] 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.

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). The π coefficients for $k = -4$ and $k = +4$ reflect effects in state-years four or more years before and four or more years after PFL adoption, respectively.

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).

4 Results

4.1 Effects on Spouses as Potential Caregivers

Table 3 presents results for our main sample of individuals with spouses who have a medical condition or limitation and experience a health shock, using our three employment outcomes and four mental health outcomes as dependent variables. Panel A presents results for the whole sample, while Panels B and C show separate estimates for women and men, respectively.

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.

Figures 1 and 2 present the corresponding event-study estimates for the first two labor market outcomes. 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 years pre-PFL 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 non-existent for men.

Appendix Table A2 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 also see an increase in the weekly number of hours worked. 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, which perhaps reflects some leave use (without any change in employment).

When it comes to mental health, Table 3 shows that PFL access is associated with a 7.0 percentage point (44 percent at the sample mean) lower likelihood of women either reporting poor mental health or using any mental health-related prescription drugs in rounds after their spouse has a health shock. The reduction in prescription drugs appears to be driven by a lower use of anti-depressant and anti-anxiety medications, although the coefficient for this outcome is not individually statistically significant. For men, we find an increased likelihood of reporting poor mental health combined with a decreased likelihood of using mental health prescription drugs, suggesting an ambiguous overall mental health impact of PFL. The event-study estimates for our aggregate mental health indicator are presented in Figure 3, with insignificant coefficients on the individual event-time indicators, reflecting our lack of statistical power for estimating them.

4.2 Effects on Parents as Potential Caregivers

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 A3 shows no evidence of intensive margin labor market impacts.

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.[22] 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).

5 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.

Our results find strong evidence that PFL access supports employment continuity for the wives of individuals who have a health shock. 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,

[22] See Appendix Table A1 for the most common diagnoses associated with the health shocks we study.

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 impacts of PFL on parent caregivers.

We also observe some impacts of PFL on the mental health of spousal caregivers. We find that PFL access is associated with a 7.0 percentage point 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 among women whose spouses have health conditions or limitations and experience a health shock. We find mixed evidence on the mental health outcomes of husband caregivers, with an increase in the likelihood of reporting poor mental health along with a reduction in the likelihood of having a mental health-related prescription drugs. Similar to the labor market outcomes, we find no evidence of mental health effects on parent caregivers.

The gendered impacts on extensive margin labor market effects 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). Thus, our results suggest that access to PFL can significantly buffer against the adverse employment effects among previously-employed healthy wives. At the same time, 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.

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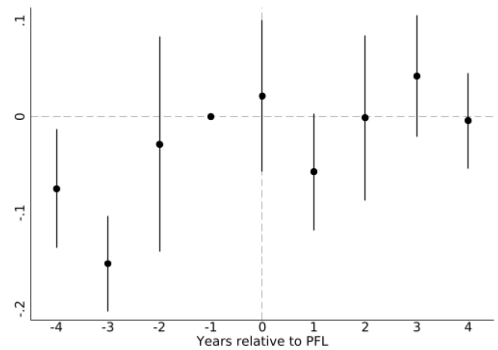
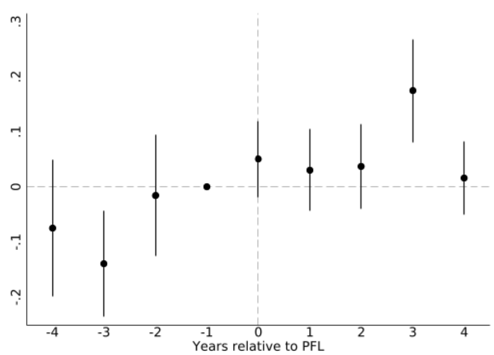
6 Figures

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

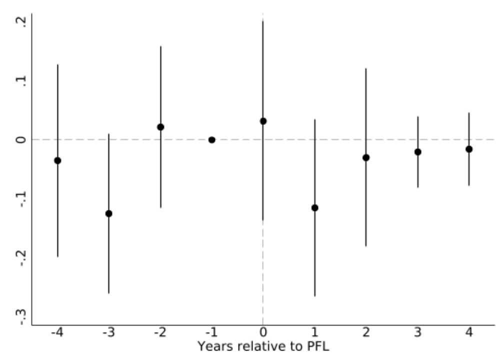
(a) All



(b) Women



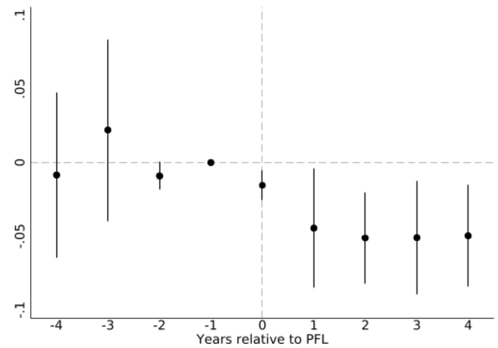
(c) Men



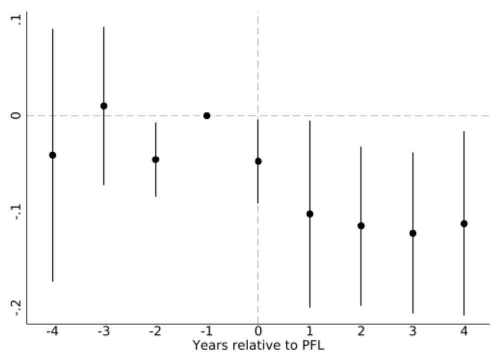
Notes: These figures plot the event-study coefficients and 95% confidence intervals from estimating equation (2). Sub-figure (a) uses the whole analysis sample, sub-figure (b) limits to women, while sub-figure (c) limits to men. The outcome is an indicator equal to 1 if the individual is employed, and 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. 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. 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.

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

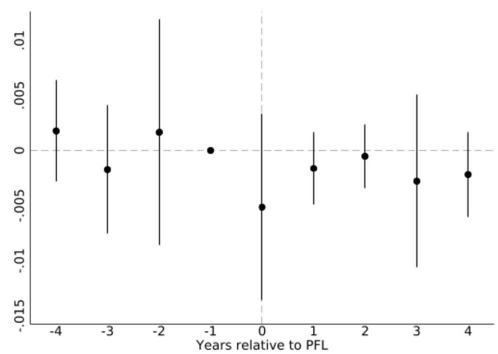
(a) All



(b) Women



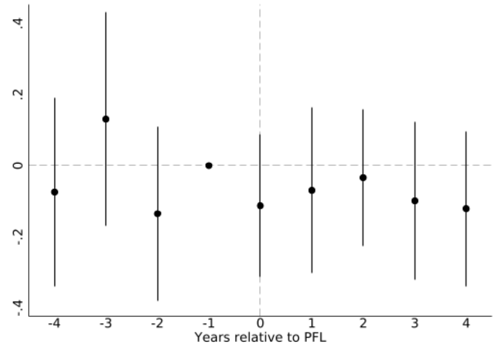
(c) Men



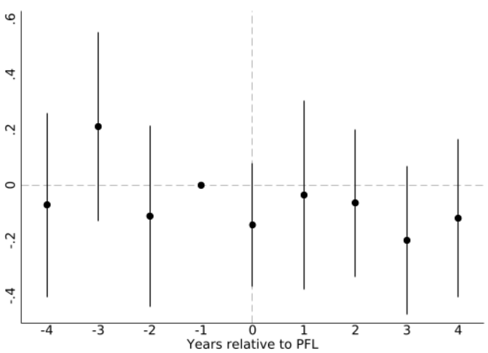
Notes: These figures plot the event-study coefficients and 95% confidence intervals from estimating equation (2). Sub-figure (a) uses the whole analysis sample, sub-figure (b) limits to women, while sub-figure (c) limits to men. The outcome is an indicator equal to 1 if the individual has left their 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. 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. 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.

Figure 3: Event-Study Estimates of Effects of PFL on Likelihood of Any Mental Health Issues Following Spousal Health Shock

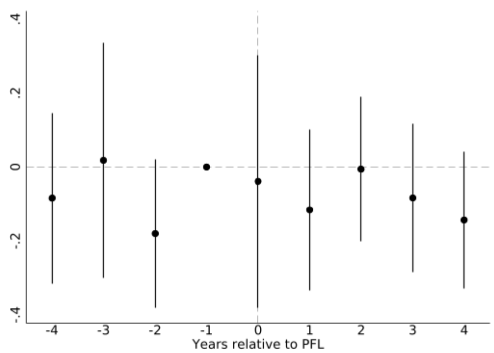
(a) All



(b) Women



(c) Men



Notes: These figures plot the event-study coefficients and 95% confidence intervals from estimating equation (2). Sub-figure (a) uses the whole analysis sample, sub-figure (b) limits to women, while sub-figure (c) limits to men. 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. 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. 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.

7 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 or 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	2.89%	2.89%
410	Acute myocardial infarction	2.74%	5.63%
786	Symptoms involving respiratory system and other chest symptoms	2.57%	8.21%
429	Ill-defined descriptions and complications of heart disease	2.54%	10.75%
780	General symptoms	2.22%	12.97%
250	Diabetes mellitus	2.11%	15.08%
436	Acute but ill-defined cerebrovascular disease	1.93%	17.00%
428	Heart failure	1.85%	18.85%
414	Other forms of chronic ischemic heart disease	1.83%	20.68%
719	Other and unspecified disorder of joint	1.79%	22.46%
575	Other disorders of gallbladder	1.75%	24.21%
722	Intervertebral disc disorders	1.70%	25.91%
401	Essential hypertension	1.61%	27.53%
959	Injury other and unspecified	1.59%	29.12%
427	Cardiac dysrhythmias	1.42%	30.54%
553	Other hernia of abdominal cavity without mention of obstruction or gangrene	1.32%	31.86%
592	Calculus of kidney and ureter	1.29%	33.14%
444	Arterial embolism and thrombosis	1.17%	34.31%
883	Open wound of finger(s)	1.16%	35.48%
366	Cataract	1.10%	36.58%

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 After Their Spouses Experience Health Shocks

	Employment Outcomes			Mental Health Outcomes			
	(1) Is employed	(2) Left job (care for home/family)	(3) Left job (other reasons)	(4) Has any MH	(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							
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							
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

Notes: This table presents results from estimating equation (1). 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) Is employed	(2) Left job (care for home/family)	(3) Left job (other reasons)	(4) Has any MH	(5) Reports poor MH	(6) Has MH RX	(7) 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 results 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

B Appendix Tables

Table A1: 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	8.70%	8.70%
959	Injury other and unspecified	3.23%	11.93%
780	General symptoms	2.78%	14.71%
486	Pneumonia, organism unspecified	2.71%	17.43%
541	Appendicitis, unqualified	2.57%	20.00%
493	Asthma	2.40%	22.40%
891	Open wound of knee, leg (except thigh), and ankle	2.12%	24.52%
079	Viral and chlamydial infection in conditions classified elsewhere and of unspecific site	2.05%	26.57%
883	Open wound of finger(s)	2.05%	28.63%
311	Depressive disorder, not elsewhere classified	1.81%	30.43%
882	Open wound of hand except finger(s) alone	1.53%	31.97%
818	Ill-defined fractures of upper limb	1.46%	33.43%
276	Disorders of fluid electrolyte and acid-base balance	1.36%	34.78%
382	Suppurative and unspecified otitis media	1.29%	36.07%
008	Intestinal infections due to other organisms	1.25%	37.32%
250	Diabetes mellitus	1.18%	38.50%
208	Leukemia of unspecified cell type	1.11%	39.62%
490	Bronchitis, not specified as acute or chronic	1.04%	40.66%
786	Symptoms involving respiratory system and other chest symptoms	1.04%	41.70%
892	Open wound of foot except toe(s) alone	0.97%	42.68%

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 A2: Effects of PFL on Intensive Margin Labor Market Outcomes of Individuals After Spouses Who Have Conditions or Limitations Experience Health Shocks

	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						
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						
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

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 A3: Effects of PFL on the Intensive Margin Labor Market Outcomes of Individuals After Children Experience Health Shocks

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