The Effect of Health Shocks on Family Unit's Income: A Staggered DiD Estimation on American Households from 1997-2015

Manolis Giannitselis, Ólafur Hákon Sigurðarson
Department of Economics and Business Economics
Aarhus BSS

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Abstract

This paper examines the causal impact of a one-time health shock on family income in the United States. We use a sample of 409 households that experience health shocks, and match 2114 control households from the PSID-SHELF (Panel Study of Income Dynamics). By applying a bias-corrected Difference-in-Differences approach with matching, we isolate the immediate economic consequences of unexpected health events. Households that experience a health shock see their annual family-size-adjusted real income decrease by approximately $3700 on average. This result is statistically significant at a 5% level and robust in multiple specifications. Higher-income families face greater declines, while low-income households register modest gains. Moreover, single-earner and single-parent households look to be especially vulnerable, whereas those with multiple potential earners vary more widely in their results. These findings highlight the importance of institutional and family-level factors in shaping the spillover effects of health shocks, contributing to a more nuanced understanding of health-related financial adjustment made among U.S. households.

1 Introduction

A severe health event can do more than just impact an individual's well-being. It can send ripples through a family's economic structure. What happens to a family in the United States (U.S.) after they are hit by shock? This topic is particularly relevant in the U.S., because of the emphasis on private-sector healthcare instead of publicly financed healthcare services. The households often face unique challenges coming from the healthcare system and labour market conditions. Health shocks can lead to significant disruptions, including increased medical expenses and reduced income, making it vital to understand how these events shape the economic outcomes of family units (FU's). In this paper we want to examine these dynamics and make it easier to understand the broader implications of health shocks in the U.S. context, where the institutional settings play a crucial role in moderating their impact. How can poor health in a family unit affect labour market outcomes such as total family income? And how can it differ between families?

Health shocks in family units can disrupt household income through reduced labour supply and increased medical expenditures. It is urgent to both understand and address the dynamics of health shocks in a U.S. where the “out of pocket” healthcare costs are among the highest globally, family structures are affected by caregiving responsibilities and extensive welfare programs are absent. Yet, the effects of health shocks extend beyond the U.S. at a more general scope. For example, in China, evidence shows that health shocks lead to substantial reductions in household income alongside significant increases in medical expenses Wang et al. (2023). It can thus be intriguing to know how general results in the U.S. hold against the rest of the world and if these differences in institutions lead to differences in outcome.

Our analysis in this paper focuses specifically on health shocks that occur without warning and do not recur. By doing so, we try to isolate immediate repercussions, distinguishing them from long-term health deterioration effects on a family’s labour supply. The main aim of the paper is thus to answer the question: What are the effects of a single continuous health shock of a family member on the family income of households in the United States? The health shocks which we analyze are not repeated, nor do they distinguish between mental and physical health.

To address our research question, we use survey panel data which contains information about household income and health shocks. In our identification strategy we use a matching DiD framework. This way we make sure that the observed effects are causally attributable to a health shock rather than confounded by other time-related factors. We utilize the bias corrected DiD estimator approach as proposed by Abadie and Imbens (2006). This allows us to account for selection bias by comparing families which experience a health shock to matched control families. We use the curated PSID-SHELF panel dataset in addition to the main PSID data, which includes information on family income, household structure, and health shocks. The matching process is performed using nearest- neighbor exact matching criteria, with family size adjusted income and state characteristics to ensure that there is balance between the treated and control groups.

Our results show that health shocks affect family income unevenly across income levels and family structures. Families below the 40th percentile see fair income gains, but these remain significantly smaller than those observed in control families, which suggests limited financial recovery. In contrast, higher-income families experience significant reductions in income, likely due to supply disruptions caused by caregiving responsibilities Van Houtven et al. (2013). By family structure, single-home families with children show large losses due to the absence of a secondary earner, while families with children show smaller reductions, supporting a partial "Added Worker Effect" (AWE) Lundberg (1985).

We contribute to the growing literature focusing on these on-time health shocks and their spillover effects on family income, extending the insights that come from the existing research on labour supply, caregiving, and welfare policies.

The remainder of the paper is organized to provide a comprehensive look at the effect of health shocks on U.S. family income. It begins with a literature review that explores existing research to identify key themes to contrast our results with. Following this, a concise theoretical framework is laid out. We then move to the institutional context and outline the data sources utilized in the research. The methodology and identification strategy are subsequently detailed to explain our approach. Finally, the main results are presented, accompanied by discussions and concluding remarks.

2 Literature Review

The economic effects of health shocks have gained significant attention in recent years, consistently showing their impact on labour supply, household income and family dynamics. These shocks do not occur in complete isolation but in contrast have rippling effects that extend to caregivers and other household members creating a waterfall of economic and emotional consequences for the family unit.

The caregiving economic toll also extends beyond immediate labour market outcomes, influencing broader family dynamics and long-term financial stability. The responsibilities of caregiving often force the household members to make trade-offs between work and care, leading to reduced labour supply on both intensive, which are the hours worked, and extensive which means the labour market participation. Caregivers are more likely to exit the labour force or reduce their working hours to accommodate caregiving responsibilities Van Houtven et al. (2013) . As expected, these adjustments create significant opportunity costs which include lost wages and career advancement opportunity losses.

Additionally, caregiving has mental consequences which can indirectly affect economic outcomes. Caregivers often experience high stress and mental health challenges, which can decrease productivity and increase staying away from work without a "good" reason Angelini and Costa-Font (2023). This financial strain can worsen household tensions which in the long-term leads to disruptions in the household itself. Another example of prolonged employment disruptions and reduced household income is the caregiving responsibilities for a chronic disease, and its emotional toll creates effects that lead to burnouts and the diminished quality of life of the caregiver Bradley et al. (2012).

Additionally, we can shift attention to the differences in how health shocks affect low-income versus high-income families. Health shocks often have disproportionately severe economic consequences for low-income households, particularly in low- and middle-income countries. These households are more likely to experience catastrophic "out of pocket" healthcare expenses, which frequently exceed thresholds of their income capacity to pay, pushing them into poverty Alam and Mahal (2014). In contrast, high-income households typically have greater access to savings, insurance, and credit enabling them to buffer against immediate financial impacts and maintain their economic stability. However, it is worth mentioning that even those high-income groups can experience significant disruptions in productivity and income. Particularly if health shocks lead to extended periods of caregiving or reduced labour supply. The long-term effects of health shocks also differ between these groups. In low-income families, people might work less to qualify for government support programs that provide financial help. This decision often means that they lose opportunities to gain skills and earn more money in the future Capatina et al. (2020). High-income families, on the other hand, are usually able to keep working and building their skills because they are less dependent on such programs and can absorb health-related costs more easily in theory. This creates a big gap between the two groups over time. Programs like public health insurance can help close this gap by giving low-income families more financial security, allowing them to work more and improve their earnings in the long run.

The financial burden of health shocks often exacerbates income instability, as households face both direct costs such as medical bills, and indirect costs like lost income. In countries like the United States, where out-of-pocket medical expenses can be exorbitant, the economic consequences can be harsh. In other countries with lower out-of-pocket medical expenses, such as China, we still observe how increased health expenditures and lost wages due to health shocks can lead to significant reductions in household income Wang et al. (2023). Although the Chinese healthcare system has some safety nets, the financial burden remains substantial. In a U.S. context, which relies upon a system that ties healthcare access to employment, we observe that households that experience health shocks often face the dual challenges of reduced income and increased healthcare costs. This creates a dependent-on-chance financial situation Datta et al. (2015). This dynamic is further compounded by families without substantial savings or insurance coverage, leaving them vulnerable to various other economic shocks.

3 Institutional Setting

The institutional framework significantly shapes the way households might react in theory to health shocks. Countries like Denmark, which provide universal healthcare and caregiving subsidies, not only aim to reduce possible inequality but also address the spillover effects of health shocks. These policies help prevent avoidable income losses and disruptions to household stability. The systems thus work as safety nets which mitigate the impact of health shocks by covering medical expenses and offering financial support to caregivers. This makes the households in these countries better equipped to maintain their consumption levels and reduce possible income losses connected with caregiving responsibilities Wang et al. (2023).

In contrast, the U.S. institutional setting has unique challenges due to its incomplete healthcare system and limited welfare provisions. The healthcare system from the years 2000 to 2015 relied heavily on employer-based insurance coverage, which left many low-income and unemployed individuals either uninsured or under-insured. The introduction of the Affordable Care Act in 2010 was an important moment, which expanded Medicaid coverage, providing insurance subsidies to low and middle- income households. However, the Affordable Care Act's effects were unevenly distributed because some states chose not to expand Medicaid. This created disparities in access to healthcare across the country Kaiser Family Foundation (2015). The "out of pocket" healthcare costs in the U.S. are amongst the highest globally, with households quite often bearing the significant financial burden when faced with a health shock. High-deductibles and co-payments often deter individuals from seeking immediate care, amplifying health issues and increasing long-term costs Collins et al. (2014). These burdens are particularly severe for the low-income families who are less likely to have savings or alternative financial choices to absorb the costs. As a result, health shocks often lead to massive financial consequences for those families, pushing them into poverty or forcing them to make some trade-off between health care and other needs to balance their life Alam and Mahal (2014).

Furthermore, the U.S. lack robust federal caregiving policies, leaving households to navigate their caregiving responsibilities with minimal support. And while programs we mentioned before like Medicaid provide some assistance, eligibility is limited, and the coverage often excludes essential services like at-home care or respite care for caregivers Van Houtven et al. (2013). This lack of support amplifies the economic consequences of health shocks, particularly for single-parent households or families with elderly dependents, who are more susceptible to experiencing significant income losses and caregiving burdens.

Although these challenges exist, there are some additional safety nets within the U.S. institutional framework. Programs such as Supplemental Security Income and Temporary Assistance for Needy Families provide limited financial assistance to low-income households affected by health shocks Bitler and Hoynes (2016). However, these programs are often criticized for their even stricter eligibility requirements and insufficient benefit levels, which fail to fully address the economic vulnerabilities of affected families.

4 Theoretical framework

Health shocks within families can have significant economic implications, particularly for the labour supply and income of family members. In our study we build the economic theory of household behaviour and the adjustments of labour supply, and we examine how a health shock to a family member affects the household income.

Households, like individuals, allocate their resources between consumption and leisure, aiming to maximize utility. This is an optimization process and it is constrained by the total income of the household and the time resources. Introducing a health shock will disrupt this balance, changing the behaviour of the household in the post-period compared to the pre-period.

Before the health shock occurs the household operates under normal conditions. The utility function is:

$$\max_{(C,L)} \quad U(C, L) \quad \text{s.t.} \quad C = w(T - L) + V \tag{1}$$

Where C is the consumption, T is all the time that is available, L stands for leisure, w is the wage rate, and V is the other income resources. In the pre-health shock period, all available time not allocated to leisure is spent working $(T - L)$ and the household income is determined by the wage rate w and the non-labour income V. The household faces no additional constraints related to caregiving or income losses due to health shocks, which makes this the baseline of the optimization.

In the post-health shock period, the optimization of the household changes since the health shock θ affects the resources of the household. θ reflects the fraction of the effective resources available after accounting for the shock. Therefore, the post-health shock budget constraint becomes:

$$C \leq \theta[w(T - L)] + V. \tag{2}$$

The parameter θ is 1 before the shock, which suggests that all resources are available, and after the shock $\theta < 1$ which means that the health shock reduces the resources due to income loss or due to caregiving. By introducing θ we capture the economic disruption caused by a health shock. The lower the θ the more the severity of the shock, which reduces both the consumption and leisure.

The theoretical responses to health shocks within households are explained through the added worker effect (AWE) Angelini and Costa-Font (2023) and the caregiver effect Bradley et al. (2012); Cahuc et al. (2014). The caregiver effect occurs when a household member reduces their labour supply to take on caregiving responsibilities. This effect usually leads to a decline in income, because caregiving responsibilities reduce the available time for market work. In contrast, the added worker effect shows an increase in labour supply by other household members in response to income loss from a health shock. This is compensatory behaviour and it is more common in lower-income households, where financial constraints require immediate labour market responses. Higher-income households may show weaker added worker effect responses, essentially because the access to professional caregiving or the financial resources reduce the need for labour supply adjustments.

Family composition and socioeconomic status significantly influence household responses to health shocks. For instance, single-parent households often experience the most severe economic disruptions, as there is no second earner to “absorb” caregiving responsibilities or to compensate for the lost income. In contrast, two-parent households might mitigate these effects through a combination of caregiver effect and added worker effect as well, redistributing labour and caregiving responsibilities between partners Maestas et al. (2023). Similarly, extended households where caregiving can be distributed among multiple members, might experience smaller disruptions in income.

5 Data

We use data from the PSID Social, Health and Economic Longitudinal File (PSID-SHELF) which is a curated and simplified version of the Panel Study of Income Dynamics (PSID), the longest running longitudinal household survey in the world, running from 1968 and tracking families across generations. To complement our main data, we add an additional health related variable from the original PSID data set to introduce a binary health shock variable into the mix. Specifically, an indicator for self-reported family health status which is derived from the question “Are any family members in poor health? “. An important element in our analysis is the choice of the years to include. Since our indicator for health from the main PSID data set was consistent and binary in the biannual period between the years 1996-2015 we limited our sample to the years 1997-2015 dropping 1996 since it would not meet the required minimum of a two-year gap to stay consistent with the rest of the biannual data.[1] The PSID has maintained high wave-to-wave re-interview response rates, typically around 94%, while tracking approximately 7,000 families around the year 2000 and expanding to over 9,000 by 2013. However, the additional self-reported family health status indicator from the main data set had a notably lower response rate, with only about half of eligible individuals answering this question.

Our primary outcome variable is the total family income, which is included in the PSID-SHELF dataset, in multiple formats. Total family income includes the earnings of all family members within the household, including the reference person, spouse or partner, children, and other family members. Income is reported based on the tax year prior to the survey year, which means that e.g. 2005 survey data reports income from the 2004 tax year. To account for the inflation, the dataset utilizes inflation-adjusted values expressed in real 2022 U.S. dollars, using the Personal Consumption Expenditures Price Index (PCEPI). Additionally, income measures are adjusted for family size by dividing the income by the square root of the total number of household members accounting for the fact that increases in household size do not typically correspond to proportional increases in earners.

We exclude households which cease to exist as family units. This occurs when a parent dies or when a child moves to live with a non-head parent, which places them outside the sample. Tracking individuals who transition between families would introduce significant complexity, as their association with a new family unit makes it difficult to maintain

[1] Another peculiarity with the data is that for unexplained reasons only 2 people reported poor health in the year 1999 limiting the range a bit further.

consistency in the analysis. To avoid such complications, we only focus on the stable family units where tracking is feasible.

6 Methodology

We divide households into income percentiles in order to make comparisons between "the rich" and the "poor" households. We split the families into two groups, above and below the 40th percentile. This way we can see if the economic impact of the shock varies based on the initial financial composition, as well as the potential disparities in how health shocks affect households with different levels of income.

Additionally, we differentiated households based on their family composition, for potential varying dynamics of how health shocks impact our outcome. We categorized them into single parent with children, two-parent households with children, and two-partner households without children. For two-parent households we further make the distinction of whether they both work or only one of them. By making these distinctions we can potentially uncover any nuanced ways in which caregiving responsibilities and income dependency interact with each other.

In regard to the timing decision, in our analysis we differentiate between continuous and intermittent (on-and-off) health shocks but treat them in the same way for consistency. Continuous health shocks refer to the cases where an individual in the household experiences an uninterrupted health condition over a period of time. In contrast, intermittent health shocks are those where the health shock comes and goes but spans a similar time frame. For example, a person with a health shock that begins in 2003 and ends in 2009 is treated the same as someone who reports that they experience multiple intermittent health shocks between 2003 and 2009. This way we can ensure that we capture the overall impact of long-term health disruptions on family income, regardless of whether the condition is continuous or intermittent Callaway and Sant'Anna (2021). By aggregating intermittent shocks into a single continuous period, we avoid unnecessary complexity, while also maintaining the focus on the cumulative economic effects of health disruptions over time. Therefore, we can make sure that such dynamic effects are appropriately captured in the Difference-in-Differences framework, avoiding the need to model each intermittent period separately, and we also maintain a balance between methodological precision and practicality, in order to get more robust and interpretable results.

7 Identification Strategy

To define and measure the concept of a health shock within the household we begin with the survey data from the PSID. In the PSID the respondents are asked whether any family member other than the respondent, usually the head of household, are currently in poor health. The original question is as follows: "Now about the rest of your family living there – are there any family members in poor health?". The raw responses to the question can include a variety of coded values, which indicate "Yes, is in poor health", "No, is not in poor health", "NA", and "Inap" for inappropriate. Therefore, our first step was to translate these responses into clear binary indicators that denote whether a household has experienced a health shock. We handle a health shock at the first occurrence in which a household reports having a family member in poor health, with no distinction between it being mental- or physical health.

Specifically, we re-code “Yes, is in poor health” as a 1, signifying that the household has at least one member in poor health and therefore qualifies as “treated” by a health shock. Households that respond “No” are coded as 0 and thus serve as potential controls for comparison.

The coding of “Inap” requires particular attention. In the PSID “Inap” indicates that the question about other family members’ health was considered “inappropriate”, occurring under various conditions. Such as, when the respondent originates from certain immigrant or Latino subsamples added later in the survey’s history or due to changes in respondent status and family composition over time. Another reason a response was deemed inappropriate was if the head or representative of the household was questioned themselves. To not lose potential controls from the main sample we opted to code all inappropriate cases in which any other family member reported a health shock as 0 but otherwise set it as missing.

After setting up this binary indicator we proceeded to refine the overall dataset to ensure that it is suited for the Difference-in-Differences method. We started with the panel of the PSID family units and first excluded observations with missing values in key variables. Then, we focused on identifying the areas of the treated families which were those that at some point reported a family member in poor health and then match them with the non-treated families that do not report such a health condition during the corresponding period. In addition, we made sure that the treated family units had at least one pre-period observation before the health shock and at least one post period observation after the health shock. The households that do not meet these time-coverage requirements were excluded, since we want to maintain the state of the common trends assumption and to ensure comparability across periods.

A couple with two kids where one adult dies remains in the dataset but if a single parent dies their kid would either drop from the dataset or be transferred to surviving family members’ household. This would cause an issue where we’d only be able to see the effects on the kids if they join a sample household vs. not a sample household. Also since our focus is family dynamics, we would prefer a more stable family unit.

All in all, we began with 1316 individuals who reported a shock in the family unit. We first removed 299 individuals who reported health shocks occurring at the very start (1996/ 1997) or at the very end (2015) of the observation window, as these cases prevented establishing a proper pre-shock baseline or measuring the post-shock effects. Next, we dropped 380 who provided no follow-up observation after reporting a health shock, making it impossible to observe a return to a “no shock” state and thereby lessening the continuity required for our analysis. This left us with 637 cases treated.

From these 637 treated observations, we removed an additional 156 that belonged to the same family unit to avoid duplication and ensure independence at the household level. This step reduced the sample to 481 unique shocks. We then eliminated another 61 cases due to multiple shocks or continuous reasons, such as double counting the same individuals reporting more than one health shock within the analysis window.

After applying all these filters, we ended up with a final sample of 420 treated observations available for the Difference-in-Differences analysis. We made this selection in order to enhance the credibility of our causal inferences and ensure that we analyze stable households with sufficient pre- and post- shock observations and no overlapping family-level duplications.

8 Empirical Strategy

In our analysis we use a matching Difference-in-Differences (DiD) framework to estimate the causal impact of health shocks on the family's income. The DiD is specifically well suited for our analysis because it uses both temporal and cross-sectional variations in the data. This means that it relies on the changes over time within the same household to observe how the income outcomes differ before and after the health shock, which allows us to track the effects of the treatment in the household which experiences the health shock – the treatment group.

The Difference-in-Differences method relies on the common trends assumption that without health shocks the treatment and control groups should show similar trends in income over time. This assumption is important, because we need to make sure that the observed differences are due to health shocks and no other factors. In addition, to make the treatment and control groups more comparable, we match households with health shock to similar households without the health shock, by using their characteristics before the shock occurred.

For the exact estimation of effects, we utilize the bias-correction methodology proposed by Abadie and Imbens (2011), to improve the comparability between the treatment and controls groups. While the initial matching ensures that the households are similar in terms of observed characteristics before the health shock, there may still be a small residual in the differences, which could potentially bias our results. The bias-correction method then adjusts for these remaining imbalances by incorporating information about how covariates influence outcomes, ensuring that the differences in income we observe are due to the health shock itself revealing the average treatment effect on the treated. Addressing this bias-correction with these AI adjusted standard errors allows us to utilize a t-test with an adjusted size to assess the significance of the estimate. By combining this approach with the DiD framework, we ensure that our estimates are not only robust but also account for the unobservable, time-invariant characteristics that might otherwise confound the results. This dual approach strengthens the causal inference regarding the impact of health shocks on family income. A simple matching-based formulation (without bias correction) takes the form of:

$$\hat{\theta}^{DID} = \left(\frac{1}{N_1}\right) \sum_{i \in T} \left((Y_{i,1} - Y_{i,0}) - \sum_{j \in C} w_{ij} (Y_{j,1} - Y_{j,0}) \right) \tag{3}$$

In this setup, $Y_{i,1}$ and $Y_{i,0}$ represent the post-treatment and pre-treatment outcomes for treated unit i, while $Y_{j,1}$ and $Y_{j,0}$ represent the corresponding outcomes for control unit j. The sets $\mathcal{T}$ and $\mathcal{C}$ denote the treated and control units, respectively, with N_1 representing the number of treated units. Weights w_{ij} are assigned to control unit j when matched to treated unit i, based on covariate similarity.[2] These weights typically sum to 1 for each treated unit, ensuring proper balance ($\sum_{j \in \mathcal{C}} w_{ij} = 1$) Abadie and Imbens (2011).

[2] If exact matching by nearest neighbors with ties, the weights evenly distribute over the matched controls. This results in an unweighted mean of the outcomes for all matched controls contributing to the counterfactual for each treated unit, i.e., w is just $\frac{1}{j}$, where j is the number of matches matched on the treated.

9 Results

To estimate the causal effect of health shocks on family income by a consistent bias-corrected estimator as proposed in Abadie and Imbens (2006, 2011) we first need to make a choice of how to match controls to treated sample. The method is not a traditional parametric regression-based framework but instead it is semi-parametric and uses a matching estimator chosen by nearest-neighbor matching. This means that great care must be taken in matching criteria choices to ensure that treatment effect is estimated for a comparable subset of treatment and control, which allows the common support assumption to hold. This flexibility allows for some covariate imbalance and heterogeneity in treatment effects, since it compares outcomes locally instead of globally but comes at the cost of relying on number of observations for both treatment and control.

Table 1: Matching criteria choice

Model:	(1)	(2)	(3a)	(3b)	(3c)
FU's Income	X				
FU's Income Percentile		X	X	X	X
State			X	X	X
DiD (AI s.e.)	-1458.32	-719.55	-2919.01	-3563.20	-3133.05
	(798.22)	(1686.35)	(1379.55)	(1471.04)	(3024.51)
p-value	0.068	0.670	0.035	0.016	0.301
obs. treated	383	420	410	481	410
obs. control	944	1353	2105	2506	320
mean matches	3.2	3.2	7.4	7.5	1
estimation time	end	end	end	start	end
method	ties	ties	ties	ties	KNN

Notes: Data comes from PSID-SHELF and the main PSID, covering families with poor health reports and controls from 1996-2015. DiD consistent bias-corrected estimator on family size adjusted family unit (FU's) income expressed in real 2022 dollars as proposed in Abadie and Imbens (2006, 2011) used to calculate average treatment effect for the treated. Standard errors and p-values are analytically derived to account for the variation introduced by the matching process.

All matching is done two years prior to the random health shock and controls are drawn exactly at same year. In table 1 model (1) we see that if exact matching is done only by the outcome variable itself (family size adjusted income in real dollars) and the matching algorithm can only find suitable matches for 383 out of the 637 observed treated.

In model (2) instead of matching on direct dollar values where numbers could be negative or zero, we calculated and matched the total population family income percentiles. This increased suitable matches to 420 but became too unbalanced for accurate estimates. By expanding the exact matching criteria from percentiles alone to include state for regional heterogeneity as seen in model (3a) we slightly reduce available matches but greatly increase the balance of the panel allowing for control observations to be matched in more dimensions. If we measure the outcome relative to treatment start instead of treatment-end we can see a great increase in both precision and observations since families' sequential yearly observation requirements are reduced if it experienced more chronic health shocks. This does not capture the post treatment effects, since a portion of the sample will effectively still be in its treatment period at the estimation time.

The 70 people included in model (3b) that are not in model (3a) will thus be those who either did not respond after reporting a health shock or are still effectively exposed to a health shock in 2015. For models (1)-(3b) we utilized nearest-neighbor matching, allowing for ties such that if the exact matching criteria found more than one suitable match it could include all suitable matching controls that matched. If we use a K-nearest neighbor matching algorithm with replacement instead we can see that treated observations stay the same between models (3a) and (3c) but the available controls, now used multiple times, significantly drop making the panel unbalanced since the two variable criteria is so lenient. Furthermore, adding more covariates only served to reduce the overall balance and thus matching on family income percentile and state gave us the most robust and stable findings for further analysis.

To add validity in the robustness of our identification strategy, we did balance tests on observable characteristics between treated and control groups. As shown in Table 1, exact matching on family income and state achieves a well-balanced comparison. This ensures that any observed effects are not driven by pre-existing differences. Additionally, the use of family size adjusted income differences mitigates further potential bias related to family size or family composition.

Table 2: Observable characteristics of family unit two years prior to health shock

Variable	**Treated**	**Control**	**% Bias**	**p-value**
FU's Income	26155	27824	-4.40%	0.51
FU's Income Percentile	39.59	39.59	0.00%	1.00
State	23.01	23.01	0.00%	1.00
Family Size	4.16	3.75	24.00%	0.00
Family Composition	2.82	2.66	22.10%	0.00
Age of the Respondent	19.15	28.61	-47.10%	0.00
Race of the Respondent	1.93	1.90	3.50%	0.58
Respondent is Living with a Spouse/Partner	3.00	2.94	3.20%	0.62
Proportion of Family Working	1.21	1.30	-8.40%	0.19
Highest Years of Education (Resp. or Spouse)	12.50	12.65	-5.20%	0.41
Highest Education Level (Resp. or Spouse)	1.49	1.55	-5.50%	0.39
Highest Earnings (Resp. or Spouse)	16889	18719	-6.60%	0.28
Homeownership Status	1.50	1.56	-10.80%	0.10
Home Equity	21479	24322	-4.60%	0.42
Home Value	43344	43951	-0.70%	0.91
FU's Total Value of Savings	3891	5246	-6.00%	0.33

Notes: Data comes from PSID-SHELF Pfeffer et al. (2019) and the main Panel Study of Income Dynamics (Panel Study of Income Dynamics), covering families with poor health reports and controls from 1996-2015. All dollar values are measured in family size-adjusted real 2022 dollars. Treated and control group means are compared using two-sample t-tests, calculated on the full dataset where data is available for both groups. The % bias represents the standardized mean difference between treated and control groups.

Since the outcome is measured at the family unit level, individual indicators like age and race are less descriptive. This is because heads of households could not report a health shock themselves. Instead, these shocks are rather reported by other family members such as their children. This does not mean the health shock was not experienced by them but quite the opposite. A lower age of respondents would indicate that other older family members were more likely to experience a health shock and thus be reported by the younger family members. We also see quite a significant difference between family composition, i.e. couple with or without children and single parents. This suggests that families which reported a health shock were more likely to be comprised of couples with a child or children than the matched controls. Since the outcome measures are family size-adjusted we look past this but take a more detailed look at how the outcomes might differ between family composition types.

After matching we observed a slightly higher proportion of white, non-Hispanic individuals in the treated group compared to the control group. However, this difference was minimal and non-significant. In terms of education, we observed both years and level completed of either the head or the spouse, which ever was higher, and found no significant imbalance.

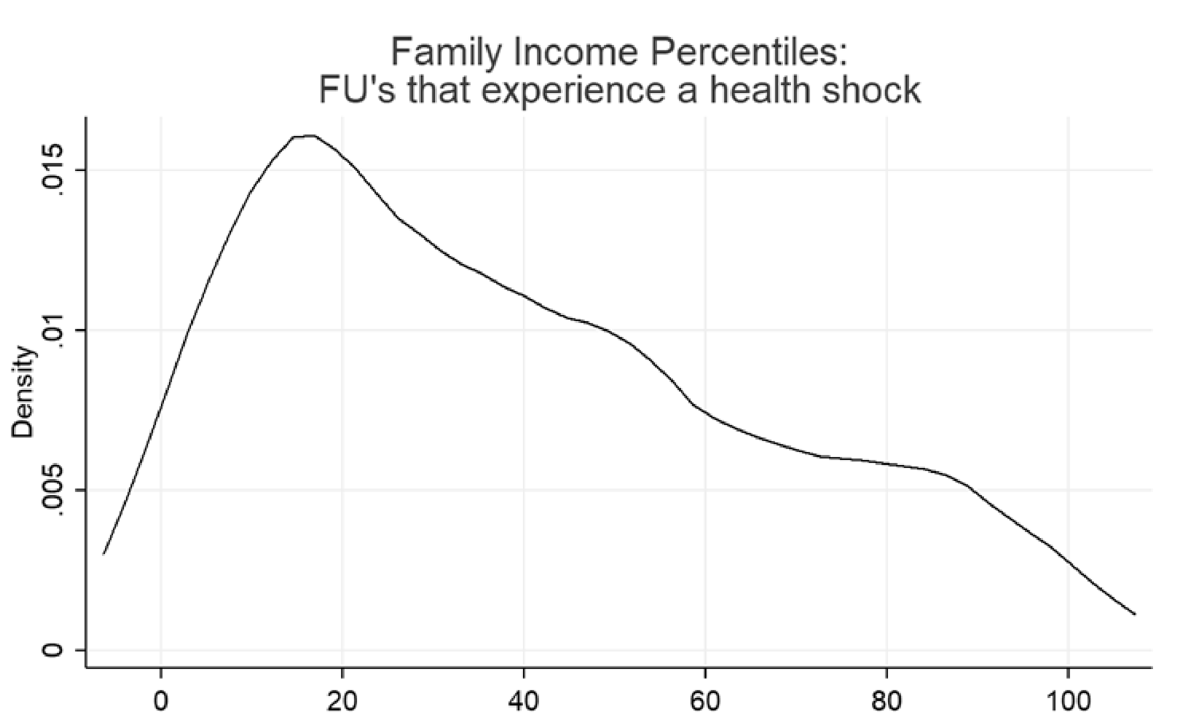
If we take a look beyond the demographic characteristics table 2 also shows various economic and financial indicators prior to the health shock for the family unit. The differences between treated and control groups in terms of highest earnings, wealth composition and home equity were small but we see a slight bias in home ownership status but only at a 10% significance level.

Overall, the results of the balance checks show us that most observable characteristics across treated and control groups support the idea that any differences in the outcome variable of family income is likely attributable to the health shock itself instead of any underlying differences between the two groups.

9.1 Heterogeneity Analysis

As observed in the balance test, there appears to be a right skew in income percentile of shocks in the treated sample. This is illustrated in Figure 1, where the aggregate distribution of total family income is shown. Applying a log transformation[3] of wages provides proportional effects but reduces the statistical significance. This is expected, as semi-parametric estimator relies on bias correction and does not assume a specific error distribution, making it less sensitive to such transformations Abadie and Imbens (2011). As shown in Table 3, while the mean family income difference remains substantial, the log transformation reduces the significance level, as the p-value increases.

Figure 1: Density Graph of Treated Family Income percentiles.



Notes: Data comes from the PSID-SHELF and the main PSID datasets. The figure displays the density of family income percentiles for the treated group. The x-axis represents income percentiles, and the y-axis shows the density. Similar to previous tables, values are estimated based on the treated sample.

[3] Dropping negative and zero values since the logarithm is undefined for these cases, and their inclusion would distort the analysis. This, of course, means we lose around 10 observations that were zero.

Table 3: Heterogeneity Analysis: DiD Estimates for FU's Income

Statistic	**FU's Income**	**log(FU's Income)**
Mean (Treated)	729.87	0.03
Mean (Controls)	4426.52	0.09
Difference-in-Differences (DiD)	-3696.65	-0.06
AI Robust S.E.	1748.57	0.04
p-value	0.035^{**}	0.136
Number of Treated	409	409
Number of Controls	2114	2095

Notes: Data comes from PSID-SHELF and the main PSID data. Means are reported for treated and control groups, with Difference-in-Differences (DiD) estimates for FU's income and its logarithmic transformation. AI robust standard errors (S.E.) are reported alongside p-values. Results are based on available observations for each group. Significance levels are reported with their p-values: *** significance at 1% level, ** significance at 5% level, * significance at 10% level.

We instead test if the mechanisms of the shock differ significantly by starting income percentile and rematch and re-estimate the effects of the health shock on different income percentile brackets as detailed in table 4 and figure 2. Across all income percentiles the effects of a health shock appear to reduce families total income in the two years following the shock as seen in column 1 table 4. The treated group's family income increased significantly less than matched control as seen in the differences between the mean differences, only increasing by 729.87 dollars while the control group saw an increase of 4426.52 dollars in the exact same period. This gives us a difference in difference estimate of -3696.65 dollars in family size adjusted real 2022 dollars.

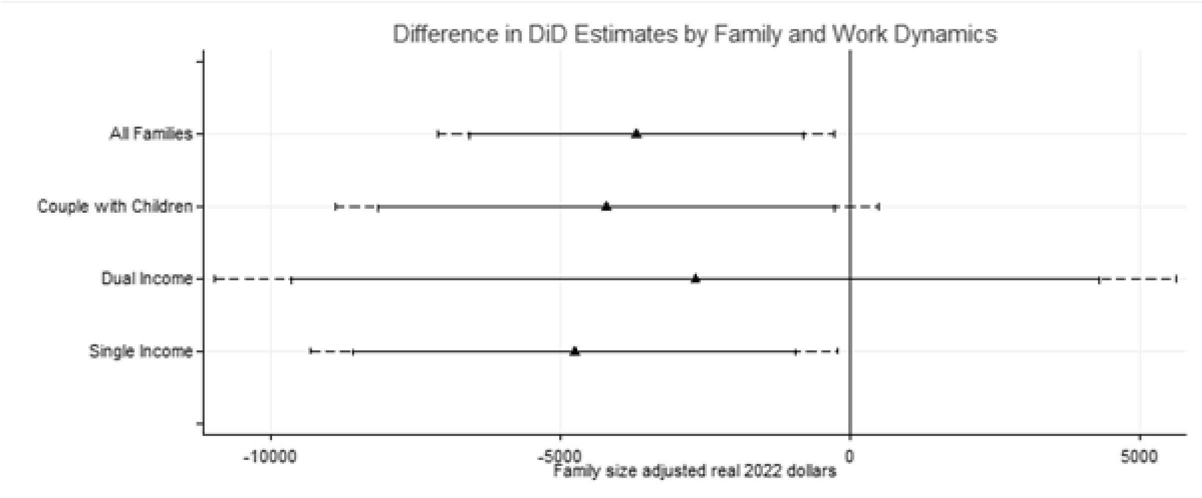
Table 4: Heterogeneity Analysis: DiD Estimates by Income Percentiles

Statistic	**All**	**<40th Per.**	**>40th Per.**	**<50th Per.**	**<30th Per.**
Mean Difference (Treated)	729.87	6200.27	-7244.71	4267.60	7455.38
Mean Difference (Controls)	4426.52	3977.53	4300.49	4740.77	4782.05
Difference-in-Differences (DiD)	-3696.65	2222.74	-11545.20	-473.17	2673.33
AI Robust S.E.	1748.57	1074.92	4004.16	1520.57	1224.69
p-value	0.035^{**}	0.040^{**}	0.004^{***}	0.756	0.030^{**}
Number of Treated	409	252	196	300	200
Number of Controls	2114	1349	1122	1580	1083

Notes: Data comes from PSID-SHELF and the main PSID data. Means are reported for treated and control groups across income percentiles. Difference-in-Differences (DiD) estimates are reported with Abadie-Imbens (AI) robust standard errors. Significance levels are reported with their p-values: *** significance at 1% level, ** significance at 5% level, * significance at 10% level.

These results contrast the literature which shows that health shocks disproportionately affect lower-income households, and that low-income families would face tremendous healthcare expenses Alam and Mahal (2014). In our case, higher-income families experience greater income reductions following a random health shock. One possible explanation could be that these families are more likely to have two income earners or higher wages, which means that they face larger possible income losses when one member reduces labour supply to provide care or recover from the shock themselves Van Houtven et al. (2013).

Figure 2: Difference in DiD Estimates by Family and Work Dynamics



Notes: This figure shows the Difference-in-Differences (DiD) estimates across different family and work dynamics categories, expressed in family size-adjusted real 2022 dollars. Horizontal lines represent the Abadie-Imbens (AI) robust standard errors for each group. The dashed vertical line at zero indicates no treatment effect. Categories include all families, couples with children, dual-income families, and single-income families. Data comes from the PSID-SHELF and the main PSID datasets.

Following the examination of all income groups, we look at differences above and below the 40th income percentile since as seen in table 2 for balance checks we observe the mean income percentile for the treated to be quite low or around 39.59. By segmenting the analysis at the mean point we can compare those that could potentially be more vulnerable to a loss in income (<40th percentile, column 2 table 4) against those that should be better off (>40th percentile, column 3 table 4). This allows us to see whether the health shock disproportionately benefits or harms the families based on their relative income status.

Since low-income families are more vulnerable to the economic consequences of health shocks, they can often reduce their labour supply to qualify for government assistance Capatina et al. (2020). While it may be necessary in the short term, it limits their ability to build skills or increase earnings in the long run. This could be why we find that for those that started off below the 40th percentile we observe a significant increase in family income relative to their baseline. However, this increase is substantially smaller than what is observed for families above the 40th percentile or in the control group, which indicates that families in lower income percentiles may face greater challenges in recovering financially after a health shock.

Another significant difference we observed in our balance panel in table 2 was between family compositions. To address this, we rematch and re-estimated the treated and controls in accordance with Abadie and Imbens (2006). In table 5 and figure 3 we look at how couples with children react as opposed to other family types and observe a reduction in family income of around -4202.70 dollars, but this is only significant at a 10% level.

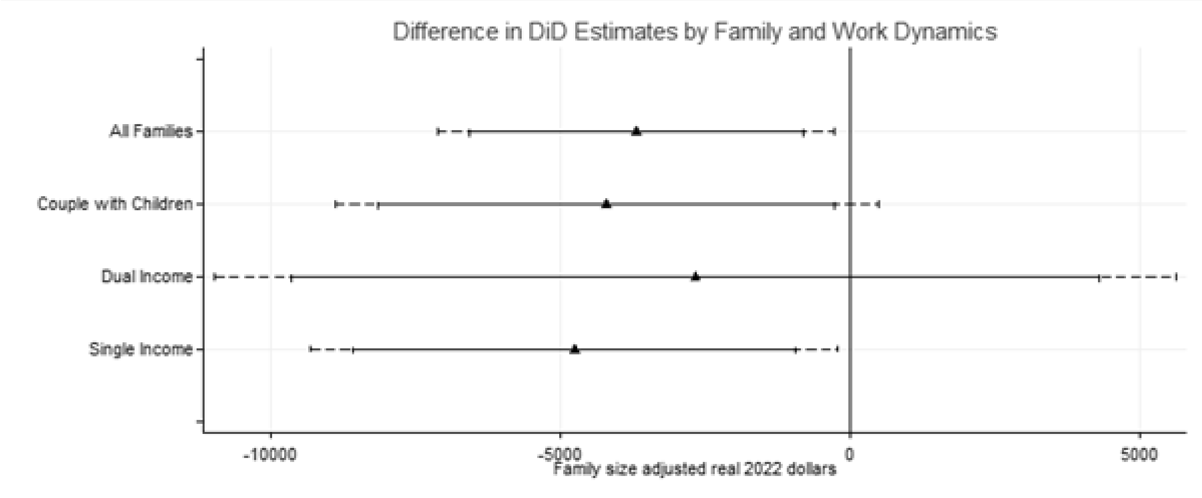
Table 5: Heterogeneity Analysis: DiD Estimates by Family Income Type

Statistic	**Couple with Children**	**Dual Income**	**Single Income**
Mean (Treated)	459.59	-2200.12	212.93
Mean (Controls)	4662.29	471.06	4974.21
Difference-in-Differences (DiD)	-4202.70	-2671.19	-4761.28
AI Robust S.E.	2393.09	4232.66	2323.10
p-value	0.080*	0.530	0.042**
Number of Treated	258	95	234
Number of Controls	1427	592	1259

Notes: Data comes from PSID-SHELF and the main PSID data. Means are reported for treated and control groups across income categories. Difference-in-Differences (DiD) estimates are calculated for each group with Abadie-Imbens (AI) robust standard errors. Significance levels are reported with their p-values: *** significance at 1% level, ** significance at 5% level, * significance at 10% level.

We then look at dual income families where both the head and spouse are employed as seen in table 5 column 2. Surprisingly there were only 95 observed families with a pair of working spouses. Our estimates did not show significance giving high standard errors alluding to very heterogeneous responses within either treatment or control. We thus looked instead at families with a single income prior to the health shock, either a single parent household or a single income pair. Here we saw on average the largest reduction in income by around -4761.28 dollars at a 5% level of significance. The significant income reduction that we see for single-income families could be due to the reduced labour supply in order to provide more care, which aligns with the caregiver effect (Van Houtven et al., 2013). In contrast, the income loss for couples with children is larger in magnitude and only significant at the 10% level. This could suggest a partial Added Worker Effect, where other family members such as the spouse or even older children increase their labour supply to account for the lost income (Lundberg, 1985).

Figure 3: Difference in DiD Estimates by Family and Work Dynamics.



Notes: This figure shows the Difference-in-Differences (DiD) estimates across different family and work dynamics categories, measured in family size-adjusted real 2022 dollars. Horizontal lines represent the Abadie-Imbens (AI) robust standard errors for each group. The dashed vertical line at zero indicates no treatment effect. Categories include all families, couples with children, dual-income families, and single-income families. Data comes from the PSID-SHELF and the main PSID datasets.

10 Discussions & Limitations

We acknowledge several limitations that may impact interpretation and external validity of our findings. Firstly, it is extremely noteworthy that heads of household could not report a health shock of their own but instead the question posed focused on the rest of the household and whether any family members were in poor health. This limits the paper to a more than single member household and required other family members to answer instead which reduced the average age of treated by a lot. This younger average age affected our ability to analyze heterogeneous responses based on family units' age. Health shocks often lead to substantial reductions in labour supply, directly affecting the individual experiencing the health event and indirectly influencing household members. It has been shown that older workers in the United Kingdom are particularly vulnerable of those shocks. Labour participation declines significantly after health shocks, with the effect being more pronounced among women and older individuals Jones et al. (2020).

Second, since the treated sample is notably small that can limit the effectiveness of our empirical strategy, potentially compromising the reliability of our results especially in subsamples of the treated. Thus the main results over all family types and income percentiles should be the most robust as they draw from the largest treated sample pool.

Additionally, it is worth mentioning that since the data was originally sampled on an individual not family level basis and then aggregated there will be a certain loss of granularity for matching estimates. Possible covariate choice is thus limited to family level variables, which are fewer than the individual ones, lowering the probability of matching good controls. These aggregate measures also go from binary to factor variables.

Another limitation of the paper lies in the sampling frequency of the data. Since data is collected biannually for an observational unit as fluid as a family unit, it can really limit the ability to capture how rapidly dynamics can change within that time frame. We can therefore never really be sure at which stage of a health shock a family unit might be in during each observation period. Abiding by the single continuous treatment period restriction to get a consistent estimator further exasperated this issue as it constrained the analysis to broader windows and potentially hid the immediate effects and transitions associated with health shocks.

Lastly, the heterogeneity in results across family income percentiles suggests a non-linear relationship of the causal effect, which may obscure the dynamics of the treatment effects across subsamples, particularly where standard errors are large relative to the estimated impacts, limiting the precision of the findings.

11 Conclusion

Health shocks impose significant and uneven economic burdens on U.S. households, with effects that vary by income and family structure. In this study we estimate an average income reduction of $3700 per household annually, using a bias-corrected Difference-in-Differences approach. Through our analysis we reveal that the economic consequences of health shocks are not uniformly distributed across households. Higher-income families experience larger income reductions, which can be attributed to the disruption of dual earner labour supply. The impact of those losses underscores the critical role of caregiving responsibilities within higher-income households, where reductions in labour supply outweigh the potential for compensatory adjustments. In contrast, lower-income families experience small gains following a health shock. These gains are likely driven by the Added Worker Effect, where other family members increase their labour supply to compensate for lost income, or through reliance on government assistance programs. However, such gains remain significantly smaller compared to income increases observed in the control group, suggesting limited financial recovery among lower-income households. Family structure further amplifies these effects. Households with the structure of single-parent or single earner are vulnerable, experiencing the largest income declines due to the absence of alternative earners to absorb caregiving duties or mitigate labour market disruptions. In contrast, dual-income households and those with extended family networks appear to have the ability to demonstrate greater resilience but vary to widely in their responses and thus do not show significant results.

Our findings contribute to the literature regarding the economic consequences of health shocks, extending evidence of the Added Worker Effect and the Caregiver Effect to a U.S. context. By achieving a robust empirical strategy, this paper shows how the family income and caregiving dynamics interact with institutional settings, such as limited healthcare access and weak caregiving support systems in the United States.

From a policy perspective, it is important to mention the need for targeted interventions to reduce the financial burden of health shocks, not only from an inequality perspective but also an efficiency one. Policies such as universal healthcare and caregiving subsidies as seen in countries such as Denmark and China would help households mitigate income losses and improve economic stability. Attention should be directed towards single-parent households and low-income families, which remain disproportionately vulnerable to the long term economic effects of health shocks.

Some limitations must be acknowledged. The biannual frequency of the data restricts the ability to capture short-term adjustments in income and labour supply following health shocks. Additionally, the analysis focuses on stable family units potentially underestimating the broader economic consequences for households that experience severe disruptions such as family disintegration. Also, the small sample size for certain subgroups limits the statistical precision of heterogeneity analyses.

Future research should explore the long-term effects of health shocks on household economic mobility, labour market participation, and maybe even wealth accumulation. Comparative studies across countries with different healthcare and welfare systems would provide further insights into the role of institutional frameworks in moderating the economic impact of health shocks.

In conclusion, in this study we demonstrate that health shocks introduce significant and heterogeneous financial burdens on U.S. households. Income level, family structure, and the instructional setting jointly determine the resilience of the household to such shocks. By addressing these vulnerabilities through well-designed policy interventions is essential to easing the financial strain and reducing inequality among the households which experience health shocks.

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