Parental Health, Aging, and the Labor Supply of Young Workers *

Sara Casella[1] and Luca Mazzone[2]

[1] *University of Pennsylvania*

[2] *International Monetary Fund*

August 17, 2023

Abstract

To what extent are young workers affected by health shocks that happen to their parents? This paper studies the short and long-term spillover effects of parents' adverse health events on their adult children. We use the unique structure of the Panel Survey on Income Dynamics (PSID) to build family networks and construct a measure of sudden health changes. Exploiting news on parents' health status, we provide evidence of the existence of family insurance in the form of time and monetary transfers, and of the importance of family ties in shaping labor market outcomes. Following the deterioration of parents' health, time spent helping them goes up, while wealth, income and hours worked by children significantly decline.

Keywords: health, family network, intergenerational transfers, wealth, earnings, time allocation

JEL Classification: E21, D91, I14, J14, J22

*The authors thank Corina Boar, Ana Costa-Ramón, Roozbeh Hosseini, Rocío Madera, Paolo Martellini, Stefano Pietrosanti, Yulya Truskinovsky, David Wiczer and participants at the Society for Labor Economics Conference, the Society for the Economics of the Household Conference, and the Barcelona Summer Forum for helpful comments and conversations. The findings and conclusions expressed are solely those of the authors and do not represent the views of IMF or its Board of Directors. All errors are our own.
Casella: scas@sas.upenn.edu, Mazzone: lmazzone@imf.org

1 Introduction

This paper studies the spillover effects of parents' adverse health events on their adult children. Though research solidly connects health disparities with lifetime earnings and wealth inequality,[1] the ripple effects of a parent's health on their children's labor market trajectories are less clear-cut. Parents' health deterioration usually comes with high medical expenses and income loss. Therefore, if children are not insulated from their parents, net transfers toward children may decrease, and the affected child might increase their labor supply due to a negative wealth effect. On the other hand, the necessity of informal care may arise upon illness.[2] If parents are in bad health, caretaking can impose significant time constraints on the children, who have to give up on other priorities (see Skira 2015, Korfhage 2019, Barczyk and Kredler 2018, Mommaerts 2020), apart from being stressful and psychologically demanding (Pinquart and Sorensen 2003). Worsening parental health can then have adverse effects on the labor market outcomes of adult children.

Exploiting data on sudden changes in parents' health status in the U.S., we document several new important findings. First, we find evidence of a significant negative pass-through of health shocks from parents to their adult children. The income of young workers whose parent receives a health shock falls by 9% compared to their peers and only recovers after about eight years. Hours worked decline by about 3%, implying that the reduction in labor supply also comes with a reduction in hourly earnings. The affected parent's wealth falls by about 27% and keeps declining, with children's wealth also significantly declining over time. In line with our hypothesis, we find that shocked parents are more likely to be helped with

[1] See De Nardi, Pashchenko, and Porapakkarm (2022) for details.

[2] Barczyk and Kredler (2018), Ko (2022), Mommaerts (2020), and Maestas, Messel, and Truskinovsky (2023) among others, document the importance of informal long-term caregiving provided by adult children to their parents.

chores and errands and to receive monetary transfers from their adult children after a shock. Finally, income losses are more severe when the affected parent is single, widowed, or divorced, especially if the mother is missing. We thus provide evidence of the importance of family ties in shaping career, savings, and time and monetary transfers.

Second, our results point to a central role of occupational sorting in explaining the decline in hourly earnings of adult children whose parents receive a health shock. Building on the intuition of Goldin (2015) that high-paying occupations have compensation schedules that are convex in hours worked, we adopt the occupations classification of Erosa et al. (2022) and divide occupations by quartile of average yearly hours worked. We then show that the disproportionate income losses of adult children are concentrated among individuals in high-hours occupations. Additional analysis of education, income, age, and wealth dimensions confirms this intuition.

Finally, we test what happens to adult children upon the passing away of one of their parents, in a context where informal care stops being relevant. The results point to the opposite effect: hours and income significantly increase and are up to 30% higher eight years after parental death. Again, the effect is particularly strong for the passing of parents that did not have a spouse or other cohabiting relatives as potential sources of informal caregiving.

To build family networks, construct health measures, and link health changes across the family to labor market outcomes we use the unique structure of the Panel Survey on Income Dynamics (PSID). Starting in 1999, the PSID started asking respondents a rich set of questions related to health and to the insurgence of medical conditions and diagnoses. Leveraging such detailed information on health status, we build a health shock for each surveyed individual that indicates the emergence of a severe condition. We show that our measure has statistically significant predictive power on subsequent disability and on measures of frailty used in the literature (see Hosseini, Kopecky, and Zhao 2021a).

Specifically, we construct our health shock variables using self-reported changes in medical diagnoses on a list of severe conditions, such as heart attacks or strokes, that capture the sudden worsening of an individual's health status. The list is taken from the US Social Security Administration's classification of health events that qualify the individual to receive disability benefits. The baseline version of the shock takes a value of one if the individual has received a new diagnosis, provided she had never received a diagnosis from the same list before. We then use the shocks to study responses in the family using a dynamic difference-in-difference approach. The outcomes are calculated on the sample of working-age children, conditional on the parent surviving during the time window we observe (that is, eight years after the shock).

Our balancing exercise suggests that, before receiving the news of a severe illness of a parent, individuals may look different from those who will not receive such news. Therefore, our empirical analysis will use the not-yet-treated as a control group to account for possible observable and unobservable heterogeneity across groups. The approach implies constructing counterfactuals to affected households using households that experience the same event a few years in the future (see Fadlon and Nielsen 2021). It therefore selects households that are fundamentally similar to each other but are different in the timing of the parent health shock. Identification comes, therefore, from comparisons of individuals who experienced the shock at different points in time.

We contribute to the literature on health, family, and labor supply in several ways. Existing literature that links labor market outcomes to health status highlights the first-order importance of health shocks, reporting large negative effects on own labor supply and earnings (Dobkin et al. 2018, Michaud and Wiczer

2018, Meyer and Mok 2019), as well as on life cycle earnings through a human capital channel (Keane, Capatina, and Maruyama 2022). Several studies also discuss the effects of health on spouses' labor supply (Fadlon and Nielsen 2021), often in the context of insurance within the household (see Blundell, Pistaferri, and Saporta-Eksten 2018); while Eriksen et al. (2021) and Breivik and Costa-Ramón (2022) find that the insurgence of illness in young children has a negative effect on income and hours worked by mothers. Inter-generational effects on labor market outcomes of health shocks, especially in a context with limited availability of long-term care options and U.S. labor market structure, remain a largely understudied topic in this area of research. An exception is Rellstab et al. (2020), who find that in the Netherlands, a country with large availability of part-time work and a very generous universal long-term care system, the unexpected hospitalization of a parent has little effect on the labor market outcomes of their working-age children.[3] Truskinovsky (2022), on the other hand, addresses the issue of self-selection into informal care by studying how caregiving obligations are impacted by employment shocks in the United States.

We also contribute to the literature that explores the relevance of family ties and inter-generational transfers for risk sharing: see, for example, Kotlikoff (1988), Hayashi, Altonji, and Kotlikoff (1996), and recently Attanasio, Meghir, and Mommarts (2018), Andersen, Johannesen, and Sheridan (2020), Boar (2021). Compared to these studies, we provide direct evidence of the importance of family ties for a specific type of realized shock. Since health shocks can be quite severe and persistent over time, they can elicit stronger family responses than temporary shocks. Moreover, while most studies of informal insurance focus on financial support provided by parents to their children, we explore the opposite direction, i.e., the extent to which children are affected by a shock to their parents and how

[3] Fadlon and Nielsen (2019) also study spillovers in the family, children included, but limited to health behavior and health outcomes only.

they respond to it, and find quite large effects.

The rest of the paper is organized as follows: Section 2 describes the data used and the incidence of health problems and disability in the U.S. population. Section 3 describes our empirical strategy. Section 4 presents our main empirical results, and discusses them in light of economic theory, with references to the role of occupations. Section 6 discusses heterogeneous effects within the family and Section 5 presents results of fatal shocks. Finally, Section 7 concludes.

2 Data

In this section we introduce the datasets we use – the Panel Study of Income Dynamics (PSID) and the Health and Retirement Survey (HRS) –, how family members are linked, the construction of health and disability measures, and we discuss the introduction of the adverse health shock.

2.1 Data Construction

The main dataset used in our analysis is the Panel Study of Income Dynamics (PSID), a longitudinal dataset started in 1968 with an initial sample of about 4800 households. The data is composed of a sample that is nationally representative of the non-immigrant population (Survey Research Center sample) and a national sample of low-income families (Survey of Economic Opportunity sample) of 1872 households (see Hill, Marsden, and Duncan 1992). Both of these samples are included in our analysis. Families are interviewed annually between 1968 and 1997 and biannually since then. The study has followed the families from the initial sample, tracing the individuals that composed those families whether or not they remained in the household. The study follows adults as they age, and follows children as they advance through childhood and adulthood, forming families of their own. All this information is collected in the PSID dataset, including files that link individuals based on their relationship with other members of their families, within and across generations.

	Pairs with:		
Year	Sibling	Parent	Grandparent
1969	52	195	1
1979	2,068	2,612	57
1989	3,556	3,927	163
1999	3,219	3,551	572
2009	4,869	4,864	1,336
2019	5,463	4,730	1,345

Table 1. Source: PSID Family Identification Mapping System User Manual.

The genealogical sample design of the PSID implies that for many sample members, their parents (biological and adoptive), grandparents, great-grandparents, and siblings are also sample members. We use the Family Identification Mapping System (FIMS) files to link each individual to her or his extended family. By "extended family" of an individual in our sample, we mean not only his or her partner, and any children, but also parents and siblings. In our framework, an "extended family" (or, for the sake of brevity, a "family") includes multiple separate households that share familial ties across generations, rather than a nuclear family within a single household.[4]

FIMS offers three distinct types of maps to keep track of the extended family. The intra-generational (SIB) map identifies various types of siblings (full siblings, half-siblings). The inter-generational (GID) map matches PSID individuals to their predecessors, going back to three generations, i.e. parents, grandparents, and great-grandparents. Finally, the prospective intergenerational map (GID PRO) identifies the starting generation (G1) as the original sample from 1968 (see Insolera and

[4]Others used different definitions of extended family when relying on PSID data. For instance, Attanasio, Meghir, and Mommarts (2018) define the extended family as "*cohabiting couple and their adult children who have broken off from the parent household.*"

Mushtaq 2019 for a detailed explanation). Descendants of original PSID households form subsequent generations, again up to three generations down (child, grandchild, and great-grandchild). Over time, keeping track of family ties resulted in a growing number of individuals and families included in the sample. This results in a final sample of several thousand extended family networks, as shown in **Table 1**.

The second source of data in our analysis is the Health and Retirement Study (HRS). The HRS is a longitudinal panel study that, starting in 1994, is conducted every other year and is representative of the U.S. population over the age of 50 and their spouses. HRS contains further information on time and monetary transfers between children and parents, which allows us to investigate further inter-generational links.

2.2 Building the Health Shock

Our goal is to build a metric that captures the inception of physical and mental health conditions. To do so, we exploit the fact that, starting in 1999, PSID started asking participants in every interview whether they had ever been diagnosed with a series of impairments. The first time a respondent answers "yes" to one of these questions marks a diagnosis's insurgence. We then collect first-time diagnoses of physical diseases and mental health conditions. Because the set of questions regarding physical conditions is quite large, we follow medical criteria that apply to the evaluation of impairments in adults aged 18 and over in disability evaluation under Social Security.[5] As the shock is entirely constituted of news to health status reported new diagnoses of severe diseases, we will also refer to our metric as "*new diagnoses*". The complete set of questions that constitute our source for constructing the health shock is shown in **Table 2**.

[5]The US Social Security Administration provides a comprehensive listing for disability evaluation. This can be found at: https://www.ssa.gov/disability/professionals/bluebook/AdultListings.htm

Because of the heterogeneous nature of the diagnoses, the shock can be built in different ways, each focusing on one aspect in which news will affect consumption, investment, and labor outcomes. We focus on the first six shocks in **Table 2**, which collect physical impairments that are likely to have a relatively immediate impact on the individual and are consistently reported. In particular, no difference in the prevalence in the general population across gender or race seems to be present in reporting cancers or impairments to the respiratory, cardiovascular, or neurological systems. We only focus on the first time an individual reports a new diagnosis and disregard all subsequent diagnoses.

In contrast, we see a substantial gap in the occurrence of impairments of SSA category 12 (mental health related) across races. This disparity in mental health diagnoses and treatment is known and discussed in the medical literature - see Nelson (2002). Research also shows that among minorities, those with socioeconomic stress are less likely to report psychological symptoms and so will be more likely to end up under-diagnosed (Williams et al. 2012). Because of this issue, our analysis abstracts from shocks of this type for now. However, because of their increasing importance, we will try to incorporate them whenever possible.

Another of the most important health questions in the PSID regards disability. It asks: "*Do you have any physical or nervous condition that limits the work you can do?*" to all heads and spouses of the panel. In addition, those individuals who respond affirmatively are asked about the severity of their condition. As shown in **Figure 1a**, reports of disability increase strongly with age. Following Meyer and Mok (2019), we decompose disabled individuals into two groups: those who answer that disability impacts their ability to work "*a lot*", "*severely*", "*completely*", or that they "*can do nothing*", are classified as severely disabled. As **Table 3** shows, disability is least common among the youngest individuals, and those who are young and disabled tend to have severe conditions. Disability becomes more common among older age groups, but the percentage of individuals with severe disability

Diagnose	SSA Category	PSID Question: *Has a doctor ever told you...*	Years Available
Lung Disease	Respiratory Disorders (3)	*you have or have had a chronic lung disease such as bronchitis or emphysema?*	1999-2019
Diabetes	Cardiovascular System (4)	*you have or have had a diabetes or high blood sugar?*	1999-2019
Heart Attack	Cardiovascular System (4)	*you have or have had a heart attack?*	1999-2019
Hypertension	Cardiovascular System (4)	*you have or have had high blood pressure or hypertension?*	1999-2019
Stroke	Neurological Disorders (7)	*you have or have had a stroke?*	1999-2019
Cancer	Malignant Neoplastic Diseases (13)	*you have or have had cancer or a malignant tumor, excluding skin cancer?*	1999-2019
Arthritis	Musculoskeletal Disorders (1)	*you have or have had arthritis or rheumatism?*	1999-2019
Other Chronic	N.A.	*you have or have had any serious, chronic condition?*	2005-2019
Mental Health Issues	Mental Disorders (12)	*you have or have had any emotional, nervous, psychiatric problems?*	1999-2019
Memory Loss	Mental Disorders (12)	*you have or have had permanent loss of memory or mental ability?*	1999-2019

Table 2. PSID questions to build the health shock

Age	N	Percentage: Disabled	of which: Severe
30-39	93,117	10%	71%
40-49	63,683	15%	62%
50-59	41,620	24%	53%
60-69	25,183	36%	49%
70-79	11,617	46%	47%

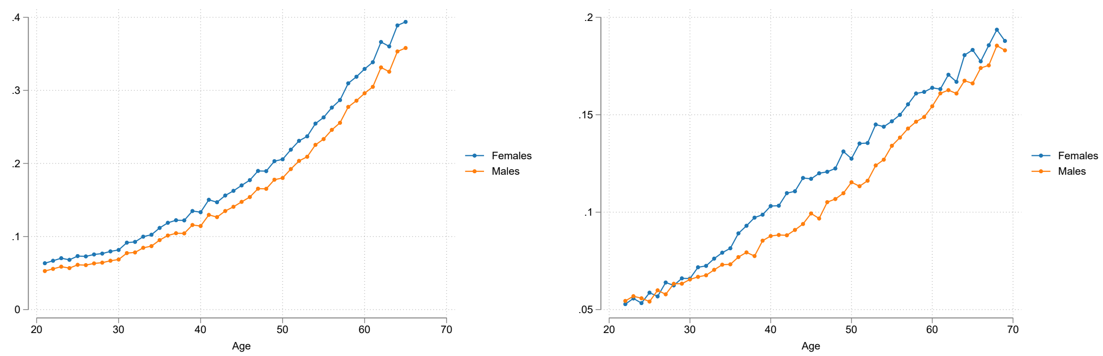
Table 3. Source: Authors' calculations on Panel Study of Income Dynamics (PSID), 1999-2019.

falls with age until it flattens at about 50%.

One might wonder about the sources of reported health and disability. Hosseini, Kopecky, and Zhao (2021a) argue that self-reported health status underestimates the average rate of deterioration of objective health. To this effect, they propose a health metric that combines several indicators, habits, and health history[6]. Their *frailty index* measures health on a finer scale than self-reported health status and has an edge over self-reported health status in predicting major outcomes (most importantly, death probability). The comparison between **Figure 1a** and **Figure 1b** shows that the frailty index and reported disability have a similar evolution pattern, with both measures increasing significantly with age.

An important concern is whether diagnoses constitute a relevant measure for other real outcomes. Since continuous measures of health have been shown to be important contributors to the heterogeneity in labor market outcomes (see, for instance, Hosseini, Kopecky, and Zhao 2021b, De Nardi, Pashchenko, and Porapakkarm 2022), a direct way to show the relevance of our shock is looking at the impact it has on the above-defined measures. In **Table 4** we look at the

[6]Precise construction of the frailty index is described in Table 1, online Appendix of Hosseini, Kopecky, and Zhao (2021a)



(a) Predicted Disability Rate with Race, Sex, State, College, Year Dummies

(b) Frailty Index Adjusted for Cohort Fixed Effects.

Figure 1. Predictive power of self-reported health status on disability and frailty index.

Age	Frailty Index			Severe Disability		
	Pre-shock	Impact	Post-shock	Pre-shock	Impact	Post-shock
30-39	0.032	0.093	0.124	2.03%	9.55%	11.55%
	(0.041)	(0.06)	(0.09)			
40-49	0.040	0.106	0.148	2.57%	9.53%	12.53%
	(0.04)	(0.07)	(0.11)			
50-59	0.043	0.103	0.166	2.89%	9.92%	14.48%
	(0.04)	(0.06)	(0.12)			
60-69	0.040	0.098	0.187	2.87%	8.4%	17.85%
	(0.037)	(0.07)	(0.13)			
70-79	0.037	0.096	0.215	5.1%	7.88%	20.35%
	(0.04)	(0.06)	(0.14)			

Table 4. Incidence of Severe Disability and Frailty around Health Shock events by age group (standard errors in parenthesis).

evolution of each metric we defined above around the identified health events.

The health shock relates to continuous health measures both on impact and persistently over time. Both health status measures are broadly constant with age, but they sharply rise with similar magnitudes when the shock hits. Over time after the shock, health deteriorates with age. This explains why the post-shock measures of frailty and disability tend to grow with age following the shock.

3 Measuring the Impact of Health Shocks

In this section, we discuss our empirical analysis and sample restrictions. We first study the effects of health deterioration using the specification:

$$y_{it} = \alpha_t + \beta A_{it} + \sum_k \delta_k D_{kit} + \varepsilon_{it} \tag{1}$$

where y_{it} is the outcome variable of interest. α_t is a time fixed effect, A_{it} is a set of dummies that includes age, race, sex, education, state, marital status, family size, whether the individual has siblings or not and whether they have health insurance or not. We also include fixed effects for the most commonly held occupation. D_{kit} is an indicator variable that equals one when the individual i is k periods from a health shock. The parameters of interest are then δ_k, which estimates the period k treatment effect. Finally, we cluster standard errors by age. Since we are primarily interested in labor market outcomes, we restrict the age of the individuals hit by health shock to be within 24 and 60.

We collect descriptive statistics on the full sample and the subsample of individuals who are hit by a health shock in **Tables 7**. The share of surveyed individuals receiving a shock is about 40% of our sample. The "treated" individuals are five years older on average and are less likely to have received a college education. Indicators like BMI are not different across groups, while diagnosed individuals are marginally more likely to have had smoking habits. The occupational health hazard as defined by Michaud and Wiczer (2018)[7], does not vary, suggesting little predictability of our diagnose variable on health and lifestyle metrics.

Since the shocked sub-population represents old individuals more than proportionally, we compare never-treated and treated and decompose income and wealth by age brackets in **Table 8**. Conditional on looking at the same ten years age brackets, we observe that treated individuals, before receiving the health shock, tend to have lower income and mostly slightly higher wealth compared to never treated individuals. We conjecture that the difference in wealth could still be caused by age differences within a bracket.

The balancing exercise suggests that, before receiving the news of a severe illness, diagnosed individuals may look different from those who will not receive such news. Therefore, in most of the paper, our empirical analysis will use the not-yet-treated as a control group to account for possible observable and unobservable heterogeneity across groups. The approach implies constructing counterfactuals to affected households using households that experience the same event a few years in the future (see Fadlon and Nielsen 2021). It therefore selects households that are fundamentally similar to each other but are different in the timing of the health shock. Identification comes, therefore, from comparisons of individuals who experienced the shock at a different point in time.

We then turn to the effect of a shock to the health of a parent on labor market outcomes of their adult children. The regression specification is similar, but the shock now refers to a health shock happening to either one parent:

[7] The occupational health hazard is calculated by assigning a health/injury risk score to Census classifications of occupations using Health and Retirement Survey Data. This classification, summarized in **Table 6**

$$y_{it} = \alpha_t + A_{it}^{own}\beta_1 + A_{it}^{parents}\beta_2 + \sum_k \delta_k D_{kit} + \epsilon_{it} \tag{2}$$

where y_{it} is the daughter or son's outcome of interest. α_t is a time fixed effect, A_{it}^{own} is a set of explanatory variables relative to the adult children that include age, race, sex, education, state, marital status, whether they have kids or not, whether they have siblings or not, whether they have cohabited with their father in the past, and their most common occupation. $A_{it}^{parents}$ is a set of explanatory variables for parents that includes whether they live in the same state as the child or not, whether they ever smoked, their marital status, education, whether they are pensioned, and whether they have health insurance or not. D_{kit} is an indicator variable that equals one when the individual i is k periods from a health shock happening to either of their parents. Again, the parameters of interest are δ_k, which estimates the period k treatment effect. Finally, we cluster standard errors by age.

We focus on the universe of working-age children 24 to 50 whose parents are both alive at the time of the shock. Moreover, we distinguish between fatal and non-fatal shocks. For non-fatal shocks, which are the main focus of our analysis, we require the parent who falls ill to be still alive eight years after the shock. We collect descriptive statistics on the full sample and the subsample of individuals whose parents are hit at least once by the health shock in **Table 9**.

70% of individuals aged 24 to 51 whose parents are still alive in our sample have at least a parent who is first diagnosed during the period we analyze. Of these, for 64%, only one parent experiences the shock, and for 36% both parents experience the health shock. **Table 10** shows characteristics of never treated and treated adult children by age. Children of parents who are diagnosed tend to be on average more educated, and have higher income and wealth. Part of these differences could be explained by the fact that, even within age brackets, more educated individuals tend to have older parents who are more subject to health shocks.

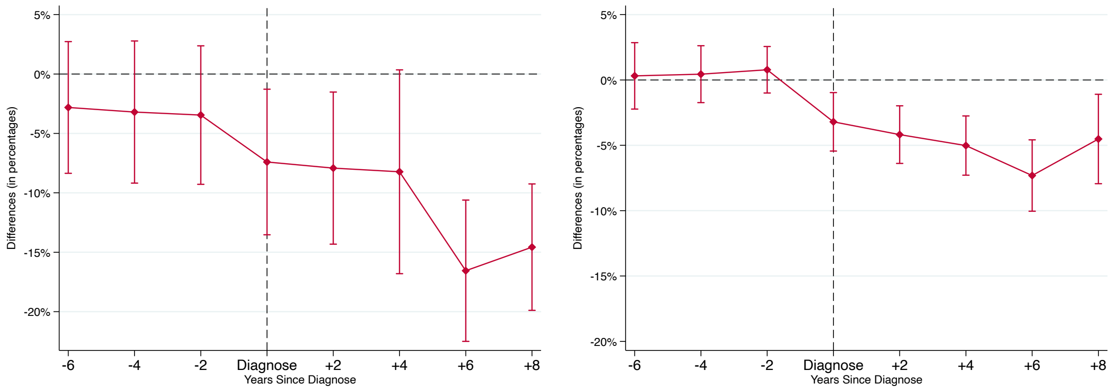
As we do for the own shock, we will use the not-yet-treated as a control group to account for possible observable and unobservable heterogeneity across groups. Identification comes, therefore, from comparisons of individuals whose parents experienced the shock at a different point in time.

Finally, a word of caution on interpreting the results comes from looking at the timing of interviews. The survey runs bi-annual waves, and some questions are relative to "the past year", while others are about the time window that goes until the present. In particular, certain outcome variables, such as income or hours worked, are typically referred to the last completed year before the questions are asked, while health questions normally refer to the present. Moreover, we know when a change in health happened compared to the two years before, but not exactly when in the two years. This implies that sometimes the estimates may suggest anticipation of the effect that does not necessarily occur in the data-generating process. The biannual nature of the survey does not offer an obvious way to deal with the issue, except for being cautious when interpreting results at a higher frequency in the two years before or after the shock.

4 Family Responses to Severe Health Events

4.1 Impact of Severe Health Events on Own Labor Market Outcomes

A first test to the relevance of health as a significant determinant of labor market outcomes requires health shocks to significantly affect the individual that receives them. We thus proceed by first looking at how our health shock impacts labor market outcomes of the treated. As mentioned, to deal with heterogeneity in the control group, we restrict the sample to only individuals who will, at some point, report the insurgence of a diagnosis. **Figure 2** shows the results from our difference-



(a) Income **(b)** Hours Worked

Figure 2. Response to Health Shock

Note: Impact of a health diagnosis on the individual that receives them. Red diamonds are point estimate with 95% confidence intervals around. All of the outcome variables are normalized by the their mean in the treated sample. Sample: 1999-2019. Control group is treated. Detail in **Table 11**

in-differences estimation in (1). The left panel reports the response of earnings, which we define as labor income plus business income.[8] The second panel shows the effect of a health shock on yearly hours, that is, the sum of worked hours in the past year for all individuals.

We can see that hours worked by an individual hit by a health shock persistently drop by around 5% compared to their peers who are not yet affected by the shock. On the other hand, income initially falls by around 8% after the diagnosis, and then becomes 15% lower six and eight years after the diagnosis.

We collect detailed estimates in **Table 11**. As evident from a back-of-the-envelope calculation, the impact of health shocks on income is primarily due to two channels: a reduction in the extensive margin of hours and a drop in the income per hour of those who stay at work. Additional results in **Table ??** highlight how the extensive margin in hours mirrors an impact on

[8]It does not include sources of passive income, like rent or dividends. Values are expressed in 2009 US dollars and then normalized by the mean income of the treated sample.

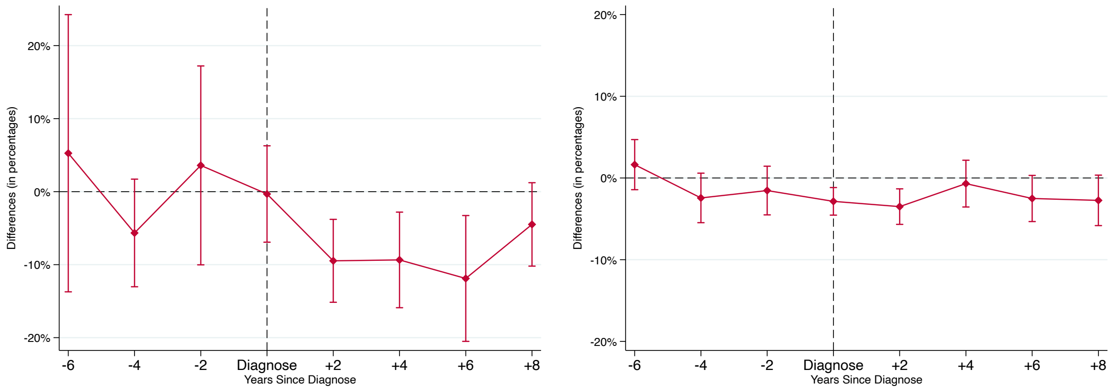
employment – impacted workers leave work for a long time, and some might even stop working for good. A potential third channel, a reduction in the intensive margin of hours worked, is muted at all horizons. These outcomes might point to a lack of flexibility in US labor markets that forces more substantial trade-offs, thus inducing a response on the extensive margin on treated workers – see Bick, Blandin, and Rogerson (2022).

In later years, a stronger effect on incomes emerges that is not linked to reduced employment or hours. An occupational shift within full-time employment is compatible with workers moving towards jobs with less stringent time demands in later years. This, in turn, would explain the drop in earnings for treated individuals who are still at work and don't work fewer hours – see Goldin (2015).

4.2 Effect of Parental Shocks on Adult Children

The last section establishes that individuals hit by a health shock suffer large consequences. But are children insulated from the shock itself? To answer the question, we run equation (2) on the same outcomes, but this time using shocks to parents' health. As mentioned, the outcomes are calculated on the sample of working adult children, with both parents alive and conditional on the parent surviving at least during the time window we observe (that is, eight years after the shock).

The baseline estimates, presented in **Figure 3**, show evidence of significant pass-through of income shocks from parents to their adult children. The overall earnings regression has a striking result: four years after onset, the impact on adult children is half as large as on the shocked parent. This suggests relevant spillovers through time allocation, career choice, or network capital, which we will investigate further and discuss in the next section. Many interpretations are possible for such an outcome. The restrictions to parents' non-fatal shocks suggest that transfers in the form of



(a) Income

(b) Hours Worked

Figure 3. Response to Parents' Health Shock

Note: Impact of a health diagnosis of a parent. Red diamond are point estimates with 95% confidence intervals bands around. Sample: 1999-2019; families where both parents were present in sample; parents survives the shock in the time window. Control group is treated.

care, as well as the heterogeneity of family ties among siblings, could play a role in explaining our results: if parents are still alive but in bad health, caretaking can impose significant time constraints on the children, who have to give up on other priorities.

The impact on hours, albeit small, is informative of the channels at play. As shown in **Table 13**, the overall impact on hours is small and significant only at short horizons. The reduction in labor supply takes place within intensive margin of hours adjustment – unreported results on employment status show no significant moves into non-employment, while the intensive margin of hours, reported in the fourth column, has a significant response at all horizons. Similarly, restricting the analysis of income effects to non-zero earners, as done in the second column, shows almost exactly the same picture as in the baseline case. Taken together, these results indicate that either changes in the productivity of adult children, or some characteristic of their employment, could be used to explain the large income effects.[9]

[9] We will explore changes in productivity, potentially due to the psychological or mental health consequences of severe health events to a close family member, in future work.

4.3 The Role of Occupations

We have shown in the previous section that income falls disproportionately compared to hours worked when a health shock hits a parent (see **Table 13**). A decline in hourly earnings might be explained by occupational sorting. This has two potential implications: the parents' diagnosis induces an occupational shift towards jobs with lower hourly pay (*occupational displacement*). Two, that at least some individuals whose parents are diagnosed work in occupations where reducing hours supply implies a more than proportional reduction in income (*convexity in hours*). In this section, we will investigate each of these potential channels.

Occupational Displacement. A straightforward explanation for the drop in the incomes of the individuals whose parents face a health shock is that switches in occupations occur in a way to allow them to devote more time to non-market work and provide care. These occupations might in turn involve lower hourly pay. Alternatively, workers might be forced to shift into occupations with lower pay because meeting caregiving demands involves moving to geographical locations where local labor markets offer less lucrative opportunities. We follow an approach similar to Huckfeldt (2022), in that we rank occupations by average hourly earnings, and then test for potential moves down the occupation ranking. We run an ordered logit regression model for occupations:

$$P(Y \leq j|X) = \frac{e^{\alpha_j - X\beta}}{1 + e^{\alpha_j - X\beta}} \quad \text{for } j = 1, \ldots, J-1 \tag{3}$$

where categories in which occupations are classified j can be defined in terms of cumulative probabilities, and α_j are threshold (or "cutpoint") parameters for each category, with $\alpha_1 < \alpha_2 < ... < \alpha_{J-1}$. We will report the odds ratio of moving down along the occupation ranking.[10]

[10] The odds ratio in this context can be interpreted as the multiplicative change in the odds of being in one category relative to a reference category for a one-unit increase in an independent

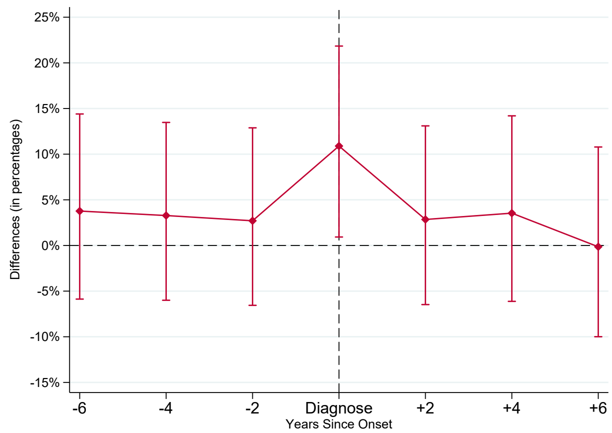


Figure 4. Odds of switching to a lower paid occupation, Ordered Logit Regression

To run this specification, we need a classification of occupations that is coarse enough to make the estimation computationally feasible. Hence, we will rely on the classification already described in **Table 6**.

Figure 4 reports the odds ratios estimated from **Equation 3** across different horizons. We observe a 10 p.p. higher probability of switching to a lower paid occupation in the same period the diagnosis occurs, and no further evidence of occupational switches thereafter. We interpret this as evidence that, while occupational displacement must contribute to the observed disproportionate impact of parental diagnoses on adult children's earnings, the bulk of these effects must occur within occupations.

Convexity in Hours. Building on the intuition of Goldin (2015) that high-paying occupations have compensation schedules that are convex in hours worked, Erosa et al. (2022) classify Census-defined occupations and indeed find that average hourly compensation is increasing in average yearly hours at the 3-digit level. In our context, if some occupations are convex in hours, then the

variable, while holding other variables constant. Given the nature of the ordered logit model, the odds ratio is proportional across different thresholds - in other words, the interpretation of this model is conditional on assuming that occupations are not only ordered in a certain way, but that the distance between any consecutive two occupations in the ranking is identical.

higher income effects for children of diagnosed individuals may be driven by the presence of a share of the treated population employed in those occupations.

To decompose the effect across sub-groups, we resort to the classification of Erosa et al. (2022) and divide occupations by quartile of average yearly hours worked. We then extend the standard D-in-D into triple D-in-D to add another layer of heterogeneous treatment effect – the heterogeneity across occupations.This implies running the following specification:

$$y_{it} = \alpha_t + A_{it}^{own}\beta_1 + A_{it}^{parents}\beta_2 + \gamma F_{i,t} + \sum_k \delta_k D_{kit} + \sum_k \delta_{2,k} F_{i,t} D_{kit} + \epsilon_{it} \tag{4}$$

where $F_{i,t}$ is an indicator function for the individual being employed in a certain occupation quartile. The coefficient of interest is the total effect of health shocks k periods after the shock on group F, $\delta_k + \delta_{2,k}$, and the differential impact on group F only, $\delta_{2,k}$. The interaction term highlights the differential impact on each group of interest, and helps us further discriminate between competing channels that produce our results. **Table 5** reports the estimate results when $F_{i,t}$ indicates the individual being employed in the top quartile of occupations by average yearly worked hours.

	Horizon	
	(a)	(b)
$\sum_k D_{kit}$	-2.19**	-1.66
	(1.24)	(1.28)
$\sum_k F_{i,t} D_{kit}$	-7.52*	-6.57**
	(3.85)	(3.30)
$\sum_k D_{kit} + \sum_k F_{i,t} D_{kit}$	-9.71***	-8.24***
	(3.78)	(3.06)

Table 5. Difference-in-Differences Coefficient Estimates.
Column (a): Average Effects in the 6 Years After Treatment. Column (b): Average Effects in the 8 Years After Treatment

The specification in column (b) gives us an average effect across the full horizon post-treatment, as explored in **Equation** (2). The observed high income effects are almost entirely driven by the heterogeneous effects of individuals in the top quartile of occupations, providing strong evidence in favor of the "convex hours" explanation. Importantly, the relative importance of occupational sorting increases with the horizon considered. We interpret this finding as suggestive that convexity in hours captures also the importance of long hours for career progression, thus generating additional penalties from exogenous downward shifts in market work.

4.4 Impact on Consumption and Wealth

We then turn to the effect of health shocks on expenditures. PSID reports many different components of consumption at the family level. Since the 1999 interviews, this allows to build a comprehensive metric of spending on non-durable goods, housing and services. We follow the variable construction of Blundell, Pistaferri, and Saporta-Eksten (2016), that allows to differentiate between healthcare expenditures and all other consumption.

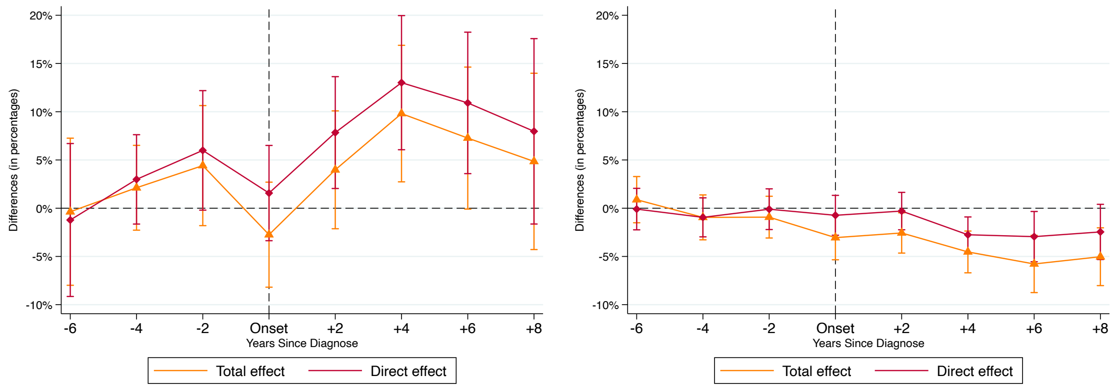
First of all, in **Figure 5** and **Figure 6**, we can see that health related expenditures, which include expenditures for hospital and nursing home, doctor, prescription drugs and insurance, rise immediately following own shock. We divide the effect into the total effect of a health shock and the direct effect only after controlling for present income. The direct effect shows that if it was not for the fall in income caused by the health shock, the expenditure towards medically related items would be even higher. From the point of view of validating our main identification strategy, it is also comforting to observe that we see no consumption response in anticipation of the shock. In addition, adult children whose parents experience a health shock increase their health expenditures as well and only after the shock is realized. We may interpret this as evidence of monetary transfers towards parents in the form of paying for healthcare, or possibly as evidence that children increase their own expenditure because of raised awareness about health issues, potentially of hereditary nature.

What about other components of non-durable and services consumption? In **Figure 5b** and **Figure 6b** we report the impact on consumption of non-durable goods and services, excluding healthcare related expenses. A health shock is likely to impact the household and its earning ability in a persistent way, so it is not surprising that consumption can decrease. Following the deterioration of health, and the substitution with healthcare-related expenditures, consumption drops until it stabilizes at around 5% lower than pre-diagnose. The decrease in consumption by individuals whose parents receive a health shock is less pronounced, and short-lived. Because most adult children are married at the time of the shock hitting their parent, a potential explanation for the lack of a strong consumption response is intra-household insurance. Alternatively, affected household could simply reduce their saving rate.[11]

A test of inter-generational insurance would require evidence of coordinated saving - or dissaving - following a shock. To perform it, we look at the effects of health shocks of net wealth, both on the nuclear family of parents and on the nuclear families of their adult children.[12] A strong channel is also at play on this margin, as indicated by the persistent negative effect on both measures of net wealth - see **Figure 7**. Together with the consumption response, the wealth dynamics panel (b) is indicative of significant dissaving: individuals whose parents are hit by a health shock are thus less able to build wealth. Because both parents and children suffer a decline in net wealth, it is also possible that part of the

[11]It is important to notice, however, that observed non-durables and services expenses are simply a measure of what the money is spent on, and significant reallocation could occur in the consumption basket - e.g. leisurely travel could decline in favor of transportation costs necessary to pay a visit to the sick parent, etc. In this sense, the impact on welfare could go either way.

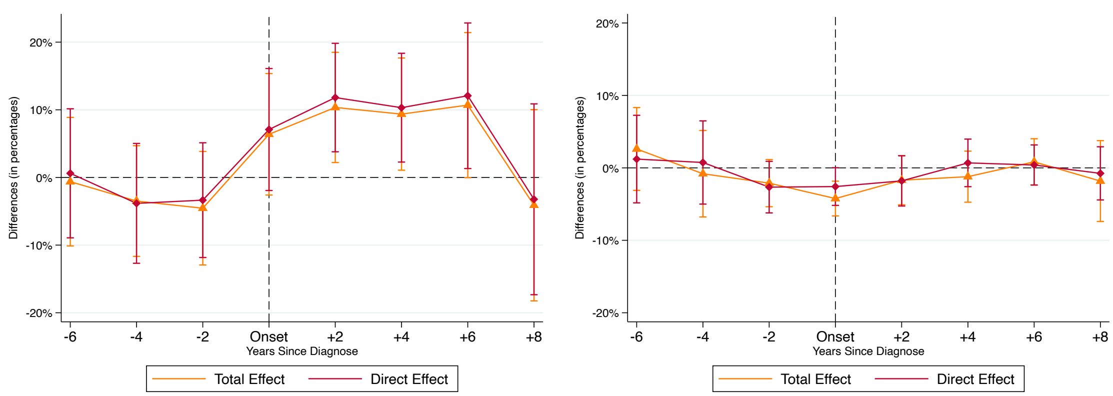
[12]To build the measure of net wealth at the family level, we follow Boar (2021).



(a) Health Related Expenditure **(b)** Non-durables and services

Figure 5. Consumption Response to Own Health Shock

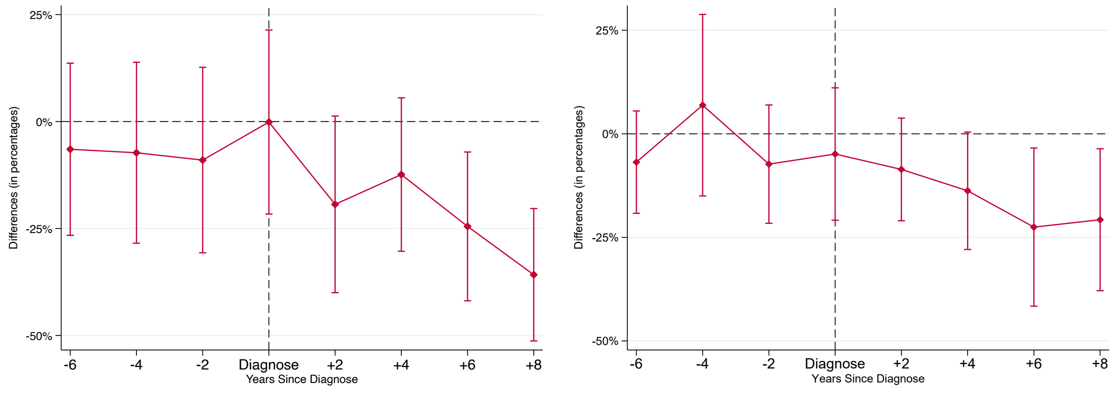
Note: Consumption of Non-Durable and Services includes spending for Food, Transport, Utilities, Recreation.; and excludes health related expenditures. Difference between total and direct effect captures impact of health on current income. Sample: 1999-2019. Control group is treated.



(a) Health Related Expenditure **(b)** Non-durables and Services

Figure 6. Consumption Response to Parent's Health Shock

Note: Impact of a health diagnosis of parents on health related expenditures and consumption of non-durable goods and services (excluding health related). Blue line is point estimate with 95% confidence intervals around.Sample: 1999-2019. Control group is treated.



(a) Wealth: Own shock

(b) Wealth: Parent shock

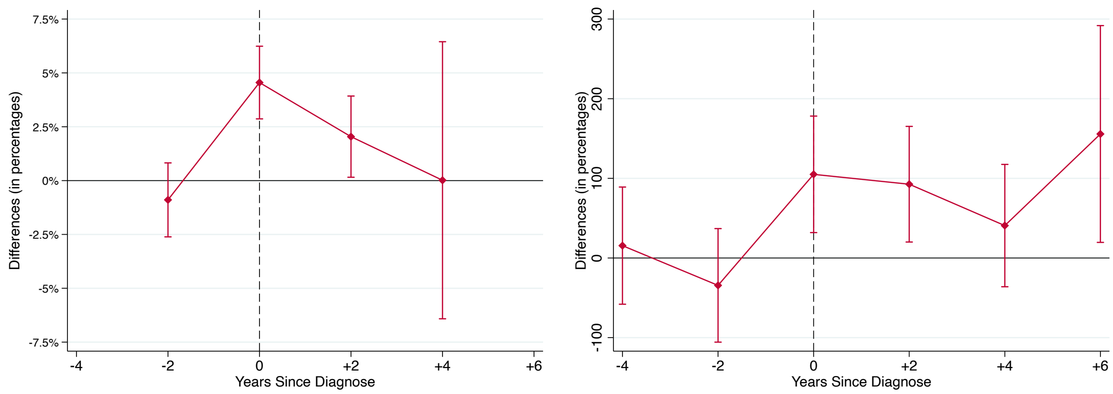
Figure 7. Wealth Response to Own and Parents' Health Shock.

Note: Impact on wealth of a shock to own health (panel a) or to parent's health (panel b). Sample: 1999-2019. Control group is treated.

reduced savings are used towards transfering monetary resources upstream in the family tree, as we will explore below. These results, taken together, point strongly in the direction of health shocks imposing spillover costs across the family network in a way that is consistent with models of the family where inter-generational altruism plays an important role in both directions (see Barczyk and Kredler 2021).

4.5 Inter-generational Linkages and Help

In order to explore inter-generational linkages we turn to Health and Retirement Survey (HRS) data. HRS contains information of two important variables: whether the respondents receive help with household chores, errands and transportation from each of their children (in years 1996-2002), and whether the respondents receive financial transfers from each of their children, and how much. Crucially, respondents in HRS are asked the same set of questions on insurgence of diagnoses as in **Table 2**. We can therefore construct the health shock following the exact same procedure



(a) Help with Chores and Errands **(b)** Monetary transfers by children

Figure 8. Impact of health shock of parents on whether the child helps the parent with chores and errands and on the amount of monetary transfers by children to their parent. Data: HRS.

and run the same set of regressions.

Figure 8a shows the impact of a parent health shock on whether the children provide transfers in time (help with chores, errands, and transportation). We can see in panel a that the probability that a child helps their parents with these daily activities goes up 5% following the health shock. Since the baseline probability that a child in the sample helps their parent with this activities is around 12%, the health shock event increases this probability by almost a half on impact. While helping with chores, errands, and transportation only represents a part of what constitutes informal care, observing a change in these activities is suggestive of a broader shift in the allocation of hours for children of shocked parents. In particular, this effect is consistent with the explanation that links the decrease in market work observed in our main regression to the role of informal caregiving. At the same time, **Figure 8b** shows that the monetary amount that children transfer to their parents goes up by 100% on average.[13] Taken together, these results point to the existence of

[13] It is useful, however, to keep in mind that the average transfers from adult children to parents are generally small. In our sample, the mean transfer from children to their parents is only 60$ (in 2009 dollars), since most children do not transfer money to their parents. Conditional on being strictly positive, the average yearly transfer from children to their parents is $2800.

inter-generational linkages and insurance.

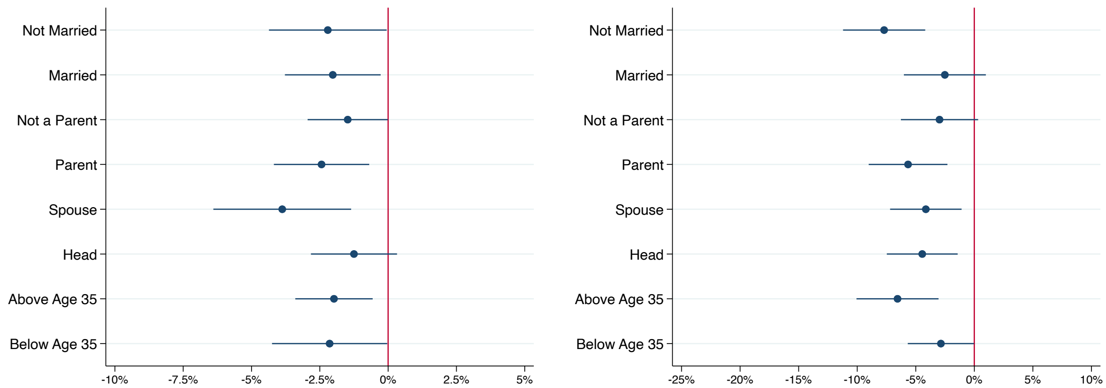
5 Heterogeneous Effects Within the Family

In order to further understand the spillover effects of health shocks within the extended family, we proceed to analyze how the labor supply responses change depending on the characteristics of parents, adult children, and the whole family network. This implies running the specification in **Equation** (4) with a battery of group variables of interest $F_{i,t}$ at the individual or parent level. In particular, we are interested in understanding whether a parental health shocks has a differential effect depending on whether the adult child has kids of her own, her marriage status, gender, age group, education, income and wealth, and if the adult child lives in the same state as the shocked parent. Moreover, if the parents are retired or not, their marital status, and their income and wealth.

We first discuss the heterogeneity analysis around the characteristics of adult children. Results are collected in **Figure 9** and **Figure 10**. A first fact that emerges from looking at the two panels together is that the variability in hours response is quite small. Two exceptions are noticeable. First, family heads display a smaller hours response than spouses. This is consistent with the informal care hypothesis, since spouses are often secondary earners and are thus relatively more likely to respond to a higher informal care demand from relatives by reducing employment.

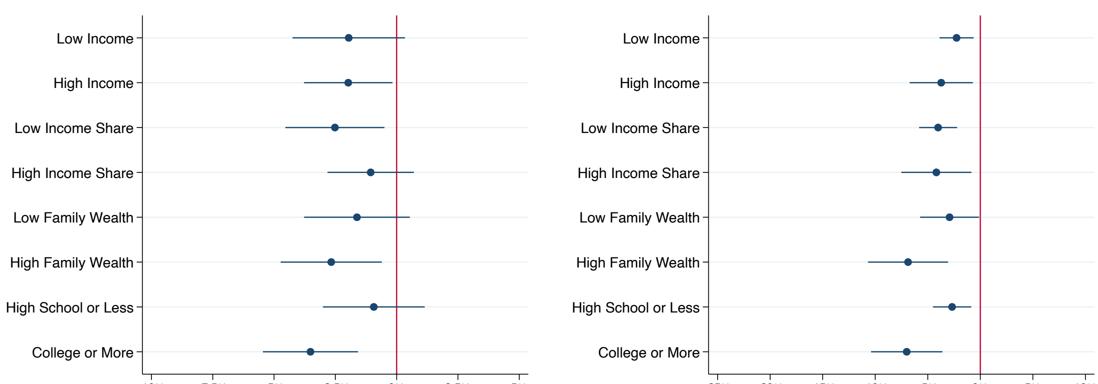
We also see a stronger reduction in the hours of college-educated workers. This could at least partially be explained by more flexible work schedules, that allow adjustments on the intensive margin of labor supply in more specialized jobs.

The impact on income is, however, painting a different story. We see more heterogeneity as older, college-educated, wealthier, and single individuals all seem to suffer larger income losses than their younger, high-school educated, poorer and



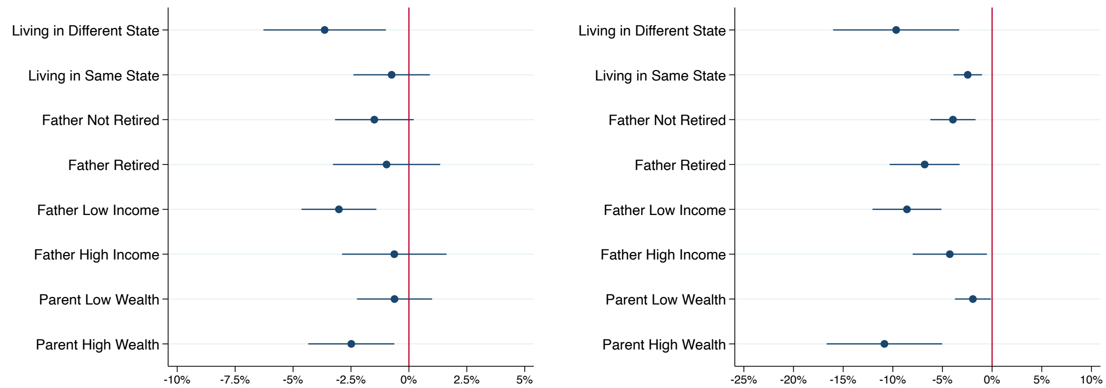
(a) Hours **(b)** Income

Figure 9. Heterogeneous Impact of Parent's Health Shock: Child Demographics
Note: Blue diamonds represent the total average effect between years +2/+8 of parent's health shock on a specific group, with 90% confidence interval around.



(a) Hours **(b)** Income

Figure 10. Heterogeneous Impact of Parent's Health Shock: Child Economic Characteristics.
Note: Blue diamonds represent the total average effect between years +2/+8 of parent's health shock on a specific group, with 90% confidence interval around.



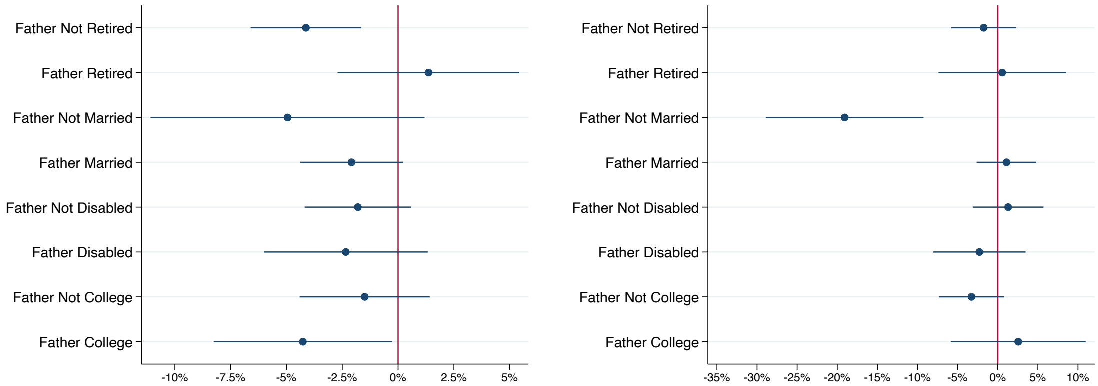
(a) Hours **(b)** Income

Figure 11. Heterogeneous Impact of Parent's Health Shock: Parent Demographics.
Note: Blue diamonds represent the total average effect between years +2/+8 of parent's health shock on a specific group, with 90% confidence interval around.

married counterparts. It is also striking to notice that, despite heads' labor supply response is almost muted, their income losses are almost identical to those of spouses, while this reversal does not seem to take place along the education dimension. We interpret this as further evidence in favor of the convexity of hours channel discussed in **Section 4.3**.

We now turn to analyzing the dimensions of heterogeneity on the parents' side. Results are displayed in **Figure 11**. One of the most striking differences regards the geographical dimension, with children of parents residing in different states at the moment of the shock reducing hours significantly more, and experiencing an even more pronounced decrease in incomes. We interpret this as strong evidence in favor of this hypothesis that long distance relocation is a potential channel to explain the strength of the observed spillover effects. Parents' wealth seems to play another large role: families with above-median levels of wealth have adult children display a stronger labor supply response, and again an amplified effect on income.

Finally, **Figure 12** and **Figure 13** display the heterogeneity analysis for shocks to fathers and mothers considered separately. Several facts are worth noticing.



(a) Hours **(b)** Income

Figure 12. Heterogeneous Impact of Father's Health Shock.
Note: Blue diamonds represent the total average effect between years +2/+8 of father's health shock on a specific group, with 90% confidence interval around.

First, the impact on hours and income of a health shock on fathers is substantially stronger when the father is single, widowed, or divorced, than when he is married. This fact points to the importance of caregiving provided by a spouse, especially female spouses. When the spouse is absent at the time of the shock, children then play a much larger role.

Second, the overall hours response to shocks to mothers is mildly stronger. It is possible that this can be explained by mothers receiving health shocks later in life than their husbands, and thus being the last healthy member of their household at the moment of their diagnose – meaning not only an increased demand for care, but also the loss of an informal caregiver in the extended family if their partner was already in poor health. Consistent with this interpretation, we see the impact on children's income being higher if the father is already disabled when the health shock happens to the mother. Again, this fact points to the importance of family relationships and caregivers in old age.

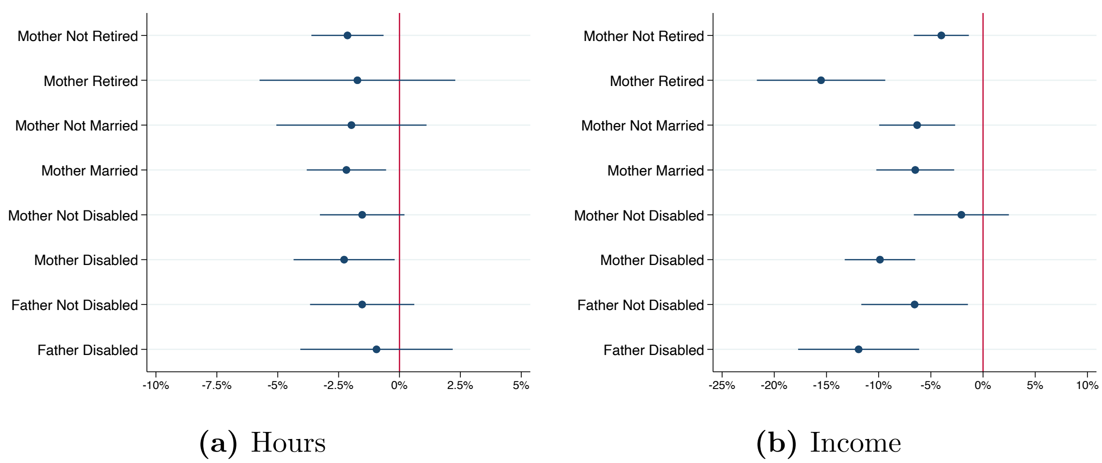


Figure 13. Heterogeneous Impact of Mother's Health Shock.
Note: Blue diamonds represent the total average effect between years +2/+8 of mother's health shock on a specific group, with 90% confidence interval around.

6 Fatal Shocks

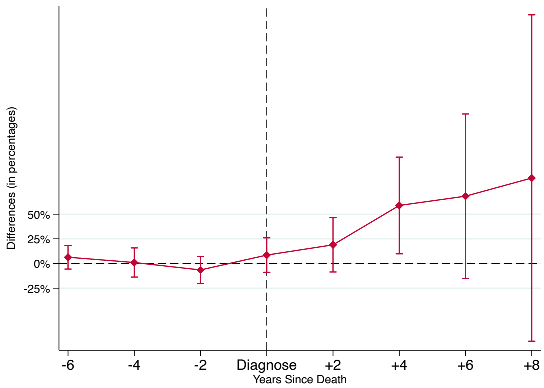
A non-fatal health shock might require prolonged care or assistance, potentially for the remainder of the parent's life. Such demands could result in a more sustained reduction in labor supply for the adult child, as they may need to provide care or make accommodations for the parent. We see this narrative as consistent with the results presented so far. A potential validation mechanism involves looking at the impact of fatal shocks. Specifically, we use the passing away of parents as an explanatory variable in the same vein as in **Equation** (2). While the wealth effects of a parent passing are ambiguous, since they depend on the relative size of expected *intra-vivos* transfers with respect to the expected bequest, death shocks appear to be useful to validate the caregiving channel.

The interpretation of the outcome of this analysis depends on what comparison group is used to evaluate the treatment. A valid concern is that unobserved heterogeneity between parents who receive fatal versus non-fatal health shocks might be present, in particular concerning the severity of the health shock. To address the issue, we again use the not-yet-treated as a control group. In other words, we restrict the sample to individuals whose parents die at some point within the sample.[14]

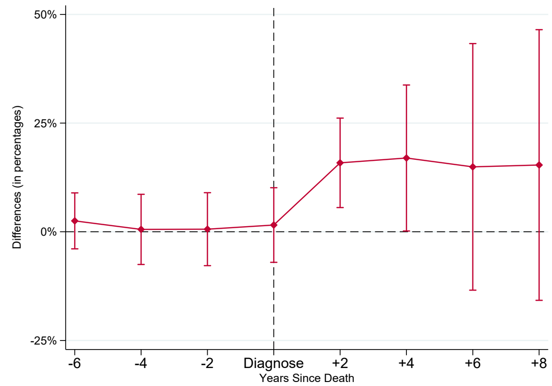
The effects on income and employment are displayed in **Figure 14** and **Table 15**. The passing away of a parent produces a strong labor supply response that drives a substantial increase in earnings. While the responses might look large, it is important to point out that they might indicate a rebound with respect to the years prior, where we expect a reduction induced by the first health shock.

Analyzing the heterogeneity of such responses provides additional insights. First,

[14] This specification carries an additional benefit for interpretation. To the extent that shocks of similar magnitude hit parents in the years preceding their passing, most adult children have received a similar shock to their labor supply. In particular, they might have similarly being compelled to provide some degree of informal care.



(a) Income



(b) Hours Worked

Figure 14. Response to Parents' Death

Note: Sample: 1999-2019. Control group is treated.

we expect the marital status of the deceased parent to matter for the kids' response. In particular, if the passed parent was married, it is reasonable to expect a sharing of caregiving demands across the extended family. **Figure 15** confirms this intuition. We see that the impact of parents' death on children's labor supply is stronger the less the parent could previously rely on a spouse or even a former spouse. The hours response does not seem to depend on the health quality of the other living parent, when present. It does matter, however, whether the individual is married - we interpret this as consistent with two potentially co-existent explanations. First, a married child is more likely to be a secondary earner and hence to have devoted more non-market time to help the parent in the years before their passing. Second, a married child is more likely to have children of their own, which further reduces the hours budget of the household, thus exerting downward pressure on the labor supply that is released after the parent dies.

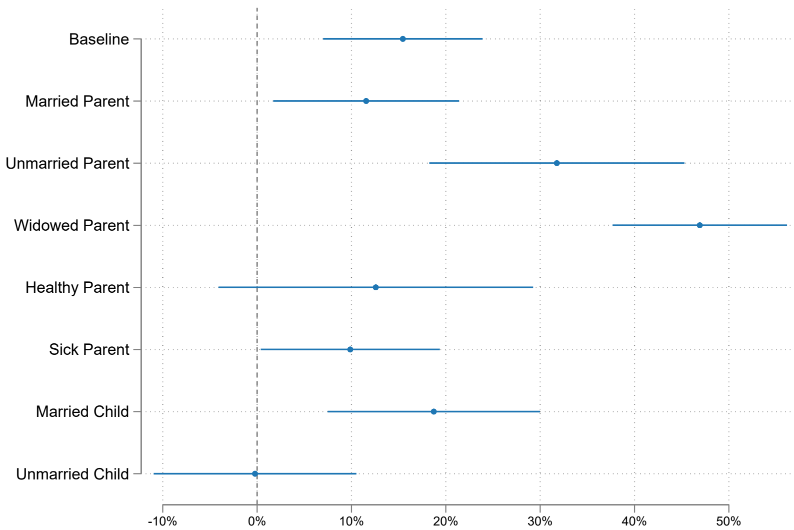


Figure 15. Hours Worked: Heterogeneous Effects in the Response to Parents' Death

7 Conclusions

This paper uses news to the health status of family members to quantify the role of inter-generational altruism and the interdependence of labor supply, saving, and location decisions. We find evidence of significant spillovers of parental health deterioration on young workers labor market outcomes and savings. Non-fatal shocks imply a significant reduction in hours and earnings, and force parents and children to dissave. On the other hand, fatal shocks are followed by an increase in labor supply, especially among younger children. We also find evidence of the existence of direct monetary help: following a health shock, the frequency of help received by immediate family members goes up.

More research is needed in highlighting the determinants of such responses. In particular, we will expand our research into looking at the role of siblings and family structure, spatial determinants, and the role of parents for schooling and the human capital investment of young kids, in order to provide a full life cycle perspective to our characterization of inter-generational linkages.

8 Tables

Occupation	Occupational Hazard	N
Managers	0.095	4,514
Professionals	0.092	5,531
Sales	0.1225	3,788
Admins	0.108	5,508
Services: Household	0.1069	649
Services: Protection	0.127	848
Services: Food	0.1612	2,142
Services: Health	0.187	1,561
Services: Personal	0.1362	2,773
Farming, Forestry, Fishing	0.1377	380
Mechanics	0.179	1,356
Construction	0.196	1,403
Precision Prod.	0.150	2,706
Machine Operators	0.203	2,048
Transport Operators	0.1907	1,915
Handlers	0.217	1,667
All	0.133	18,806

.

Table 6. Occupational Hazard Classification

Note: This table is based on HRS data and calculations from Michaud and Wiczer (2018). Notice the sum of observations per each occupation exceeds the total number of individuals, as most individuals hold at least two occupations in their lifetime.

	Full Sample		Active Labor Force	
	All	Diagnosed	All	Diagnosed
A. Demographics				
Age	43	48	41	45
Male	45%	45%	48%	48%
White	61%	62%	62%	62%
College	33%	30%	36%	33%
Family Size	2.91	2.83	2.95	2.91
Marital Status (head)				
Married	51%	52%	53%	55%
Separated, Widowed,Divorced	24%	27%	21%	23%
Single	26%	21%	27%	22%
B. Income and Wealth				
Unemployment	6%	6%	7%	7%
Labor Income (/000)	$37	$34	$45	$44
Wealth (family, /000)	$276	$307	$245	$270
C. Other				
BMI > 30	22%	21%	22%	22%
Ever Smoked	29%	33%	27%	30%
Occupation Hazard	0.13	0.13	0.13	0.13
Number of Individuals	15,166	6,058	13,822	5,573

Source: Panel Study of Income Dynamics (1999 - 2019). Monetary values are in 2009 US dollars. Sample: All surveyed individuals age 24-79 excluding those who were already diagnosed with something when the sample starts. Diagnosed: individuals who will receive one of the diagnoses as described in **Table 2** at some point in their life after the start of the sample.

Table 7. Descriptive Statistics: Own Shock

	Full Sample		Active Labor Force	
	Non-Treated	Treated*	Non-Treated	Treated*
A. Income and Wealth				
Unemployment				
Age 30-40	5.5%	6.7%	6.2%	7.5%
Age 40-50	4.1%	5.6%	4.6%	6.3%
Age 50-60	4.6%	3.15%	5.5%	3.7%
Labor Income (/000)				
Age 30-40	$41	$36	$44	$40
Age 40-50	$51	$44	$56	$49
Age 50-60	$52	$49	$60	$56
Wealth (family, /000)				
Age 30-40	$130	$112	$126	$108
Age 40-50	$289	$299	$287	$273
Age 50-60	$484	$530	$479	$497
B. Education				
College				
Age 30-40	41%	33%	42%	33%
Age 40-50	39%	29%	40%	30%
Age 50-60	38%	34%	41%	36%
Individual Obs.	7,454	6,058	7,146	5,573

*: Values for treated individuals are calculated for the periods preceding the shock. We define as Non-Treated individuals who have never received a diagnosis in the past and do not receive a diagnosis in our sample. We define as Treated individuals who have never received a diagnosis prior to 1999 and will receive one at some point in our sample. Source: Panel Study of Income Dynamics (1999 - 2019). Monetary values are in 2009 US dollars. Sample: All surveyed individuals age 24-79.

Table 8. Balancing: Own Shock

	Full Sample		Active Labor Force	
	All	Parent Diagnosed	All	Parent Diagnosed
A. Demographics				
Age	34	34	34	34
Male	47%	47%	50%	50%
White	74%	75%	74%	75%
College	44%	46%	46%	47%
Family Size	2.96	2.96	2.89	2.89
Marital Status (head)				
Married	46%	46%	47%	48%
Separated, Widowed,Divorced	16%	16%	15%	14%
Single	38%	38%	38%	38%
B. Income and Wealth				
Unemployment	5.3%	5.3%	6%	6%
Labor Income (/000)	$44	$44	$48	$49
Wealth (family, /000)	$200	$205	$192	$198
C. Other				
Ever Smoked	23%	23%	23%	22%
Occupation Hazard	0.13	0.13	0.13	0.13
Number of Individuals	4,658	3,277	4,353	3,086

Source: Panel Study of Income Dynamics (1999 - 2019). Monetary values are in 2009 US dollars. Sample: All surveyed individuals age 24-50 whose parents are still alive. Parent diagnosed: individuals whose at least one parent will receive one of the diagnoses as described in **Table 2** at some point in their life after the start of the sample.

Table 9. Descriptive Statistics: Parent Shock

	Full Sample		**Active Labor Force**	
	Non-Treated	Treated*	Non-Treated	Treated*
A. Income and Wealth				
Unemployment				
Age 24-30	5%	6.6%	5.5%	7.3%
Age 30-40	3.4%	3%	3.8%	3.3%
Age 40-50	5%	1.8%	5.7%	2%
Labor Income (/000)				
Age 24-30	$30	$31	$31	$33
Age 30-40	$46	$53	$51	$58
Age 40-50	$49	$78	$58	$86
Wealth (family, /000)				
Age 24-30	$142	$169	$106	$132
Age 30-40	$123	$218	$131	$219
Age 40-50	$192	$422	$215	$430
B. Education				
College				
Age 24-30	43%	54%	43%	53%
Age 30-40	50%	57%	51%	58%
Age 40-50	35%	35%	37%	37%
Individual Obs.	1,361	3,277	1,252	3,086

*: Values for treated individuals are calculated for the periods preceding the shock.
We define as Non-Treated individuals whose parents have never received a diagnosis in the past and do not receive a diagnosis in our sample. We define as Treated individuals whose parents have never received a diagnosis prior to 1999 and will receive one at some point in our sample.
Source: Panel Study of Income Dynamics (1999 - 2019). Monetary values are in 2009 US dollars.
Sample: All surveyed individuals age 24-50.

Table 10. Balancing: Parent Shock

Years Since Shock	Income		Hours	
	all	> 0	all	> 0
-6	-2.815	-3.636	.3133	-.147
	(-0.86)	(-1.13)	(0.21)	(-0.15)
-4	-3.2	-3.878	.4425	-.2338
	(-0.90)	(-1.08)	(0.34)	(-0.25)
-2	-3.455	-3.513	.7805	.631
	(-1.00)	(-1.04)	(0.74)	(0.80)
0	-7.405**	-5.775	-3.203**	-1.001
	(-2.04)	(-1.59)	(-2.42)	(-1.15)
2	-7.919**	-4.753	-4.181***	-.3226
	(-2.09)	(-1.28)	(-3.21)	(-0.34)
4	-8.227	-5.319	-5.019***	-1.806*
	(-1.62)	(-1.01)	(-3.74)	(-2.02)
6	-16.55***	-12.97***	-7.312***	-2.998**
	(-4.71)	(-3.76)	(-4.53)	(-2.43)
8	-14.57***	-13.15***	-4.516**	-1.003
	(-4.63)	(-4.39)	(-2.23)	(-0.68)
Year FE	✓	✓	✓	✓
Gender FE	✓	✓	✓	✓
Education FE	✓	✓	✓	✓
Race FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓
Family Size FE	✓	✓	✓	✓
Marital Status FE	✓	✓	✓	✓
Has Siblings FE	✓	✓	✓	✓
Has Health Ins. FE	✓	✓	✓	✓
Adj. R2	0.139	0.133	0.167	0.138
Observations	24118	21102	24118	21199
Clusters	35	35	35	35

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11. Impact of own health shocks on income and hours. Age: 24-60. Standard errors are clustered by age. Sample: 1999-2019

Years Since Shock	Wealth	Consumption		Health Expenditure	
		Total	Direct	Total	Direct
-6	-8.619	.8862	.9208	-.3644	-.286
	(-0.72)	(0.63)	(0.67)	(-0.08)	(-0.06)
-4	-10.31	-.9495	-.5703	2.12	2.372
	(-0.91)	(-0.69)	(-0.46)	(0.82)	(0.89)
-2	-12	-.9246	-.3772	4.415	4.59
	(-0.92)	(-0.72)	(-0.31)	(1.20)	(1.26)
0	-8.139	-3.049**	-2.277*	-2.743	-2.086
	(-0.65)	(-2.25)	(-1.74)	(-0.85)	(-0.66)
2	-27.02*	-2.564**	-1.529	3.98	4.664
	(-2.00)	(-2.08)	(-1.30)	(1.10)	(1.33)
4	-16.68	-4.531***	-3.89***	9.807**	10.25**
	(-1.41)	(-3.54)	(-3.51)	(2.34)	(2.50)
6	-39.33***	-5.779***	-4.024**	7.268	8.464*
	(-3.14)	(-3.29)	(-2.67)	(1.67)	(1.95)
8	-51.57***	-5.027***	-3.262*	4.85	6.004
	(-5.19)	(-2.84)	(-1.99)	(0.90)	(1.09)
Family Income			2.1e-04***		1.3e-04***
			(5.13)		(4.19)
Year FE	✓	✓	✓	✓	✓
Gender FE	✓	✓	✓	✓	✓
Education FE	✓	✓	✓	✓	✓
Race FE	✓	✓	✓	✓	✓
Age FE	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓	✓
Family Size FE	✓	✓	✓	✓	✓
Marital Status FE	✓	✓	✓	✓	✓
Has Siblings FE	✓	✓	✓	✓	✓
Has Health Ins. FE	✓	✓	✓	✓	✓
Adj. R2	0.0677	0.350	0.441	0.147	0.154
Observations	24676	21852	21834	21852	21834
Clusters	35	35	35	35	35

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12. Impact of own health shocks on wealth, consumption of non-durable goods and services (excluding health-related expenditures), and health-related expenditures. The total effect of health on consumption refers to our standard regression. Direct effect additionally controls for family income and indicates a health shock effect on consumption that is not mediated by a fall in current income. Standard errors are clustered by age. Age: 24-60. Sample: 1999-2019.

Years Since Shock	Income		Hours	
	all	> 0	all	> 0
-6	5.263	5.464	1.634	.6256
	(0.47)	(0.51)	(0.91)	(0.39)
-4	-5.658	-4.555	-2.442	-1.919
	(-1.31)	(-1.14)	(-1.38)	(-1.44)
-2	3.597	4.333	-1.536	-.9626
	(0.45)	(0.55)	(-0.88)	(-0.76)
0	-.3217	-.6326	-2.86***	-2.996***
	(-0.08)	(-0.17)	(-2.89)	(-2.96)
2	-9.475***	-7.698**	-3.503**	-2.189**
	(-2.85)	(-2.53)	(-2.75)	(-2.22)
4	-9.351**	-10.18**	-.6887	-1.307
	(-2.44)	(-2.64)	(-0.41)	(-0.96)
6	-11.89**	-12.26**	-2.509	-2.718*
	(-2.36)	(-2.40)	(-1.52)	(-2.03)
8	-4.489	-5.308	-2.74	-2.441*
	(-1.34)	(-1.47)	(-1.51)	(-1.81)
Year FE	✓	✓	✓	✓
Gender	✓	✓	✓	✓
Education	✓	✓	✓	✓
Race	✓	✓	✓	✓
Age	✓	✓	✓	✓
State	✓	✓	✓	✓
Occupation	✓	✓	✓	✓
Family Size	✓	✓	✓	✓
Marital Status	✓	✓	✓	✓
Has Siblings	✓	✓	✓	✓
Parent Has Health Ins.	✓	✓	✓	✓
Parent Lives in Same State	✓	✓	✓	✓
Parent Education	✓	✓	✓	✓
Parent Marital Status	✓	✓	✓	✓
Mother Retired	✓	✓	✓	✓
Father Retired	✓	✓	✓	✓
Cohabited with Father	✓	✓	✓	✓
Adj. R2	0.157	0.156	0.183	0.140
Observations	7138	6568	7137	6597
Clusters	26	26	26	26

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13. Impact of health shocks to parents on non-cohabiting adult children's income and hours worked. Age: 24-51. Conditional on both parents being alive and not passing away following the health shock. Standard errors are clustered by age. Sample: 1999-2019

Years Since Shock	Wealth	Consumption		Health Expenditure	
		Total	Direct	Total	Direct
-6	-6.839	.9559	-.58	-6.379	-8.132*
	(-0.95)	(0.36)	(-0.21)	(-1.40)	(-1.76)
-4	6.912	-1.255	-1.103	-6.475	-5.997
	(0.54)	(-0.41)	(-0.37)	(-1.24)	(-1.15)
-2	-7.319	-2.11	-3.012	-6.15	-7.01
	(-0.88)	(-1.07)	(-1.50)	(-1.25)	(-1.42)
0	-4.882	-4.158***	-3.785***	-4.713	-4.486
	(-0.52)	(-3.00)	(-3.01)	(-1.05)	(-1.00)
2	-8.597	-3.071*	-2.179	-7.952*	-6.818*
	(-1.19)	(-1.73)	(-1.27)	(-1.94)	(-1.71)
4	-13.76	-1.084	-.1841	-2.281	-1.19
	(-1.66)	(-0.51)	(-0.09)	(-0.76)	(-0.39)
6	-22.52*	-.064	.8682	-.5344	.4101
	(-2.02)	(-0.04)	(0.56)	(-0.13)	(0.10)
8	-20.74**	-1.668	-.8926	-2.343	-1.187
	(-2.07)	(-0.69)	(-0.39)	(-0.43)	(-0.22)
Family Income			1.5e-04**		1.8e-04*
			(2.13)		(1.77)
Year FE	✓	✓	✓	✓	✓
Gender	✓	✓	✓	✓	✓
Education	✓	✓	✓	✓	✓
Race	✓	✓	✓	✓	✓
Age	✓	✓	✓	✓	✓
State	✓	✓	✓	✓	✓
Occupation	✓	✓	✓	✓	✓
Family Size	✓	✓	✓	✓	✓
Marital Status	✓	✓	✓	✓	✓
Has Siblings	✓	✓	✓	✓	✓
Parent Has Health Ins.	✓	✓	✓	✓	✓
Parent Lives in Same State	✓	✓	✓	✓	✓
Parent Education	✓	✓	✓	✓	✓
Parent Marital Status	✓	✓	✓	✓	✓
Mother Retired	✓	✓	✓	✓	✓
Father Retired	✓	✓	✓	✓	✓
Cohabited with Father	✓	✓	✓	✓	✓
Adj. R2	0.0880	0.267	0.319	0.121	0.134
Observations	7831	6983	6975	7809	7800
Clusters	26	26	26	26	26

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14. Impact of health shocks to parents on non-cohabiting adult children's wealth, consumption of non-durable goods and services (excluding health-related expenditures), and health-related expenditures. The total effect of health on consumption refers to our standard regression. Direct effect additionally controls for family income and indicates a health shock effect on consumption that is not mediated by a fall in current income. Age: 24-51. Conditional on both parents being alive and not passing away following the health shock. Standard errors are clustered by age. Sample: 1999-2019

Years Since Death	Hours		Income	
	all	> 0	all	> 0
-6	-3.6	-3.5	-4.3	-4.4
	(5.0)	(2.5)	(4.9)	(3.8)
-4	0.5	-0.3	-8.2	-8.0*
	(5.0)	(2.6)	(5.3)	(4.2)
-2	-3.4	-2.7	-15.3***	-13.3***
	(3.1)	(2.3)	(4.4)	(3.2)
0	-5.2	-3.4	-6.4	-5.4
	(5.4)	(3.3)	(6.6)	(5.4)
2	9.4	2.7	7.3	2.8
	(5.7)	(3.0)	(10.4)	(8.0)
4	13.9*	7.7**	12.2	8.9
	(7.1)	(3.2)	(12.4)	(9.4)
6	6.9	4.7	19.0*	16.0*
	(7.5)	(3.0)	(9.5)	(8.4)
8	27.6**	12.3**	30.7**	20.6*
	(12.0)	(5.0)	(13.6)	(10.3)
Age FE	✓	✓	✓	✓
Sex FE	✓	✓	✓	✓
Race FE	✓	✓	✓	✓
Education FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Family Size FE	✓	✓	✓	✓
Health Insurance (Parents)	✓	✓	✓	✓
Has Kids	✓	✓	✓	✓
Has Siblings	✓	✓	✓	✓
Same State Parents	✓	✓	✓	✓
Marital Status	✓	✓	✓	✓
N	4132	3700	4133	3685

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15. Impact of Parents' Death on non-cohabiting Adult Children. Age: 21-40. Standard errors are clustered by age. All values are expressed in percentage points. Sample: 1999-2019 TO UPDATE

Years Since Shock	Income	Hours
-6	23.3	1.609
	(0.93)	(0.72)
-4	-3.237	-3.385
	(-0.81)	(-1.42)
-2	6.226	-4.766**
	(0.37)	(-2.07)
0	-9.057**	-3.415
	(-2.70)	(-1.60)
2	-10.7***	-1.527
	(-3.07)	(-0.80)
4	-8.186***	-2.236
	(-2.86)	(-1.24)
6	-11.96***	-1.905
	(-2.87)	(-0.83)
8	-9.351***	-3.163*
	(-3.23)	(-1.78)
-6 × Married	-24.45	1.362
	(-0.94)	(0.51)
-4 × Married	-.522	2.183
	(-0.08)	(0.62)
-2 × Married	-6.132	4.766
	(-0.35)	(1.54)
0 × Married	16.63***	1.717
	(2.83)	(0.58)
2 × Married	5.254	-.8797
	(1.21)	(-0.35)
4 × Married	2.147	.9185
	(0.50)	(0.42)
6 × Married	3.733	-.2547
	(0.76)	(-0.10)
8 × Married	11.65**	.9454
	(2.18)	(0.50)
Adj. R2	0.177	0.158
Observations	11205	11203
Clusters	26	26

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16. Response to Parent's Shock: Heterogeneous Effects by Marital Status

Years Since Shock	Income	Hours
-6	-.0311	3.089
	(-0.01)	(1.12)
-4	-2.354	-3.817**
	(-0.55)	(-2.24)
-2	-8.209*	-4.303*
	(-1.94)	(-2.03)
0	.6336	-1.362
	(0.16)	(-0.58)
2	-5.912*	-1.035
	(-1.96)	(-0.67)
4	-8.322***	-1.273
	(-2.82)	(-0.62)
6	-4.941	-2.083
	(-1.37)	(-1.17)
8	3.654	-1.524
	(0.78)	(-0.80)
-6 × Has Kids	11.93	-1.21
	(0.83)	(-0.37)
-4 × Has Kids	-1.797	2.891
	(-0.25)	(0.95)
-2 × Has Kids	16.93	4.007
	(1.46)	(1.33)
0 × Has Kids	1.805	-1.547
	(0.29)	(-0.49)
2 × Has Kids	-2.474	-1.597
	(-0.55)	(-0.84)
4 × Has Kids	2.054	-.6661
	(0.43)	(-0.27)
6 × Has Kids	-7.267	.0832
	(-1.39)	(0.04)
8 × Has Kids	-9.593	-1.651
	(-1.48)	(-0.79)
Adj. R2	0.177	0.163
Observations	11205	11203
Clusters	26	26

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17. Response to Parent's Shock: Heterogeneous Effects by Parental Status

Years Since Shock	Income	Hours
-6	-7.391*	-.981
	(-1.73)	(-0.39)
-4	-2.837	-4.39
	(-0.68)	(-1.38)
-2	-2.771	-3.98
	(-0.69)	(-1.24)
0	-1.596	-4.727**
	(-0.53)	(-2.33)
2	-5.912*	-5.475**
	(-1.80)	(-2.22)
4	-5.989*	-4.199
	(-1.84)	(-1.44)
6	-8.296**	-2.844
	(-2.07)	(-0.96)
8	-.983	-2.981
	(-0.33)	(-1.24)
-6 × Head	22.04	5.335**
	(1.60)	(2.10)
-4 × Head	-.2148	3.977
	(-0.04)	(1.09)
-2 × Head	8.329	3.521
	(0.72)	(0.99)
0 × Head	4.537	3.424
	(0.90)	(1.32)
2 × Head	-2.006	4.924*
	(-0.40)	(1.73)
4 × Head	-1.182	3.706
	(-0.31)	(1.27)
6 × Head	-1.215	1.417
	(-0.33)	(0.46)
8 × Head	-2.199	.453
	(-0.47)	(0.17)
Adj. R2	0.186	0.175
Observations	11205	11203
Clusters	26	26

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18. Response to Parent's Shock: Heterogeneous Effects, Head or Spouse

Years Since Shock	Income	Hours
-6	13.7	1.123
	(0.68)	(0.68)
-4	-4.1	-.8161
	(-0.53)	(-0.38)
-2	6.775	-.6718
	(0.50)	(-0.28)
0	1.834	-2.933
	(0.26)	(-1.69)
2	-11.08**	-1.878
	(-2.61)	(-1.25)
4	-9.938**	-1.085
	(-2.24)	(-0.55)
6	-12.2***	-1.904
	(-3.12)	(-1.02)
8	-3.751	-3.06**
	(-0.70)	(-2.17)
-6 × Young	-11.98	2.371
	(-0.58)	(0.80)
-4 × Young	.9505	-2.139
	(0.12)	(-0.82)
-2 × Young	-7.908	-1.933
	(-0.57)	(-0.63)
0 × Young	-.48	1.092
	(-0.07)	(0.57)
2 × Young	6.756	-.3358
	(1.57)	(-0.14)
4 × Young	5.475	-1.079
	(1.18)	(-0.45)
6 × Young	5.148	-.1391
	(1.17)	(-0.06)
8 × Young	2.701	.9165
	(0.42)	(0.41)
Adj. R2	0.176	0.158
Observations	11205	11203
Clusters	26	26

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 19. Response to Parent's Shock: Heterogeneous Effects by Age

Years Since Shock	Income	Hours
-6	17.61	4.354*
	(1.10)	(1.80)
-4	-.4835	-1.202
	(-0.22)	(-0.58)
-2	11.2	-2.318
	(1.02)	(-1.13)
0	-.274	-1.91
	(-0.10)	(-1.15)
2	-4.588*	-.802
	(-1.86)	(-0.45)
4	-1.845	-.0159
	(-0.57)	(-0.01)
6	-6.606**	-1.083
	(-2.07)	(-0.55)
8	-2.283	-1.827
	(-0.99)	(-0.94)
-6 × College	-23.05	-4.237
	(-1.32)	(-1.12)
-4 × College	-7.468	-1.782
	(-0.92)	(-0.57)
-2 × College	-20.28	1.396
	(-1.55)	(0.57)
0 × College	4.416	-.9148
	(0.56)	(-0.35)
2 × College	-6.213	-2.877
	(-1.52)	(-1.32)
4 × College	-11.76*	-3.834
	(-1.93)	(-1.56)
6 × College	-6.535	-1.99
	(-1.12)	(-0.85)
8 × College	-.1328	-1.629
	(-0.02)	(-0.54)
Adj. R2	0.177	0.158
Observations	11205	11203
Clusters	26	26

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 20. Response to Parent's Shock: Heterogeneous Effects by Education

Years Since Shock	Income	Hours
-6	.4106	4.427*
	(0.12)	(1.83)
-4	-2.62	-2.303
	(-1.07)	(-1.07)
-2	.2195	-1.994
	(0.08)	(-0.93)
0	.4662	-2.501
	(0.23)	(-1.46)
2	-5.601**	-2.093
	(-2.31)	(-1.11)
4	-4.874**	-2.419
	(-2.40)	(-1.17)
6	-6.489**	-1.367
	(-2.07)	(-0.55)
8	-3.74**	-1.939
	(-2.19)	(-0.92)
-6 × High Income	10.41	-4.057
	(0.62)	(-1.27)
-4 × High Income	-1.874	.6124
	(-0.27)	(0.20)
-2 × High Income	4.103	.3897
	(0.32)	(0.13)
0 × High Income	2.583	.4097
	(0.39)	(0.17)
2 × High Income	-3.241	.0152
	(-0.77)	(0.01)
4 × High Income	-2.993	1.744
	(-0.50)	(0.58)
6 × High Income	-4.445	-.9189
	(-0.79)	(-0.29)
8 × High Income	5.34	-.9172
	(0.72)	(-0.31)
Adj. R2	0.200	0.167
Observations	11205	11203
Clusters	26	26

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 21. Response to Parent's Shock: Heterogeneous Effects by Family Income

Years Since Shock	Income	Hours
-6	-6.67*	3.5
	(-1.84)	(1.43)
-4	-2.816	-2.578
	(-0.78)	(-1.02)
-2	-3.136	-2.388
	(-1.01)	(-1.01)
0	-.3613	-2.187
	(-0.11)	(-1.52)
2	-4.404	-2.911
	(-1.55)	(-1.42)
4	-4.79*	-1.337
	(-1.99)	(-0.58)
6	-9.063***	-2.591
	(-2.82)	(-1.36)
8	-4.667*	-3.232*
	(-1.99)	(-1.74)
-6 × High Income Share	28.1	-2.269
	(1.53)	(-0.74)
-4 × High Income Share	-.3447	1.701
	(-0.05)	(0.51)
-2 × High Income Share	12.11	1.679
	(0.91)	(0.63)
0 × High Income Share	5.307	.3509
	(0.73)	(0.17)
2 × High Income Share	-4.972	2.104
	(-0.92)	(0.87)
4 × High Income Share	-3.625	-.3425
	(-0.65)	(-0.14)
6 × High Income Share	.9289	1.883
	(0.19)	(0.90)
8 × High Income Share	6.729	2.188
	(1.02)	(0.79)
Adj. R2	0.209	0.215
Observations	11205	11203
Clusters	26	26

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 22. Response to Parent's Shock: Heterogeneous Effects by Income Share

Years Since Shock	Income	Hours
-6	3.536	3.32
	(1.36)	(1.66)
-4	-2.203	-2.887
	(-0.92)	(-1.34)
-2	1.011	-.9615
	(0.44)	(-0.47)
0	2.634	-1.813
	(1.31)	(-1.18)
2	-3.502	-1.176
	(-1.67)	(-0.55)
4	-3.817*	-2.052
	(-1.85)	(-1.09)
6	-7.2**	-2.036
	(-2.37)	(-0.92)
8	-1.715	-1.213
	(-0.92)	(-0.61)
-6 $\times$ High Wealth	5.059	-2.176
	(0.26)	(-0.68)
-4 $\times$ High Wealth	-3.406	1.936
	(-0.47)	(0.63)
-2 $\times$ High Wealth	2.665	-2.004
	(0.18)	(-0.72)
0 $\times$ High Wealth	-2.858	-1.115
	(-0.38)	(-0.44)
2 $\times$ High Wealth	-9.524**	-2.226
	(-2.51)	(-0.75)
4 $\times$ High Wealth	-7.117*	.8705
	(-1.73)	(0.34)
6 $\times$ High Wealth	-4.744	.3085
	(-1.11)	(0.11)
8 $\times$ High Wealth	.253	-3.145
	(0.03)	(-1.03)
Adj. R2	0.188	0.160
Observations	11205	11203
Clusters	26	26

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 23. Response to Parent's Shock: Heterogeneous Effects by Wealth

Years Since Shock	Income	Hours
-6	-5.485	1.751
	(-0.67)	(0.53)
-4	-2.147	-.8545
	(-0.28)	(-0.23)
-2	-8.838	-4.113
	(-1.27)	(-1.13)
0	.2998	-6.184**
	(0.04)	(-2.70)
2	-9.333	-5.316*
	(-1.47)	(-1.98)
4	-17.18**	-4.238
	(-2.46)	(-1.45)
6	-21.72**	-6.365**
	(-2.22)	(-2.42)
8	-7.987	-.229
	(-0.84)	(-0.08)
-6 × Same State Parent	17.03	.8733
	(1.29)	(0.22)
-4 × Same State Parent	-2.112	-1.547
	(-0.27)	(-0.37)
-2 × Same State Parent	14.62*	3.083
	(1.81)	(0.83)
0 × Same State Parent	1.826	5.003**
	(0.18)	(2.08)
2 × Same State Parent	2.727	4.28
	(0.42)	(1.35)
4 × Same State Parent	13.4*	3.338
	(1.85)	(0.88)
6 × Same State Parent	16.15	5.693*
	(1.65)	(1.77)
8 × Same State Parent	7.676	-3.037
	(0.74)	(-0.89)
Adj. R2	0.176	0.158
Observations	11205	11203
Clusters	26	26

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 24. Response to Parent's Shock: Heterogeneous Effects, Parents live in same state or not

Years Since Shock	Income	Hours
-6	2.553	3.713**
	(0.72)	(2.26)
-4	-3.718	-2.648
	(-0.94)	(-1.69)
-2	-1.774	-2.054
	(-0.49)	(-1.19)
0	2.594	-2.308*
	(0.79)	(-1.76)
2	-7.087**	-1.502
	(-2.50)	(-0.95)
4	-5.785*	-3.026*
	(-1.88)	(-2.04)
6	-8.657**	-1.648
	(-2.43)	(-1.09)
8	-2.48	-2.816*
	(-0.83)	(-1.77)
-6 × Father Retired	17.4	-5.101*
	(0.49)	(-1.78)
-4 × Father Retired	-.4335	2.838
	(-0.05)	(0.97)
-2 × Father Retired	14.78	1.802
	(0.61)	(0.58)
0 × Father Retired	-5.725	.6244
	(-0.78)	(0.20)
2 × Father Retired	-3.278	-1.73
	(-0.53)	(-0.78)
4 × Father Retired	-6.369	5.885*
	(-0.91)	(1.86)
6 × Father Retired	-4.865	-1.02
	(-0.91)	(-0.41)
8 × Father Retired	-1.196	1.38
	(-0.18)	(0.50)
Adj. R2	0.176	0.158
Observations	11205	11203
Clusters	26	26

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 25. Response to Parent's Shock: Heterogeneous Effects by Father Retirement Status

Years Since Shock	Income	Hours
-6	19.22	2.774
	(1.04)	(1.08)
-4	-.7162	-2.109
	(-0.18)	(-0.85)
-2	11.17	-1.45
	(0.88)	(-0.58)
0	-2.237	-3.084**
	(-0.77)	(-2.14)
2	-9.426***	-2.35
	(-3.61)	(-1.28)
4	-7.799***	-2.057
	(-3.28)	(-1.11)
6	-9.165**	-2.805
	(-2.63)	(-1.22)
8	-5.532**	-4.984***
	(-2.11)	(-3.01)
-6 × Father High Income	-26.68	-2.027
	(-1.23)	(-0.65)
-4 × Father High Income	-9.86	-.0436
	(-1.10)	(-0.02)
-2 × Father High Income	-18.12	.2773
	(-1.30)	(0.10)
0 × Father High Income	5.396	1.93
	(0.91)	(0.83)
2 × Father High Income	1.021	.4977
	(0.22)	(0.20)
4 × Father High Income	.2811	1.852
	(0.05)	(0.85)
6 × Father High Income	-4.656	1.178
	(-0.81)	(0.42)
8 × Father High Income	7.293	6.262**
	(0.88)	(2.63)
Adj. R2	0.169	0.158
Observations	9737	9736
Clusters	26	26

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 26. Response to Parent's Shock: Heterogeneous Effects by Father Income

Years Since Shock	Income	Hours
-6	6.984	3.505
	(1.70)	(1.49)
-4	.4109	-2.346
	(0.14)	(-1.03)
-2	1.935	-1.492
	(0.71)	(-0.68)
0	1.444	-1.378
	(0.74)	(-0.98)
2	-3.793*	-1.07
	(-1.71)	(-0.63)
4	-2.799	-1.379
	(-1.03)	(-0.72)
6	-7.358**	-2.264
	(-2.29)	(-1.21)
8	-3.325	-1.402
	(-1.22)	(-0.75)
-6 × Parents High Wealth	-1.58	-2.184
	(-0.09)	(-0.69)
-4 × Parents High Wealth	-9.022	.652
	(-1.31)	(0.23)
-2 × Parents High Wealth	.6418	-.6121
	(0.05)	(-0.22)
0 × Parents High Wealth	-.0548	-2.033
	(-0.01)	(-0.90)
2 × Parents High Wealth	-8.201**	-2.214
	(-2.32)	(-1.23)
4 × Parents High Wealth	-9.039**	-.6749
	(-2.10)	(-0.24)
6 × Parents High Wealth	-4.204	.7375
	(-1.03)	(0.35)
8 × Parents High Wealth	3.744	-2.756
	(0.48)	(-0.81)
Adj. R2	0.180	0.158
Observations	11205	11203
Clusters	26	26

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 27. Response to Parent's Shock: Heterogeneous Effects by Parents Wealth

Years Since Shock	Income	Hours
-6	-.1677	9.819***
	(-0.03)	(3.16)
-4	-3.694	.1579
	(-0.80)	(0.05)
-2	-3.763	-.7547
	(-0.68)	(-0.34)
0	6.777	-3.228
	(1.08)	(-1.58)
2	-3.245	-2.799
	(-0.76)	(-1.55)
4	.1707	-2.29
	(0.02)	(-0.93)
6	-6.628	-5.504**
	(-1.18)	(-2.63)
8	-.3271	-5.921*
	(-0.05)	(-1.80)
-6 × Father Retired	58.45	-12.24**
	(0.68)	(-2.29)
-4 × Father Retired	-2.654	3.4
	(-0.22)	(0.64)
-2 × Father Retired	-4.155	.5098
	(-0.36)	(0.12)
0 × Father Retired	-6.839	7.459*
	(-0.68)	(1.83)
2 × Father Retired	-3.777	2.799
	(-0.43)	(0.72)
4 × Father Retired	-.7668	8.881*
	(-0.07)	(1.87)
6 × Father Retired	4.361	3.668
	(0.40)	(1.12)
8 × Father Retired	13.35	6.607
	(0.91)	(1.39)
Adj. R2	0.155	0.175
Observations	7056	7055
Clusters	26	26

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 28. Response to Father Shock: Heterogeneous Effects by Father Retirement Status

Years Since Shock	Income	Hours
-6	-2.158	8.873
	(-0.11)	(1.16)
-4	-7.834	2.688
	(-0.58)	(0.33)
-2	-5.132	-1.533
	(-0.40)	(-0.21)
0	-6.011	-.3199
	(-0.60)	(-0.05)
2	-23.25*	.0259
	(-1.93)	(0.00)
4	-19.77*	-3.926
	(-1.72)	(-0.60)
6	-37.8**	-6.609
	(-2.63)	(-1.15)
8	-28.07**	-9.298
	(-2.33)	(-1.36)
-6 $\times$ Father Married	20.06	-2.463
	(0.56)	(-0.29)
-4 $\times$ Father Married	3.658	-1.724
	(0.23)	(-0.19)
-2 $\times$ Father Married	-.3658	.9918
	(-0.02)	(0.13)
0 $\times$ Father Married	11.42	-.5013
	(0.92)	(-0.08)
2 $\times$ Father Married	20.81	-2.154
	(1.64)	(-0.34)
4 $\times$ Father Married	22.01	5.125
	(1.64)	(0.73)
6 $\times$ Father Married	36.31**	2.44
	(2.38)	(0.36)
8 $\times$ Father Married	35.96**	6.052
	(2.31)	(0.82)
Adj. R2	0.154	0.172
Observations	7056	7055
Clusters	26	26

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 29. Response to Father Shock: Heterogeneous Effects by Father Marital Status

Years Since Shock	Income	Hours
-6	-4.422	6.432**
	(-0.91)	(2.76)
-4	-7.796	2.16
	(-1.52)	(0.81)
-2	-2.013	-2.221
	(-0.33)	(-0.98)
0	8.221	-1.191
	(1.04)	(-0.57)
2	-5.943	-4.261**
	(-1.48)	(-2.10)
4	-1.039	1.569
	(-0.17)	(0.73)
6	.9495	-2.831
	(0.13)	(-1.55)
8	13.41	-1.681
	(1.44)	(-0.47)
-6 × Father Disabled	59.77	-1.686
	(0.89)	(-0.36)
-4 × Father Disabled	7.919	-4.671
	(0.74)	(-1.08)
-2 × Father Disabled	-6.993	2.581
	(-1.05)	(0.61)
0 × Father Disabled	-7.381	1.017
	(-0.82)	(0.31)
2 × Father Disabled	3.712	5.035
	(0.52)	(1.35)
4 × Father Disabled	2.291	-1.742
	(0.23)	(-0.45)
6 × Father Disabled	-10.71	-2.491
	(-0.97)	(-0.72)
8 × Father Disabled	-15.73	-2.973
	(-1.23)	(-0.62)
Adj. R2	0.155	0.177
Observations	7024	7023
Clusters	26	26

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 30. Response to Father Shock: Heterogeneous Effects by Father Disability Status

Years Since Shock	Income	Hours
-6	29.81	9.337**
	(0.92)	(2.48)
-4	-2.911	3.258
	(-0.52)	(0.88)
-2	-1.715	.5243
	(-0.49)	(0.19)
0	2.345	2.1e-05
	(0.70)	(0.00)
2	-3.321	.17
	(-0.84)	(0.08)
4	2.232	2.384
	(0.46)	(1.03)
6	-12.32**	-4.789**
	(-2.28)	(-2.17)
8	-5.261	-3.749
	(-1.11)	(-1.03)
-6 × Father College	-42.13	-7.529
	(-1.29)	(-1.59)
-4 × Father College	-3.896	-6.204
	(-0.34)	(-1.19)
-2 × Father College	-10.09	-3.521
	(-0.87)	(-0.76)
0 × Father College	6.098	-2.247
	(0.51)	(-0.73)
2 × Father College	-4.001	-6.629
	(-0.38)	(-1.34)
4 × Father College	-7.612	-5.36
	(-0.73)	(-1.29)
6 × Father College	19.65	1.098
	(1.33)	(0.24)
8 × Father College	25.19	-.1855
	(1.27)	(-0.03)
Adj. R2	0.155	0.173
Observations	7056	7055
Clusters	26	26

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 31. Response to Father Shock: Heterogeneous Effects by Father Education

Years Since Shock	Income	Hours
-6	3.152	.444
	(0.64)	(0.18)
-4	-2.58	-4.925**
	(-0.44)	(-2.51)
-2	.5775	-3.092
	(0.11)	(-1.45)
0	-2.415	-3.499**
	(-0.59)	(-2.28)
2	-4.982*	-.8403
	(-1.77)	(-0.60)
4	-6.242*	-3.489*
	(-1.83)	(-1.88)
6	-6.62*	-1.382
	(-1.78)	(-0.96)
8	-4.955*	-2.831*
	(-1.82)	(-1.81)
-6 × Mother Retired	4.493	1.148
	(0.28)	(0.32)
-4 × Mother Retired	8.002	7.896*
	(0.62)	(1.76)
-2 × Mother Retired	38.49	5.731
	(0.78)	(1.51)
0 × Mother Retired	14.86	4.169
	(1.13)	(1.04)
2 × Mother Retired	-4.804	.7758
	(-0.47)	(0.22)
4 × Mother Retired	-15.91	1.552
	(-1.61)	(0.40)
6 × Mother Retired	-22.5**	1.96
	(-2.65)	(0.48)
8 × Mother Retired	-22.54***	-2.655
	(-2.97)	(-0.54)
Adj. R2	0.171	0.159
Observations	9608	9606
Clusters	26	26

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 32. Response to Mother Shock: Heterogeneous Effects by Mother Retirement Status

Years Since Shock	Income	Hours
-6	1.685	-2.816
	(0.17)	(-0.81)
-4	-6.054	-4.984
	(-0.91)	(-1.31)
-2	-6.635	-4.612
	(-1.11)	(-1.56)
0	-6.12	-1.289
	(-1.52)	(-0.51)
2	-8.194*	1.409
	(-1.76)	(0.50)
4	-11.58**	-4.292
	(-2.76)	(-1.66)
6	-12.95***	-3.217
	(-3.03)	(-1.09)
8	-3.293	-1.794
	(-0.67)	(-0.53)
-6 × Mother Married	3.589	5.005
	(0.32)	(1.24)
-4 × Mother Married	8.713	2.703
	(0.89)	(0.65)
-2 × Mother Married	21.91	3.907
	(1.28)	(1.23)
0 × Mother Married	9.861	-2.043
	(1.04)	(-0.69)
2 × Mother Married	3.118	-3.248
	(0.44)	(-0.95)
4 × Mother Married	3.234	1.622
	(0.59)	(0.56)
6 × Mother Married	2.646	3.288
	(0.43)	(0.95)
8 × Mother Married	-10.04	-2.485
	(-1.36)	(-0.55)
Adj. R2	0.168	0.159
Observations	9608	9606
Clusters	26	26

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 33. Response to Mother Shock: Heterogeneous Effects by Mother Marital Status

Years Since Shock	Income	Hours
-6	4.46	-.2711
	(0.72)	(-0.13)
-4	.984	-4.878**
	(0.18)	(-2.29)
-2	1.711	-1.533
	(0.32)	(-0.68)
0	7.317	-1.187
	(1.04)	(-0.81)
2	-.6467	-.7738
	(-0.12)	(-0.44)
4	-2.969	-2.297
	(-0.47)	(-0.89)
6	-3.262	.9833
	(-0.57)	(0.56)
8	-4.972	-4.04*
	(-0.88)	(-1.81)
-6 × Mother Disabled	-.6555	.9158
	(-0.08)	(0.22)
-4 × Mother Disabled	-4.09	2.458
	(-0.47)	(0.58)
-2 × Mother Disabled	13.77	-1.62
	(0.65)	(-0.64)
0 × Mother Disabled	-13.21	-2.831
	(-1.41)	(-1.37)
2 × Mother Disabled	-11.11	.1942
	(-1.65)	(0.07)
4 × Mother Disabled	-11.99	-1.705
	(-1.65)	(-0.58)
6 × Mother Disabled	-13.26**	-2.958
	(-2.48)	(-0.96)
8 × Mother Disabled	-8.133	1.505
	(-1.11)	(0.43)
Adj. R2	0.167	0.162
Observations	9535	9533
Clusters	26	26

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 34. Response to Mother Shock: Heterogeneous Effects by Mother Disability Status

Years Since Shock	Income	Hours
-6	6.7	-1.668
	(0.64)	(-0.49)
-4	6.291	-7.52**
	(0.53)	(-2.37)
-2	2.796	-3.344
	(0.28)	(-1.17)
0	11.79	-2.25
	(0.94)	(-1.10)
2	-.7952	-2.557
	(-0.11)	(-1.10)
4	-9.511	-2.5
	(-1.33)	(-0.98)
6	-13.6*	.3251
	(-1.82)	(0.14)
8	-13.5**	-1.398
	(-2.28)	(-0.44)
-6 × Father Disabled	-8.573	4.208
	(-0.57)	(0.64)
-4 × Father Disabled	-10.26	10.03*
	(-0.83)	(2.01)
-2 × Father Disabled	19.6	5.621
	(0.71)	(1.23)
0 × Father Disabled	-23.5*	.7392
	(-1.87)	(0.20)
2 × Father Disabled	-14.38	1.23
	(-1.40)	(0.31)
4 × Father Disabled	-5.993	2.584
	(-0.71)	(0.82)
6 × Father Disabled	-4	9.0e-04
	(-0.62)	(0.00)
8 × Father Disabled	-6.233	-1.459
	(-0.78)	(-0.29)
Adj. R2	0.149	0.177
Observations	6158	6157
Clusters	26	26

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 35. Response to Mother Shock: Heterogeneous Effects by Father Disability Status

References

Andersen, Asger Lau, Niels Johannesen, and Adam Sheridan. 2020. "Bailing Out the Kids: New Evidence on Informal Insurance from One Billion Bank Transfers." *Working Paper* .

Attanasio, Orazio, Costas Meghir, and Corina Mommarts. 2018. "Insurance in extended family networks." *NBER Working Paper 21059* .

Barczyk, Daniel and Matthias Kredler. 2018. "Evaluating Long-Term-Care Policy Options, Taking the Family Seriously." *The Review of Economic Studies* 85 (2):766–809.

———. 2021. "Blast from the past: The altruism model is richer than you think." *Journal of Economic Theory* 198:105375.

Bick, Alexander, Adam Blandin, and Richard Rogerson. 2022. "Hours and wages." *The Quarterly Journal of Economics* 137 (3):1901–1962.

Blundell, Richard, Luigi Pistaferri, and Itay Saporta-Eksten. 2016. "Consumption inequality and family labor supply." *American Economic Review* 106 (2):387–435.

———. 2018. "Children, time allocation, and consumption insurance." *Journal of Political Economy* 126 (S1):S73–S115.

Boar, Corina. 2021. "Dynastic precautionary savings." *The Review of Economic Studies* 88 (6):2735–2765.

Breivik, Anne-Lise and Ana Costa-Ramón. 2022. "The career costs of children's health shocks." *University of Zurich, Department of Economics, Working Paper* 399.

De Nardi, Mariacristina, Svetlana Pashchenko, and Ponpoje Porapakkarm. 2022. "The lifetime costs of bad health." *NBER Working Paper 23963* .

Dobkin, Carlos, Amy Finkelstein, Raymond Kluender, and Matthew J Notowidigdo. 2018. "The economic consequences of hospital admissions." *American Economic Review* 108 (2):308–52.

Eriksen, Tine L. Mundbjerg, Amanda Gaulke, Niels Skipper, and Jannet Svensson. 2021. "The impact of childhood health shocks on parental labor supply." *Journal of Health Economics* 78:102486.

Erosa, Andrés, Luisa Fuster, Gueorgui Kambourov, and Richard Rogerson. 2022. "Hours, occupations, and gender differences in labor market outcomes." *American Economic Journal: Macroeconomics* 14 (3):543–590.

Fadlon, Itzik and Torben Heien Nielsen. 2019. "Family health behaviors." *American Economic Review* 109 (9):3162–91.

———. 2021. "Family labor supply responses to severe health shocks: Evidence from Danish administrative records." *American Economic Journal: Applied Economics* 13 (3):1–30.

Goldin, Claudia. 2015. "Hours flexibility and the gender gap in pay." *Center for American Progress* .

Hayashi, Fumio, Joseph Altonji, and Laurence J. Kotlikoff. 1996. "Risk-sharing between and within families." *Econometrica* 64 (2):261–294.

Hill, Martha S, Peter V Marsden, and Greg J Duncan. 1992. *The panel study of income dynamics: A user's guide*. Institute for Social Research, University of Michigan.

Hosseini, Roozbeh, Karen A Kopecky, and Kai Zhao. 2021a. "The evolution of health over the life cycle." *Review of Economic Dynamics* .

———. 2021b. "How important is health inequality for lifetime earnings inequality?" *FRB Atlanta Working Paper* .

Huckfeldt, Christopher. 2022. "Understanding the scarring effect of recessions." *American Economic Review* 112 (4):1273–1310.

Insolera, Nouras and Mohammad Mushtaq. 2019. "PSID Family Identification Mapping System User Manual: Release 2019." *Institute for Social Research, University of Michigan* .

Keane, Michael, Elena Capatina, and Shiko Maruyama. 2022. "Health Shocks and the Evolution of Earnings over the Life-Cycle." *CEPAR working paper* .

Ko, Ami. 2022. "An Equilibrium Analysis of the Long-Term Care Insurance Market." *Review of Economic Studies* 89:1993–2025.

Korfhage, Thorben. 2019. "Long-Run Consequences of Informal Elderly Care and Implications of Public Long-Term Care Insurance." *SOEPpapers Working Paper* .

Kotlikoff, Laurence J. 1988. "Intergenerational transfers and savings." *Journal of Economics Perspectives* 2 (2):41–58.

Maestas, Nicole, Matt Messel, and Yulya Truskinovsky. 2023. "Caregiving and Labor Supply: New Evidence from Administrative Data." Tech. rep., National Bureau of Economic Research.

Meyer, Bruce D and Wallace KC Mok. 2019. "Disability, earnings, income and consumption." *Journal of Public Economics* 171:51–69.

Michaud, Amanda and David Wiczer. 2018. "Occupational hazards and social disability insurance." *Journal of Monetary Economics* 96:77–92.

Mommaerts, Corina. 2020. "Long-Term Care Insurance and the Family." *Working Papers* .

Nelson, Alan. 2002. "Unequal treatment: confronting racial and ethnic disparities in health care." *Journal of the national medical association* 94 (8):666.

Pinquart, Martin and Silvia Sorensen. 2003. "Differences Between Caregivers and Noncaregivers in Psychological Health and Physical Health: A Meta-Analysis." *Psychology and Aging* 18 (2):250–267.

Rellstab, Sara, Pieter Bakx, Pilar Garcia-Gomez, and Eddy van Doorslaer. 2020. "The kids are alright - labour market effects of unexpected parental hospitalisations in the Netherlands." *Journal of Health Economics* 69:102275.

Skira, Meghan. 2015. "Dynamic Wage and Employment Effects of Elder Parent Care." *International Economic Review* 56 (1):63–93.

Truskinovsky, Yulya. 2022. "Employment Shocks, Unemployment Insurance, and Caregiving." *University of Wisconsin–Madison Center for Financial Security Working Paper WI21-08* .

Williams, Monnica Terwilliger, Lloyd Kevin Chapman, Judy Wong, and Eric Turkheimer. 2012. "The role of ethnic identity in symptoms of anxiety and depression in African Americans." *Psychiatry research* 199 (1):31–36.

Appendices

A Appendix Tables

B A Simple Model of Joy of Giving and Health

- Update with the new things in slides

We describe a simple model of reaction to parents' health. We assume that children care about their own consumption c_t and their parents' health and well-being h_t. In addition, they also care about time spent with their parents t_t^P and monetary transfers towards their parents m_t^P, which we assume go towards medical expenditures. This can be interpreted as children caring directly about these two objects, or children caring about their parents' health only, and in turn health depends on time spent together and medical expenses.

The problem of an adult children looks like:

$$\max_{c_t, t_t^p, m_t^p} \mathbb{E}_0 \sum_{t=0}^{T} \beta^t u(c_t, h_t^p, t_t^p, m_t^p) \ , \tag{B1}$$

subject to:

$$a_{t+1} = (1+r_t)a_t + w_t(1-t_t^p) - p_t^m m_t^p - c_t + T(h_t^P) \tag{B2}$$

where a_t are assets, w_t is wage, p_t^m is the relative price of out-of-pocket medical expenditures, and $T(h_t^P)$ are monetary transfers from parents, which depend on parental health. Notice that here we make the simplifying assumption that individuals are endowed with one unit of time, and they can use it to either work or spend time caring for their parents.

We assume that wages and parents' health are stochastic and follow the processes:

$$w_t = \Pi_t^w + u_t^w \quad , \text{ with } \ \Pi_t^w = \Pi_{t-1}^w + \nu_t^w \tag{B3}$$

$$h_t^p = \Pi_t^h + u_t^h \quad , \text{ with } \ \Pi_t^h = \Pi_{t-1}^h + \nu_t^h \tag{B4}$$

The first order conditions that describe optimality are:

$$u_{c,t}(\cdot) = \beta(1+r)\mathbb{E}_t\left[u_{c,t+1}(\cdot)\right] \tag{B5}$$

$$u_{t^p,t}(\cdot) = w_t \cdot u_{c,t}(\cdot) \tag{B6}$$

$$u_{m^p,t}(\cdot) = p_t^m \cdot u_{c,t}(\cdot) \tag{B7}$$

Define cash–on–hand as:

$$CA_t = a_t(1+r) + w_t(1-t_t^p) - p_t^m m_t^p + T(h_t^P) \ , \tag{B8}$$

then the consumption policy function can be represented as:

$$\log c_t = f^c\left(h_t^p, m_t^p, t_t^p, CA_t, \Pi_t^h, \Pi_t^w\right) \tag{B9}$$

We are interested in the response of consumption to a transitory or permanent shock in the wage or in parental health. Taking the derivative with respect to the transitory wage shock:

$$\frac{\partial \log c_t}{\partial u_t^w} = f_m^c \cdot \underbrace{\frac{\partial m_t^p}{\partial u_t^w}}_{=0} + f_{t^p}^c \cdot \underbrace{\frac{\partial t_t^p}{\partial u_t^w}}_{=0} + f_{CA}\left((1-t_t^p) - w_t \underbrace{\frac{\partial t_t^p}{\partial u_t^w}}_{=0}\right) \tag{B10}$$

$$\Longrightarrow \frac{\partial \log c_t}{\partial u_t^w} = \underbrace{f_{CA}^c(1-t_t^p)}_{\text{resources effect}} \tag{B11}$$

We make the assumption that medical expenses and time spent with parents do not depend on transitory wealth shocks. In other words, children keep their transfers of out-of-pocket medical expenses and time spent helping parents close to a satiation point that varies with parental health only.

Similarly, taking the derivative with respect to the transitory health shock:

$$\frac{\partial \log c_t}{\partial u_t^h} = \underbrace{f_h^c + f_m^c \frac{\partial m_t^p}{\partial u_t^h} + f_{t^p}^c \frac{\partial t_t^p}{\partial u_t^h}}_{\text{marginal utility effect } \approx 0?} + \underbrace{f_{CA}^c \left(-\frac{\partial t_t^p}{\partial u_t^h} w_t - \frac{\partial m_t^p}{\partial u_t^h} p_t^m - \frac{\partial T_t}{\partial u_t^h} \right)}_{\text{resources effect}} \tag{B12}$$

It is clear that consumption can vary for two reasons: because changes in parental health change the marginal utility of consumption, and because they change resources. In particular, when health deteriorates resources can change for three reasons: because time spent with parents goes up (and so labor income declines), because medical expenditures for the parents go up, and because received transfers may go down.

In the same way, the policy for time spent with parents can be represented as:

$$\log t_t^P = f^{t^P} \left(c_t, h_t^p, m_t^p, CA_t, \Pi_t^h, \Pi_t^w \right) \tag{B13}$$

then the derivative with respect to transitory wage shocks:

$$\frac{\partial \log t_t^P}{\partial u_t^w} = f_c^{t^P} \cdot \frac{\partial c_t}{\partial u_t^w} + f_m^{t^P} \cdot \underbrace{\frac{\partial m_t^p}{\partial u_t^w}}_{=0} + f_{CA}^{t^P} \left((1 - t_t^p) - w_t \underbrace{\frac{\partial t_t^p}{\partial u_t^w}}_{=0} \right) \tag{B14}$$

Taking the derivative wrt the transitory health shock:

$$\frac{\partial \log t_t^P}{\partial u_t^h} = \underbrace{f_h^{t^P} + f_m^{t^P} \frac{\partial m_t^p}{\partial u_t^h} + f_{t^p}^{t^P} \frac{\partial t_t^p}{\partial u_t^h}}_{\text{"warm glow"}} + \underbrace{f_{CA}^{t^P} \left(-\frac{\partial t_t^p}{\partial u_t^h} w_t - \frac{\partial m_t^p}{\partial u_t^h} p_t^m + \frac{\partial T_t}{\partial u_t^h} \right)}_{\text{resources effect}} \tag{B15}$$

When parental health changes, it has two effects on time spent with parents and hence on labor supply: we dub the first the "warm glow" effect, which describes how much children are going to change the time spent with parents as a response to parental health deterioration simply because they care about them, and a resources effect which describes how much children change their time spent helping parents because they might now be poorer. We expect the first term to be positive and the second to be negative for a deterioration in health.

Let's now look at the permanent shocks:

$$\frac{\partial \log c_t}{\partial \nu_t^w} = f_m^c \cdot \frac{\partial m_t^p}{\partial \nu_t^w} + f_{t^p}^c \cdot \frac{\partial t_t^p}{\partial \nu_t^w} + \underbrace{f_{\Pi^w}^c}_{\text{resp. to permanent shock}} + f_{CA}\left((1 - t_t^p) - w_t \frac{\partial t_t^p}{\partial \nu_t^w}\right) \tag{B16}$$

$$\frac{\partial \log c_t}{\partial \nu_t^h} = f_h^c + f_m^c \frac{\partial m_t^p}{\partial \nu_t^h} + f_{t^p}^c \frac{\partial t_t^p}{\partial \nu_t^h} + \underbrace{f_{\Pi^h}^c}_{\text{resp. to permanent shock}} + f_{CA}^c\left(-\frac{\partial t_t^p}{\partial \nu_t^h} w_t - \frac{\partial m_t^p}{\partial \nu_t^h} p_t^m\right) \tag{B17}$$