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

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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

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1 Introduction

This paper studies the spillover effects of parents' adverse health events on their adult children. Differences in health status constitute a fundamental factor in determining individual lifetime earnings and wealth inequality.[1] However, the inter-generational effects of parents' health on labor market outcomes remain largely unexplored. Labor market outcomes are highly dependent on parental background, as individuals benefit from heterogeneous levels of monetary and non-monetary transfers from families. Family ties can also matter in the other direction. When parents lose self-sufficiency or cannot perform essential tasks because of deteriorating health, their offspring can be called to offer support and informal care.

The resulting effect on labor market outcomes is ex-ante ambiguous. 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, because of the possible necessity of informal care or because the existence of parental support (in the form of guidance or implicit insurance) is valuable for one's career, worsening parental health can have adverse effects on the labor market outcomes of adult children.[2]

Exploiting sudden changes in parents' health status, we find evidence of a negative effect of non-fatal parents' shocks on children's outcomes. The income of young workers whose parent receives a health shock is 12% lower than that of their comparable peers and only recovers after about eight years. The affected parent's wealth immediately falls by about 15% and keeps declining over time, and children's wealth also significantly declines over time. We also find that the help

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

[2] Barczyk and Kredler (2018) and Mommaerts (2020), among others, document the importance of informal long-term caregiving provided by adult children to their parents in the U.S.

received by family members goes up. We thus provide evidence of the importance of family ties in shaping career, savings, and time and monetary transfers.

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). Less is known, and to our knowledge almost no empirical study has been conducted so far, on the immediate and long-term impact on adult children and close family members' labor market outcomes and wealth. [3] Inter-generational effects on labor market outcomes, in particular, remain a largely unexplored topic in this area of research.

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 they respond to it.

[3] Fadlon and Nielsen (2019) study spillovers in the family, children included, but limited to health behavior and health outcomes only. Breivik and Costa-Ramón (2022), instead, study spillovers of health shocks in a framework very similar to ours, but looking at the impact on parents' outcomes of shocks to young children.

We use the unique structure of the Panel Survey on Income Dynamics (PSID) to build family networks, construct health measures, and link health changes across the family to labor market outcomes. 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).

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 at least during the time window we observe (that is, eight years after the shock).

We document several important findings. First, we find evidence of a significant pass-through of health shocks from parents to their adult children: Four years after onset, the impact on adult children is half as large as the impact on the shocked parent. The restrictions to parents' non-fatal shocks suggest that transfers in the form of informal care could explain our results: If parents are in bad health, care-taking 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 psychologically demanding (Pinquart and Sorensen 2003). In addition, adult children could suffer income losses because of the loss of some implicit insurance provided by healthy parents, forcing them into careers with lower long-term returns by increasing the cost of educational investments, location choice, or simply productive risk taking. We also find evidence that the reduction in income is concentrated among women, individuals who live in a different state than their parents at the moment of the shocks, and less educated individuals.

Finally, we test what happens to adult children upon the passing away of one of their parents, in a context where informal care is 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. The effect is particularly strong for younger children, who may give up on education and enter the labor force sooner.

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 economics of the family. Section 5 presents results of fatal shocks, and section 6 discusses heterogeneous effects within the family. Finally, Section 7 concludes. We will further explore the channels using Health and Retirement Study in the near future.

2 Data

In this section we introduce the dataset we use, 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

We use 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 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**.

2.2 Building the Health Shock

One 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 in 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 2** shows, disability is least

[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.*"

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

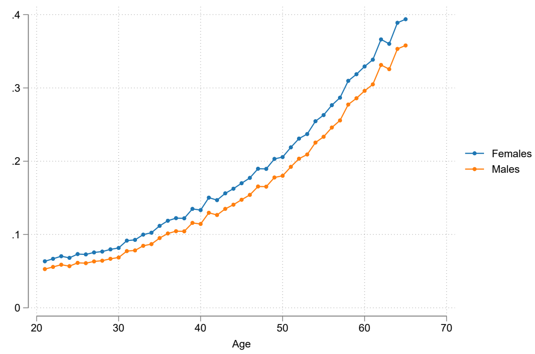
common among the youngest individuals and those who are young and disabled tend to have severe conditions. Disability becomes more common among older age groups, but the percentage of individuals with severe disability falls with age, until it flattens at about 50%.

One might wonder about the sources of reported 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[5]. 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).

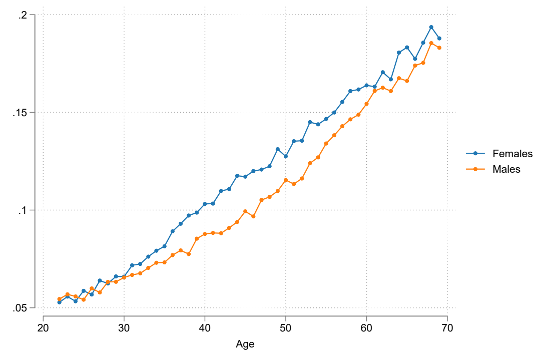
The comparison between **Figure 1a** and **Figure 1b** shows that the frailty index and reported disability have a similar evolution pattern, with both measures increasing significantly with age.

We build a metric that relies on a broad set of questions and captures the inception of physical and mental health conditions. To do so, we exploit the fact that, starting in 1999, PSID started asking participants whether they had been diagnosed a series of impairments. We then collect first-time diagnoses of physical

[5] Construction of the frailty index is described in Appendix [[Table 23 in their paper]]



(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.

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 age 18 and over in disability evaluation under Social Security.[6] 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 the construction of the health shock is shown in **Table A4**.[7]

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. The first six shocks in **Table A4** collect physical impairments that are likely to have a relatively immediate impact on the individual and are consistently reported. In particular, no difference with respect to prevalence in the general population across gender or race seem to be present in the reporting

[6]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`

[7]Some of these questions are also considered in the construction of the frailty index. We include a more extensive set of severe conditions and treat diagnoses of mental health disability in the same way as a severe diagnosis regarding physical health.

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

of cancers or impairments to the respiratory, cardiovascular or neurological systems.

In contrast, we see a strong gap in the occurrence of impairments of SSA category 12 (mental health related) across races. Disparity in diagnoses and treatment of mental health 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 underdiagnosed (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.

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 3** we look at the 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

We first study the effects of health deterioration on own earnings and hours using the specification:

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

where y_{it} is the outcome variable of interest. α_t is a time fixed effect, X_{it} is a set of explanatory variables that includes age, race, sex, education, state fixed effects and controls, when applicable, for wealth or income, indicators for being above Body Mass Index (BMI) of 30, or if individual is a smoker. We also include fixed effects for the most common held occupation, industry of employment, and family size. D_{kit} is an indicator variable that equals one when the individual i is k periods either (i) from disability onset or (ii) from a health shock depending on the specification.

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 the onset of disability or a health shock happening to either one parent:

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

where y_{it} is the daughter or son's outcome of interest. α_t is a time fixed effect, X_{it}^{own} is a set of explanatory variables relative to adult children that includes age, race, sex, education, state fixed effects, and $X_{it}^{parents}$ is a set of explanatory variables for parents that includes their state of residence, marital status, wealth, and some health controls (again if either is above BMI of 30, or if either is a smoker). D_{kit} is an indicator variable that equals one when the individual i is k periods from a health shock happening to either one of their parents.

We collect descriptive statistics on both the full sample and the subsample of individuals who are hit at least once by the health shock in **Table A2**. The share of surveyed individuals that receive at least one shock is about 25% and looks qualitatively very close to the full sample in our data. The "treated" individuals are marginally more likely to be white; they are eight years older on average and are more likely to have received a college education. Instead, indicators like BMI and smoking habits are not different across groups. Likewise, the occupational health hazard as defined by Michaud and Wiczer (2018)[8] does not vary, suggesting little predictability of our diagnose variable on health and lifestyle metrics. Reported income and wealth for the shocked individuals are slightly below the full average.

Because the average age of the diagnosed is close to the one of the full sample, differences in higher orders of the age distribution can be at play and can explain the reported differences. A possible issue is that the shocked sub-population represents old individuals more than proportionally, while the individuals who received a diagnosis tend, by definition, to have a lower life expectancy. We decompose income and wealth by age brackets in **Table A3.**. Conditional on looking at the same age brackets, we observe similar unemployment, income, and wealth numbers. The college education differentials exposed in the aggregate table

[8]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 is summarized in **Table A1**

are shown to depend mostly on composition effects.

In sum, the balancing exercise suggests that diagnosed individuals, prior to receiving the news of a serious illness, are not substantially different from those who will not receive such news. Nonetheless, in most of the paper, our empirical analysis will use the not-yet-treated as a control group to account for possible unobservable heterogeneity across groups. The approach implies constructing counterfactuals to affected households by using households that experience the same event a few years in the future (see Fadlon and Nielsen 2021), and therefore selects households that are fundamentally similar to each other.

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, some outcome variables are typically referred to the last completed year before the questions are asked, while health questions are normally referred to the present. In addition, taking leads and lags around events is complicated by the change in frequency that occurs after 1997. When looking at disability onsets, we harmonize the treatment variable pre-1997 so that the resulting series is consistent over time. This, however, implies that sometimes the estimates can suggest an anticipation of the effect that is not necessarily taking place 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 frequencies in the two year before or after the shock. The issue is less severe for the construction of health shocks from diagnoses that are consistently reported every two years because they are collected only from 1999 onwards.

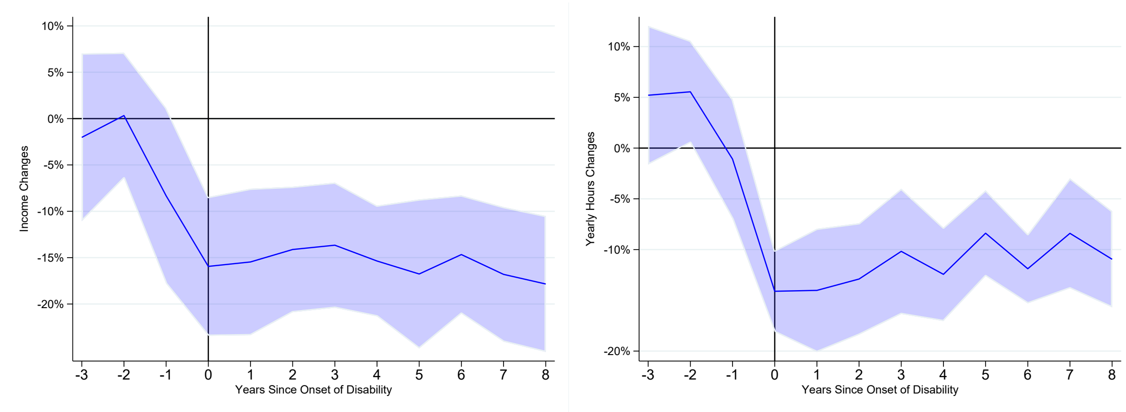
4 Family Responses to Severe Health Events

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, and estimate equation (1) under two different specifications. In the first case, we look at the onset of disability - hence the variable D_{kit} equals one when the individual i is k periods from the first time she responded affirmatively to the disability question in **Figure 1a**. To deal with unobserved heterogeneity in the control group, we restrict the sample to only individuals who will, at some point, report a disability. As a robustness check, we do the same analysis also conditional on individuals reporting a severe disability. The results on earnings and worked hours are displayed in **Figure 2**. The left panel reports the response of earnings, that is annualized labor income with business income.[9] The second panel shows the effect of disability onset on yearly hours, that is simply the sum of worked hours in the past year for individuals that are in the labor force.

Following the onset of disability, both hours and earnings decrease sharply, then relative earnings losses accumulate over time. The hours response likely captures an occupational or task shift, away from most demanding roles. This is consistent with the earnings dynamics, consistently drifting downwards, possibly as a result of diverging career paths for treated and non-treated individuals. Taking the extensive margin into account does not change the message: earnings decrease to a maximum

[9]It does not include sources of passive income, like rent or dividends. Values are expressed in 2015 US dollars.



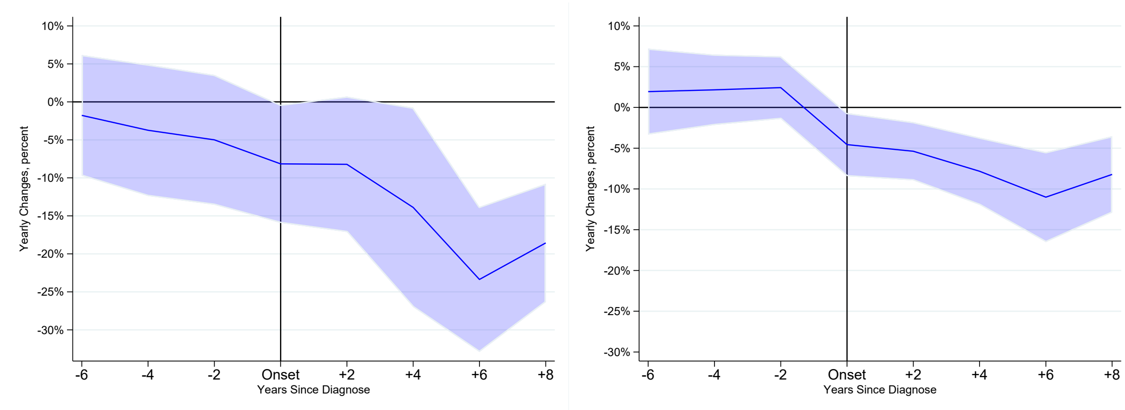
(a) Income **(b)** Hours Worked

Figure 2. Response to Disability Onset

Note: Sample: 1969-2019. All observations are conditional on disability turning severe. We observe individuals every year for the period 1968-1997, and every two years afterwards. We interpolate yearly values for 1999-2019. Control group is treated. Race, Sex, Year, Age, Education, State, Most common occupation when working, Family size dummies.

of 8% annually in the 8 years after onset. Labor participation also goes down by 5%.

We then estimate equation (1) using the health shock. Results are shown in **Figure** 3. While the hours response has a very similar magnitude, the build-up to the long run response of earnings is slower, consistent with the intuition that diagnoses can emerge before symptoms become severe enough (a discussion on the role of asymptomatic health risk in shaping the behavioral response to shocks is offered in Keane, Capatina, and Maruyama 2022). Underlying trends in the labor market could play a role, as the sample of health shocks covers the 1999-2019 period, while the disability regressions go as far as the 1960s. To the extent that labor market outcomes are more polarized in the last two decades, it is possible that the impact is larger in the most recent period. Another potential explanation lies in the fact that shocks themselves might be different, and that the health shock captures events that are more severe. This explanation would help reconcile our results with Fadlon and Nielsen (2021), who find an earnings impact of about 20% for the most



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

Figure 3. Response to Health Shock

Note: Sample: 1999-2019. Control group is treated. Detail in **Table 4**

severe onset of disability, and about 10% for the baseline case.

Detailed estimates are collected in **Table 4**. As evident from a back-of-the-envelope calculation, the impact of health shocks on income is mostly 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 A5** highlight how the extensive margin in hours simply mirrors an impact on employment - impacted workers leave work for a long time, and some might even stop working for good. A potential third channel, that is 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 stronger 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. Occupational shift within full-time employment is 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).

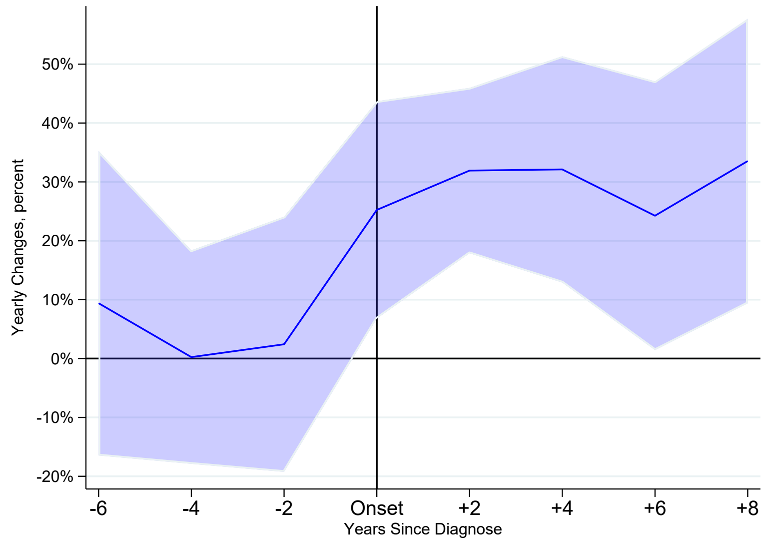


Figure 4. Response to Health Shock: Time Receiving Help

Note: Sample: 1999-2019. Control group is treated. Detail in **Table 4**

4.2 Inter-generational Linkages and Help

We then use the same specification to start looking at inter-generational linkages. **Figure 4** shows the effect on the time when individual has received help from relatives outside her own household. The measure does not speak to the magnitude of help - for instance, a "week of help" could indicate that a relative helped with medical expenses with a relevant sum of money, then the individual went back to economic self-sufficiency the following week. However, it does indicate that the family network provides sustained and persistent insurance: the time when individual receives help jumps up on impact and remains persistently higher even 8 or 10 years after the shock. In addition, **Table A5** provides the response on the extensive margin: while there is significant and positive response, most of this help happens to be concentrated on the intensive margin. In other words, transfer channels that were already operating prior to the shock are used more when the individual is hit.

Years Since Shock	Time Receiving Help	Hours		Income	
		all	> 0	all	> 0
-6	9.4	1.9	0.2	-1.8	-3.1
	(15.3)	(2.6)	(1.1)	(3.9)	(3.3)
-4	2.0	2.1	0.6	-3.7	-4.0
	(10.7)	(2.1)	(1.0)	(4.3)	(3.6)
-2	2.4	2.4	0.8	-5.0	-4.9
	(12.8)	(1.9)	(0.9)	(4.2)	(3.6)
0	25.2**	-4.6**	-0.7	-8.2**	-5.8
	(10.9)	(1.9)	(0.8)	(3.8)	(3.6)
2	31.9***	-5.4***	-0.0	-8.2*	-4.2
	(8.3)	(1.8)	(0.8)	(4.4)	(4.0)
4	32.1***	-7.8***	-1.0	-13.9**	-8.5
	(11.4)	(2.0)	(0.8)	(6.5)	(5.8)
6	24.3*	-11.0***	-1.6	-23.4***	-15.3***
	(13.5)	(2.7)	(1.1)	(4.7)	(4.4)
8	33.5**	-8.2***	-0.7	-18.6***	-13.6***
	(14.3)	(2.3)	(1.3)	(3.9)	(3.8)
Family Size FE	✓	✓	✓	✓	✓
Age FE	✓	✓	✓	✓	✓
Sex FE	✓	✓	✓	✓	✓
Race FE	✓	✓	✓	✓	✓
Education FE	✓	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Health Insurance	✓	✓	✓	✓	✓
N	37090	37404	32685	37414	32574

Percentage changes. Standard errors in parentheses

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

Table 4. Impact of Own Health Shocks. Age: 23-60. Standard errors are clustered by age. All values are expressed in percentage points. Sample: 1999-2019

4.3 Effect of Parental Shocks on Adult Children

The last paragraph establishes that other extended family members respond to a member's shock by providing help. But are they 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. The outcomes are calculated on the sample of working adult children, conditional on the parent surviving at least during the time window we observe (that is, eight years after the shock). We also restrict family structure to include only those in which both parents were present when the individual was growing up. [10] The baseline estimates, presented in **Figure 5**, 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 the impact 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 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.

However, the impact on hours indicates other channels potentially being at play. As shown in **Table 5**, the impact on hours is small and significant only at short horizons. Since different forces are active here, the null result might compound the response of some individuals who substitute work for care with

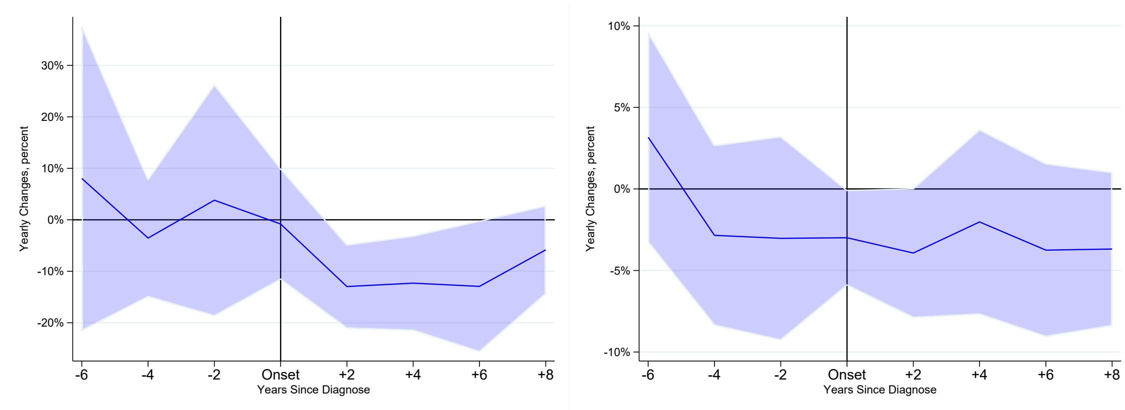
[10] We approach this restriction with two different strategies. A first strategy is to drop observations of individuals for which we observe no father. A second strategy is to keep only observations of individuals who cohabited with both their parents for at least some time before age 18. Both strategies allow for divorced parents. The main aim is to put aside, for now, families constituted of single mothers that receive, or expect to receive, no help from the father. The two strategies produce almost identical results.

Years Since Shock	Hours		Income	
	all	> 0	all	> 0
-6	3.1	0.9	10.2	8.3
	(3.2)	(1.6)	(12.7)	(10.0)
-4	-2.8	-1.7	-1.8	-0.4
	(2.7)	(1.4)	(5.1)	(3.9)
-2	-3.0	-0.6	6.8	6.7
	(3.1)	(1.4)	(9.9)	(8.1)
0	-3.0**	-1.5*	2.0	1.9
	(1.4)	(0.8)	(5.0)	(4.0)
2	-3.9*	-1.3	-10.3***	-6.5***
	(2.0)	(1.0)	(3.3)	(2.3)
4	-2.0	-0.9	-9.0**	-7.0**
	(2.8)	(1.2)	(3.5)	(2.8)
6	-3.8	-1.4	-10.0**	-7.8**
	(2.6)	(1.4)	(4.5)	(3.6)
8	-3.7	-0.9	-2.9	-2.0
	(2.3)	(0.9)	(4.0)	(3.5)
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	11054	10164	11066	10136

Standard errors in parentheses

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

Table 5. Impact of Health Shocks to Parents on non-cohabiting Adult Children. Age: 21-50. Conditional on having cohabited with both parents. Standard errors are clustered by age. All values are expressed in percentage points. Sample: 1999-2019



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

Figure 5. Response to Parents' Health Shock

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

those who increase participation as a response to a negative wealth shock. Two competing explanations for an effect on earnings but not hours can still be presented. For one, adult children's provision of informal care forces them into decisions about occupation or location that impact earnings per hour. For another, adult children could suffer income losses because of the loss of some implicit insurance provided by healthy parents, who would force them into careers that have lower long-term returns.

4.4 Impact on Wealth and Consumption

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 [11]. 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 6**. The impact suggests that either adult children are forced to support their parents

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

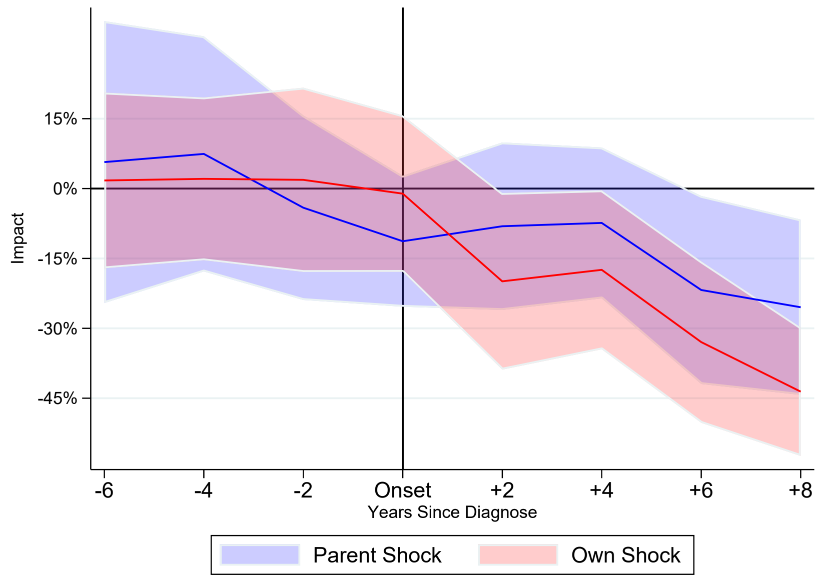
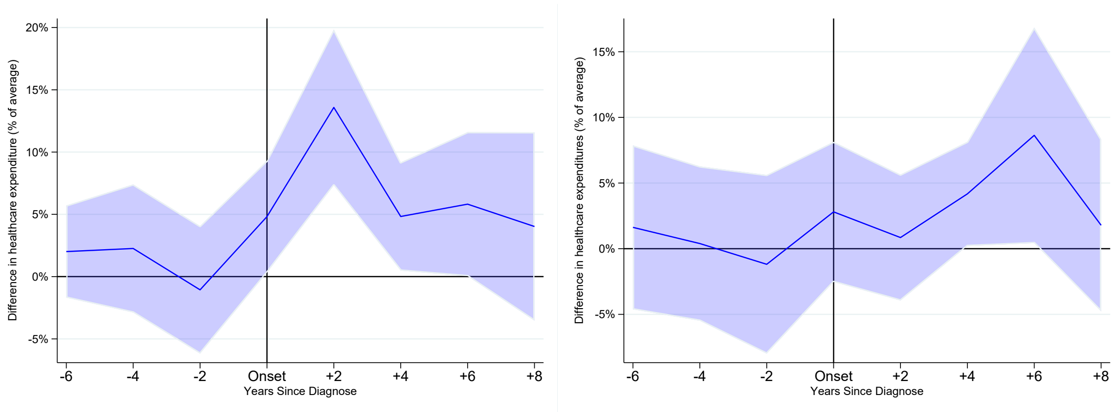


Figure 6. Wealth Response to Health Shock

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

monetarily, or that parents in bad health cannot offer the economic support (and transfers) they would otherwise provide. Because both parents and children suffer a decline in net wealth, both explanations are possible. This result points 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).

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** 7, we can see that health related expenditures, which include expenditures for hospital and nursing home, doctor, prescription drugs and insurance, rise immediately

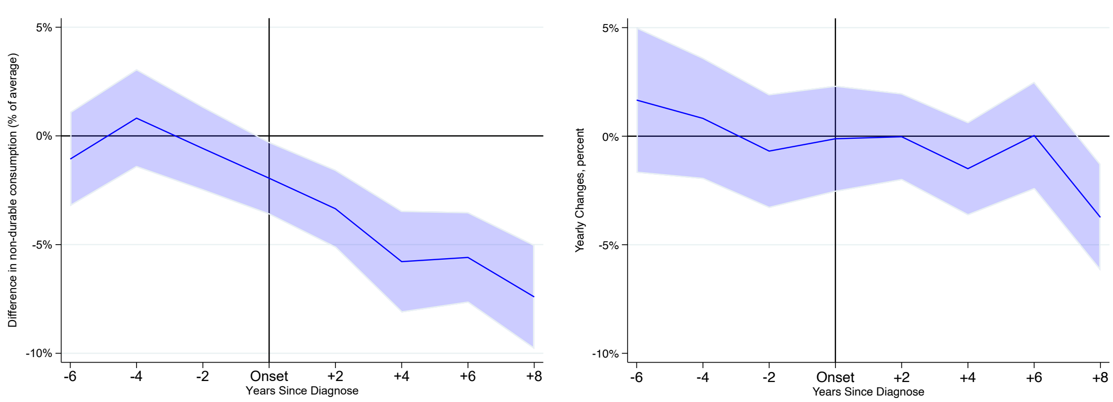


(a) Own Shock

(b) Parent's Shock

Figure 7. Health Related Expenditures Response to Own and Parents' Health Shock.

Note: Differences as percentage of average. Sample: 1999-2019. Control group is treated.



(a) Own Shock

(b) Parent's Shock

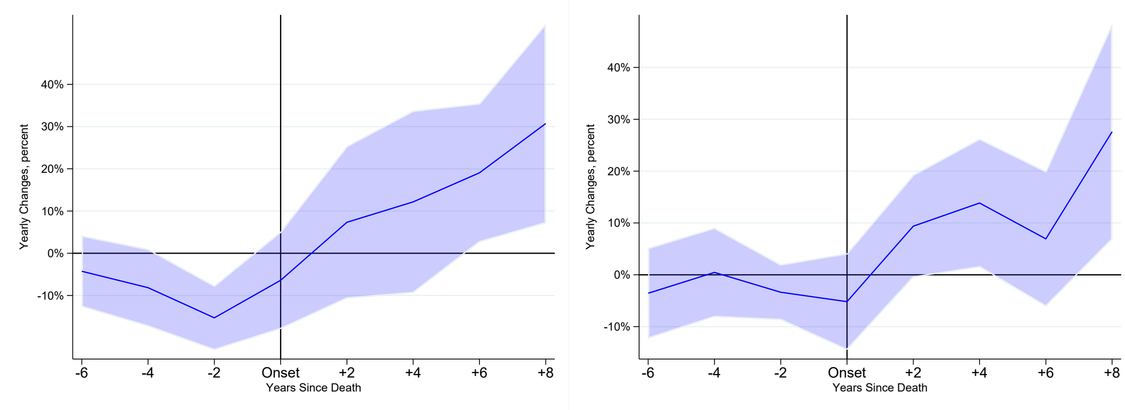
Figure 8. Consumption of Non-durable Goods and Services Response to Own and Parents' Health Shock, excluding health related expenses.

Note: Differences as percentage of average. Sample: 1999-2019. Control group is treated.

following own shock. Interestingly, adult children whose parents experience a health shock increase their health expenditures as well, but the effect starts being significant 4 years after the parent is diagnosed. While we interpret this is as evidence of intra-family monetary transfers, it is also reassuring to observe that the adult children start contributing *after* their parents have started to increase their spending, implying the transfer acts as a help of last resort, when the parent family is closer to distress. What about other components of non-durable and services consumption? In **Figure** 8 we report the impact on consumption of non-durable goods and services, excluding healthcare related expenses. Health shock 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. We know from **Figure** 5 that the income of adult children falls persistently after parents are hit by a health shock, but while their overall earning potential might not be as impacted, consumption falls less than their parents' and the change is not significant until the medium run. At that point, the disaccumulation of wealth, together with lower earnings and the increase in healthcare expenditures, are all consistent with a drop in non-health consumption, that we see becoming significant in year 8.

5 Fatal Shocks

In this section, we use the passing away of parents as an explanatory variable in the same vein as in equation (2). The objective is to discriminate between alternative explanations of our results. In particular, we wish to discriminate the implicit



(a) Income

(b) Hours Worked

Figure 10. Response to Parents' Death

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

insurance channel from the informal care channel[12]. The effects on income and employment are displayed in **Figure 10** and **Table 6**. The passing away of a parent produces a strong labor supply response that drives a substantial increase in earnings. This finding is compatible with a wealth effect, while it provides a significant challenge to the implicit insurance or the parents' network assumption. In addition, we see that income and hours are both declining before the event, which is consistent with some deaths being due to a gradual worsening of health conditions and thus to the informal care channel playing a role in adult children's labor market outcomes.

[12] A parent passing away implies a potential reduction in transfers, especially in the long run, which should work as a wealth shock. However, a similar channel is at play when a health shock hits parents since we know from previous chapters that the effect on earnings and wealth of parents is strong on impact. In that sense, the ability of the death shock to discriminate between the other two channels should remain intact.

6 Heterogeneous Effects Within the Family

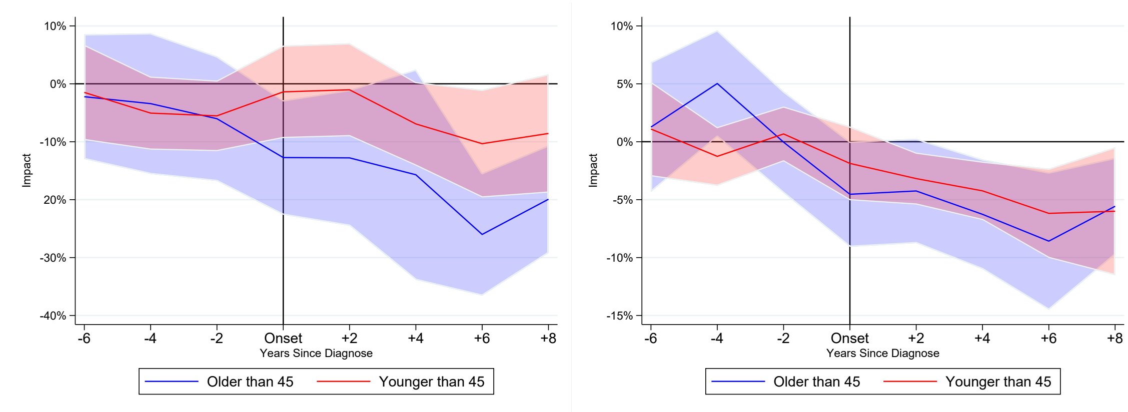
We extend the standard D-in-D into triple D-in-D to add another layer of heterogeneous treatment effect - the heterogeneity across family members. This implies running the following specification:

$$y_{it} = \alpha_t + X_{it}^{own}\beta_1 + X_{it}^{parents}\beta_2 + \gamma F_i + \sum_k \delta_{1,k} D_{kit} + \sum_k \delta_{2,k} F_i D_{kit} + \epsilon_{it} \tag{3}$$

where F_i is the group variable of the individual. The interaction term should not only highlight the differential impact on each group of interest, but also help us further discriminate between competing channels that produce our results. We first run specification in equation 3 by looking at own shocks. We look at interactions with age, marriage status, gender and education. While there is no noticeable difference in the effects among gender and education, age and family structure interact with health shocks. First, older workers suffer more from health shocks. Their response is significantly stronger in the earnings dimension, only in part due to a stronger hours response. This is consistent with health deteriorating more rapidly in older age, and as thus could simply show that older individuals are simply facing a shock that is somehow different in nature. The differential impact across marriage status offers a less straightforward dynamics: while the income overall has a similar response, singles respond more. This suggests the income response differential might come from occupational reallocation, suggesting a stronger attachment to the labor force of married individuals. [13]

We then run again specification in equation 3 on parents' shocks. This time the

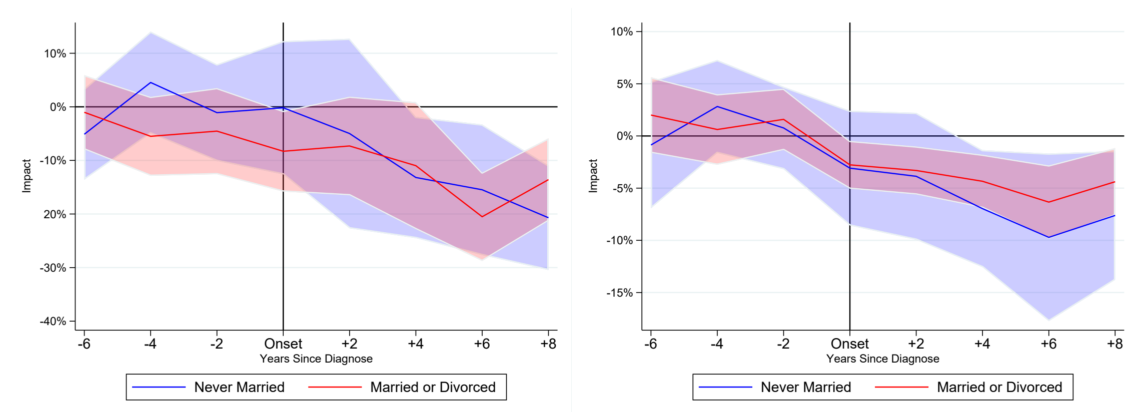
[13] This result is apparently in contradiction with the idea that singles, having no additional income to support themselves, would be less prone to move their labor supply - see Lundberg (1985). However, the picture can be more complicated if we account for the fact that married couples might have competing care demand by their kids.



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

Figure 12. Own Shock: Response by Age Group

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

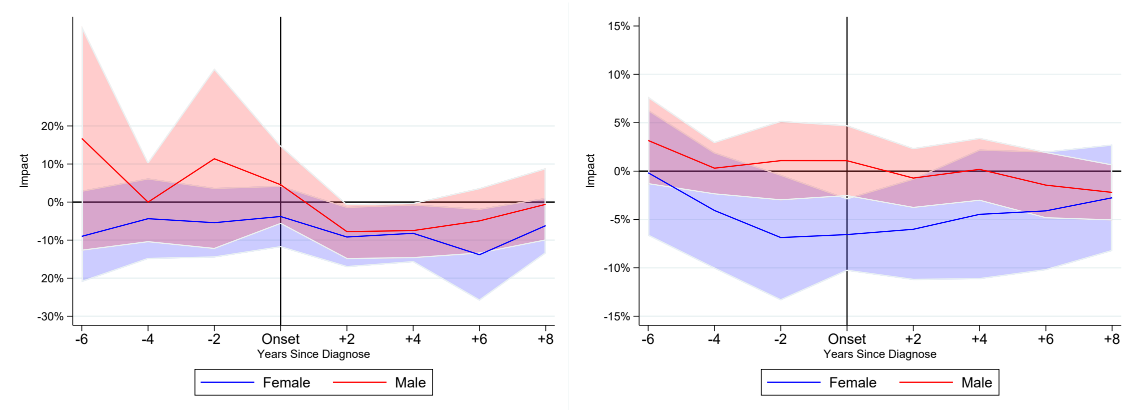


(a) Income **(b)** Hours Worked

Figure 14. Own Shock: Response by Marriage Status

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

set of interaction variables includes: whether the adult child has kids of her own, her marriage status, gender, age group, and education, whether parents face severe disability after the shock, and finally if the adult child lives in the same state as the shocked parent. We detect no significant heterogeneity across the presence of kids, nor between age groups. We observe small differences between female and male adult children, with the latter suffering more persistent effects on incomes mostly



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

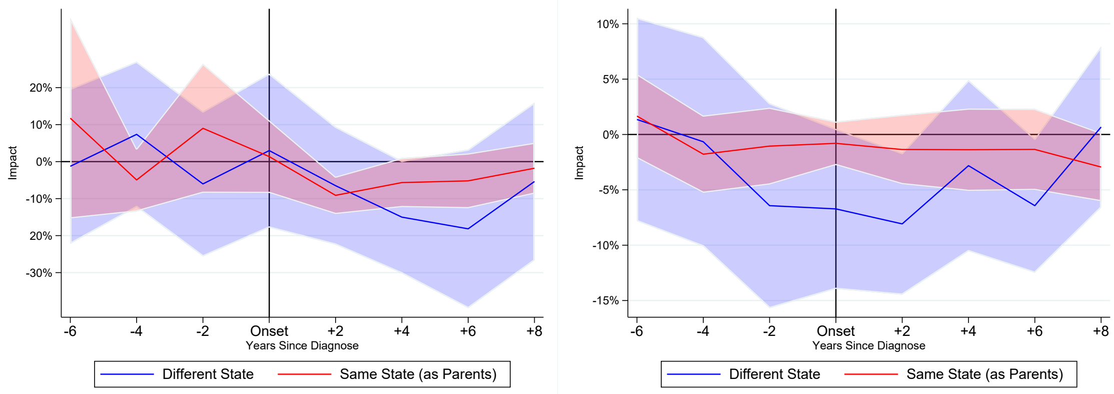
Figure 15. Parent's Shock: Response by Gender

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

through a reduction in hours. This is consistent with the informal care hypothesis, since female workers are often secondary earners and are thus relatively more likely to respond to a higher informal care demand from relatives by reducing employment.

When looking at the differential impacts of health shocks across state of residence, the importance of informal care networks is coming again as a potential explanation. Longer distance from parents amplify the effect of health shocks, with children reducing hours significantly more, and suffering larger income losses later in time. Whether this is due to a forced relocation of adult children or occupational switches will require additional investigation.

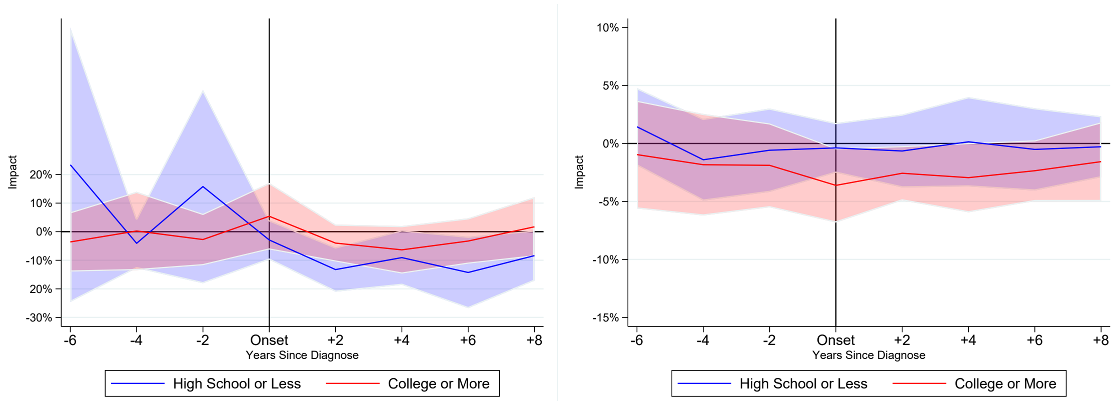
The role of education does in fact suggest that occupational characteristics could help explain differential impacts across adult children. In **Figure 18** we see that while non-college educated workers are hit harder at all horizon when a parent is suffering a health shock, college-educated workers respond by reducing hours on the intensive margin. Frictions in the ability to reduce working hours while keeping the same job might be occupation-specific, and this suggests hours flexibility could be the main factor behind the differential impact across education groups.



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

Figure 16. Parent's Shock: Response by Place of Residence

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



(a) Income **(b)** Hours Worked (> 0)

Figure 18. Parent's Shock: Response by Education

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

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 6. 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

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, the role of occupational switches into more flexible occupations, and the role played by differences in household wealth and income.

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Appendices

A Data

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

. 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.

Table A1. Occupational Hazard Classification

Note: This table is based on HRS data and calculations from Michaud and Wiczer (2018)

	Full Sample		Active Labor Force	
	All	Diagnosed	All	Diagnosed
A. Demographics				
Age	41	49	40	49
Male	45%	45%	47%	48%
White	61%	66%	62%	66%
Family Size	2.92	2.91	2.97	2.96
Marital Status (head)				
Married	64%	67%	66%	68%
Separated, Divorced	15%	16%	14%	15%
Single	17%	14%	18%	15%
Other	4%	3%	2%	2%
B. Income and Wealth				
Unemployment	6%	6%	7%	7%
Labor Income (/000)	\$30	\$29	\$40	\$39
Wealth (family, /000)	\$165	\$182	\$147	\$161
C. Other				
College	37%	26%	37%	28%
BMI > 30	22%	21%	22%	22%
Ever Smoked	30%	35%	28%	32%
Occupation Hazard	0.13	0.13	0.13	0.13
Individual Obs.	26,212	8,549	22,761	7,461

Source: Panel Study of Income Dynamics (1999 - 2019). Monetary values are in 2009 US dollars. Sample: All surveyed individuals age 18-79. Diagnosed: individuals who will receive one of the diagnoses as described in **Table A4** at some point in their life.

Table A2. Descriptive Statistics

	Full Sample		Active Labor Force	
	Non-Treated	Treated*	Non-Treated	Treated*
A. Income and Wealth				
Unemployment				
Age 30-40	8.5%	7.5%	8.8%	8.0%
Age 40-50	6.3%	6.2%	7.0%	6.8%
Age 50-60	4.4%	4.0%	4.7%	4.4%
Labor Income (/000)				
Age 30-40	$32	$31	$35	$33
Age 40-50	$34	$34	$38	$37
Age 50-60	$37	$40	$45	$45
Wealth (family, /000)				
Age 30-40	$48	$39	$46	$36
Age 40-50	$55	$38	$54	$38
Age 50-60	$143	$142	$136	$130
B. Education				
College				
Age 30-40	28%	27%	29%	27%
Age 40-50	25%	24%	26%	24%
Age 50-60	30%	32%	33%	33%
Individual Obs.	26,212	8,549	22,761	7,461

*: Values for treated individuals are calculated for the periods preceding the shock.
Source: Panel Study of Income Dynamics (1999 - 2019). Monetary values are in 2009 US dollars.
Sample: All surveyed individuals age 18-79.

Table A3. Balancing

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 A4. PSID questions to build the health shock

Years Since Shock	Receiving Help	Employment	Participation
-6	0.5	0.2	1.0
	(0.6)	(1.2)	(0.8)
-4	0.7	0.1	0.8
	(0.5)	(0.1)	(0.7)
-2	0.6	-0.5	0.3
	(0.5)	(0.7)	(0.7)
0	1.4***	-2.0**	-1.8**
	(0.5)	(1.0)	(0.8)
2	1.4**	-2.5**	-3.1***
	(0.6)	(0.1)	(0.6)
4	1.3**	-3.5***	-2.2***
	(0.6)	(1.0)	(0.8)
6	0.6	-3.9***	-3.0***
	(0.5)	(1.2)	(1.0)
8	0.9	-1.3	-1.5
	(0.6)	(1.0)	(1.0)
Family Size FE	✓	✓	✓
Age FE	✓	✓	✓
Sex FE	✓	✓	✓
Race FE	✓	✓	✓
Education FE	✓	✓	✓
Occupation FE	✓	✓	✓
State FE	✓	✓	✓
Year FE	✓	✓	✓
Health Insurance	✓	✓	✓
N	23884	24126	24385

Percentage Changes. Standard errors in parentheses

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

Table A5. Response to Own Shock: Additional Results

Years Since Shock	Income		Hours	
	all	> 0	all	> 0
-6	-5.1	-3.8	-0.9	0.3
	(4.2)	(3.2)	(3.0)	(1.6)
-4	4.5	0.9	2.8	-0.1
	(4.7)	(3.9)	(2.2)	(1.2)
-2	-1.0	0.0	0.8	1.7
	(4.4)	(3.7)	(1.9)	(1.2)
0	-0.2	3.2	-3.1	0.8
	(6.1)	(4.7)	(2.7)	(1.7)
2	-5.0	-1.5	-3.9	-0.7
	(8.7)	(7.4)	(3.0)	(1.8)
4	-13.2**	-7.8*	-7.0**	-0.7
	(5.6)	(4.6)	(2.8)	(1.6)
6	-15.5**	-7.1	-9.7**	-2.3
	(6.0)	(5.1)	(4.0)	(2.2)
8	-20.7***	-15.7***	-7.6**	-1.5
	(4.8)	(4.2)	(3.0)	(2.1)
$-6 \times$ married	2.8	0.2	2.6	-0.1
	(6.4)	(4.8)	(3.5)	(1.8)
$-4 \times$ married	-15.8**	-9.9*	-2.5	0.6
	(6.3)	(4.9)	(2.6)	(1.6)
$-2 \times$ married	-7.6	-6.1	-1.0	-1.5
	(6.3)	(4.9)	(2.0)	(1.4)
$0 \times$ married	-13.5	-13.2	-0.3	-1.9
	(9.3)	(7.9)	(2.6)	(1.9)
$2 \times$ married	-7.5	-4.9	-0.3	1.0
	(13.2)	(11.3)	(3.3)	(2.2)
$4 \times$ married	-4.8	-2.9	1.8	-0.4
	(9.2)	(8.7)	(2.8)	(1.8)
$6 \times$ married	-17.8**	-15.3***	2.4	0.9
	(7.6)	(5.6)	(4.2)	(2.3)
$8 \times$ married	-1.9	-0.2	2.4	1.1
	(8.4)	(7.4)	(3.4)	(2.1)
Family Size FE	✓	✓	✓	✓
Age FE	✓	✓	✓	✓
Sex FE	✓	✓	✓	✓
Race FE	✓	✓	✓	✓
Education FE	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Health Insurance	✓	✓	✓	✓
N	40156	34954	40146	35110

Standard errors in parentheses

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

Table A6. Response to Own Shock: Heterogeneous Effects by Marriage Status

Years Since Shock	Income		Hours	
	all	> 0	all	> 0
-6	-2.2	-3.4	1.3	-0.5
	(5.3)	(3.9)	(2.8)	(1.1)
-4	-3.4	-4.3	5.0**	1.7
	(6.0)	(4.3)	(2.3)	(1.3)
-2	-6.0	-3.0	0.0	1.2
	(5.3)	(4.2)	(2.2)	(0.9)
0	-12.7**	-8.0**	-4.5*	-0.841
	(4.9)	(3.9)	(2.2)	(1.0)
2	-12.8**	-6.9	-4.3*	0.2
	(5.8)	(4.6)	(2.2)	(1.0)
4	-15.7*	-8.9	-6.3**	-0.8
	(9.0)	(6.9)	(2.3)	(1.0)
6	-26.0***	-15.6***	-8.6***	-0.8
	(5.2)	(4.3)	(2.9)	(1.2)
8	-20.0***	-13.1***	-5.6**	0.2
	(4.6)	(3.7)	(2.0)	(1.2)
$-6 \times$ young	-0.4	1.8	-0.2	1.6
	(6.4)	(4.6)	(3.7)	(1.6)
$-4 \times$ young	-3.1	0.3	-7.3**	-2.6
	(6.6)	(4.7)	(3.0)	(1.6)
$-2 \times$ young	1.9	-0.1	0.3	-1.0
	(6.2)	(4.6)	(2.7)	(1.3)
$0 \times$ young	11.8*	8.0	2.1	0.8
	(6.2)	(4.8)	(3.3)	(1.7)
$2 \times$ young	11.7*	8.0	-0.3	-0.3
	(6.8)	(5.6)	(2.8)	(1.5)
$4 \times$ young	8.0	5.4	0.0	-0.2
	(9.0)	(7.0)	(3.0)	(1.2)
$6 \times$ young	14.0**	9.9*	-0.7	-1.9
	(6.5)	(5.3)	(4.0)	(2.1)
$8 \times$ young	10.1	7.5	-3.3	-2.8
	(7.6)	(6.3)	(4.6)	(3.0)
Family Size FE	✓	✓	✓	✓
Age FE	✓	✓	✓	✓
Sex FE	✓	✓	✓	✓
Race FE	✓	✓	✓	✓
Education FE	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Health Insurance	✓	✓	✓	✓
N	40156	34954	40146	35110

Standard errors in parentheses

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

Table A7. Response to Own Shock: Heterogeneous Effects by Age

Years Since Shock	Income		Hours	
	all	> 0	all	> 0
-6	-5.833	-7.117**	1.335	-0.0617
	(3.474)	(2.802)	(1.579)	(0.820)
-4	-6.363*	-7.580***	1.219	-0.495
	(3.367)	(2.727)	(1.582)	(0.952)
-2	-8.076***	-5.606**	-0.263	0.663
	(2.832)	(2.444)	(1.447)	(0.772)
0	-9.030***	-6.093**	-4.081**	-1.035
	(2.928)	(2.651)	(1.634)	(1.024)
2	-12.56***	-6.621*	-4.597***	0.167
	(4.230)	(3.505)	(1.452)	(0.826)
4	-15.20***	-9.494**	-6.105***	-1.032
	(5.509)	(4.379)	(1.533)	(0.956)
6	-22.14***	-12.90***	-8.498***	-1.000
	(4.589)	(4.000)	(2.201)	(1.187)
8	-21.66***	-14.91***	-7.006***	-0.0889
	(3.019)	(2.693)	(1.965)	(1.433)
$-6 \times$ college	11.75	13.89*	-1.426	1.235
	(10.58)	(7.990)	(2.297)	(1.281)
$-4 \times$ college	1.577	6.959	-0.648	2.951*
	(10.01)	(7.351)	(2.164)	(1.717)
$-2 \times$ college	8.497	6.051	1.094	-0.103
	(11.19)	(8.815)	(2.241)	(1.789)
$0 \times$ college	0.451	1.249	3.121	1.771
	(12.31)	(10.21)	(2.348)	(1.957)
$2 \times$ college	12.59	7.820	2.493	-0.607
	(15.21)	(12.28)	(2.240)	(1.597)
$4 \times$ college	-0.797	1.019	2.047	0.255
	(18.76)	(15.87)	(2.845)	(1.751)
$6 \times$ college	-15.98	-14.29	2.595	-2.102
	(10.54)	(9.151)	(3.057)	(2.309)
$8 \times$ college	3.628	-0.596	4.935	-2.293
	(14.90)	(11.51)	(3.563)	(2.589)
Family Size FE	✓	✓	✓	✓
Age FE	✓	✓	✓	✓
Sex FE	✓	✓	✓	✓
Race FE	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Health Insurance	✓	✓	✓	✓
N	40156	34954	40146	35110

Standard errors in parentheses

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

Table A8. Response to Own Shock: Heterogeneous Effects by Education

Years Since Shock	Income		Hours	
	all	> 0	all	> 0
-6	-1.9	-1.8	-1.1	-0.9
	(3.5)	(2.8)	(2.3)	(1.2)
-4	-1.2	-2.0	-0.2	-0.7
	(3.8)	(2.6)	(2.2)	(1.1)
-2	-0.6	-1.0	-0.6	0.0
	(3.7)	(2.9)	(1.9)	(0.9)
0	-4.9	-2.8	-4.8**	-1.6
	(3.3)	(2.6)	(2.0)	(1.2)
2	-5.3	-2.1	-4.0*	-0.4
	(5.1)	(4.7)	(2.1)	(1.2)
4	-11.9**	-8.3**	-4.6*	-0.8
	(4.9)	(3.7)	(2.3)	(1.2)
6	-17.3***	-9.9**	-8.7***	-1.5
	(5.0)	(4.2)	(2.7)	(1.3)
8	-12.6***	-8.8**	-4.4*	1.4
	(4.5)	(3.5)	(2.6)	(1.6)
$-6 \times$ male	-3.7	-4.3	5.1*	2.8
	(11.6)	(9.4)	(2.7)	(1.7)
$-4 \times$ male	-13.2	-9.3	3.2	2.5
	(11.3)	(8.0)	(2.6)	(1.6)
$-2 \times$ male	-14.0	-7.2	1.6	1.6
	(10.4)	(7.8)	(2.4)	(1.4)
$0 \times$ male	-11.4	-7.6	2.8	2.2
	(11.2)	(8.5)	(2.7)	(1.6)
$2 \times$ male	-12.0	-6.5	-0.5	1.0
	(13.4)	(10.4)	(3.0)	(1.9)
$4 \times$ male	-11.5	-3.6	-3.5	-0.5
	(16.5)	(12.4)	(3.7)	(1.8)
$6 \times$ male	-25.0**	-17.0*	0.1	-0.4
	(11.0)	(8.9)	(3.2)	(1.5)
$8 \times$ male	-23.3*	-15.8	-4.8	-4.6*
	(13.4)	(10.0)	(3.7)	(2.3)
Family Size FE	✓	✓	✓	✓
Age FE	✓	✓	✓	✓
Race FE	✓	✓	✓	✓
Education FE	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Health Insurance	✓	✓	✓	✓
N	40156	34954	40146	35110

Standard errors in parentheses

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

Table A9. Response to Own Shock: Heterogeneous Effects by Gender

Years Since Shock	Income		Hours	
	all	> 0	all	> 0
-6	-1.3	-1.9	1.4	-0.3
	(10.3)	(7.6)	(4.5)	(3.2)
-4	7.4	5.5	-0.7	-0.7
	(9.7)	(7.6)	(4.6)	(3.4)
-2	-6.0	-5.3	-6.4	-5.2*
	(9.6)	(7.2)	(4.5)	(2.6)
0	3.0	2.0	-6.7*	-4.4*
	(10.2)	(8.1)	(3.5)	(2.6)
2	-6.5	-1.7	-8.0**	-2.5
	(7.8)	(6.0)	(3.1)	(2.3)
4	-15.0*	-10.6*	-2.8	-1.3
	(7.5)	(5.6)	(3.8)	(2.6)
6	-18.2*	-12.6	-6.4**	-3.0
	(10.5)	(8.0)	(3.0)	(2.4)
8	-5.4	-2.8	0.7	2.7
	(10.5)	(8.6)	(3.6)	(2.1)
$-6 \times$ same state	13.0	11.0	0.7	1.1
	(17.3)	(13.6)	(4.9)	(3.6)
$-4 \times$ same state	-12.3	-8.8	-1.5	-1.2
	(10.3)	(8.0)	(5.4)	(3.9)
$-2 \times$ same state	15.0	13.3	5.2	5.4**
	(10.4)	(8.3)	(4.6)	(2.6)
$0 \times$ same state	-1.6	-1.1	5.7	3.6
	(12.5)	(9.7)	(4.2)	(2.8)
$2 \times$ same state	-2.6	-4.6	6.4	1.5
	(8.3)	(6.3)	(4.2)	(2.6)
$4 \times$ same state	9.4	6.1	1.1	0.3
	(8.5)	(6.6)	(4.6)	(3.0)
$6 \times$ same state	13.0	8.5	4.8	2.3
	(10.9)	(8.3)	(3.9)	(2.7)
$8 \times$ same state	3.6	1.2	-4.3	-4.6*
	(11.4)	(9.1)	(4.3)	(2.4)
Sex FE	✓	✓	✓	✓
Age FE	✓	✓	✓	✓
Race FE	✓	✓	✓	✓
Education FE	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Health Insurance	✓	✓	✓	✓
Has Kids	✓	✓	✓	✓
Has Siblings	✓	✓	✓	✓
Married	✓	✓	✓	✓
N	11014	10122	11002	10150

Standard errors in parentheses

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

Table A10. Response to Parent's Shock: Heterogeneous Effects by Place of Residence

Years Since Shock	Income		Hours	
	all	> 0	all	> 0
-6	23.4	18.1	3.8	1.4
	(23.6)	(18.3)	(2.5)	(1.6)
-4	-4.1	-3.6	-0.6	-1.4
	(4.3)	(3.1)	(2.3)	(1.7)
-2	15.8	14.2	-2.1	-0.6
	(16.6)	(13.6)	(2.8)	(1.8)
0	-2.9	-1.3	-2.0	-0.4
	(3.4)	(2.7)	(1.6)	(1.1)
2	-13.3***	-8.1***	-2.6	-0.6
	(3.8)	(2.9)	(2.2)	(1.5)
4	-9.1*	-5.4	-2.0	0.1
	(4.7)	(3.8)	(2.8)	(1.9)
6	-14.3**	-9.2*	-3.0	-0.5
	(6.1)	(4.6)	(2.5)	(1.7)
8	-8.4*	-6.5*	-2.0	-0.3
	(4.3)	(3.3)	(2.2)	(1.3)
$-6 \times$ college	-31.4	-24.4	-4.8	-2.4
	(28.2)	(21.4)	(4.5)	(2.8)
$-4 \times$ college	4.6	5.8	-3.1	-0.5
	(17.1)	(13.1)	(3.3)	(3.2)
$-2 \times$ college	-21.9	-19.0	-0.8	-1.4
	(20.0)	(16.1)	(4.0)	(2.7)
$0 \times$ college	14.9	8.0	-0.9	-3.4
	(13.7)	(10.2)	(2.9)	(2.3)
$2 \times$ college	4.4	2.0	-1.5	-2.0
	(8.3)	(6.2)	(3.3)	(2.2)
$4 \times$ college	-5.1	-7.9	0.0	-3.2
	(11.1)	(9.0)	(4.0)	(2.8)
$6 \times$ college	7.0	1.2	0.6	-1.9
	(9.9)	(8.0)	(3.0)	(2.0)
$8 \times$ college	12.2	9.5	-1.4	-1.4
	(13.6)	(10.5)	(3.8)	(2.5)
Sex FE	✓	✓	✓	✓
Age FE	✓	✓	✓	✓
Race FE	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Health Insurance	✓	✓	✓	✓
Has Kids	✓	✓	✓	✓
Has Siblings	✓	✓	✓	✓
Married	✓	✓	✓	✓
N	11014	10122	11002	10150

Standard errors in parentheses

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

Table A11. Response to Parent's Shock: Heterogeneous Effects by Education

B A Simple Model of Altruism and Health

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:

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

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

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:

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

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