FAMILY SPILLOVERS IN HEALTHCARE CONSUMPTION:
EVIDENCE FROM A SOUTHERN HEALTHCARE PAYOR

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Abstract

This paper studies how family spillovers affect healthcare consumption through behavioral changes where risks and consequences of health events are shared and transmitted in the family. By exploiting an unpredictable shock, a heart attack, to a family member, I draw a causal link to their dependents' average medical expenditures. The spouse's heart attack is used as a source of exogenous variation in healthcare consumption of non-injured family members since this event is relatively unpredictable and random for non-injured family members. Under this setting, I aim to compare the healthcare consumption in the pre- and post-shock periods to estimate family spillovers. For this purpose, I use claims data provided by a southern healthcare payor in the U.S. providing detailed information on the healthcare consumption of family members and various member-level characteristics, such as demographic and socioeconomic characteristics, chronic conditions, and income. I employ an OLS regression to compare the average health consumption before and after the spouse's heart attack. The results show that the family spillover effect has a statistically significant and positive impact on non-injured family members' healthcare consumption. In particular, I find that non-injured family members increased their average medical expenses by $571 in the post-period of their spouses' heart attack relative to prior to the health shock. Moreover, I explore the effect of the health shock on different subgroups. The following subgroups show a statistically significant increase in average medical expenses after experiencing a health shock: individuals without chronic conditions, individuals who identify as White, females, and those with lower levels of education.

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1 Introduction

The spillover effect is often used to describe a phenomenon in which an event in one setting affects another setting that may seem unrelated at first glance. In the healthcare industry, the spillover effect may occur in several ways. For example, changes in the healthcare consumption of a patient may have health implications for a wider social network around the patient. Deri (2015), using data from the Canadian National Population Health Survey, found that a patient's healthcare utilization—measured by the office visits—changed by the behavior of other individuals around him. Debnath and Jain (2020), using administrative claims data from a publicly financed tertiary healthcare program in India, found that peers increase awareness of the tertiary healthcare program and increase program utilization. On the other hand, Ali and Dwyer (2010) focus more on the negative health impacts of the spillover effect and show that social networks increase the likelihood of drinking participation among adolescents.

Although the impact of social networks has been increasingly recognized in healthcare utilization, relatively little attention is given to the role of family. The effect of an illness experienced by a family member may impose positive or negative externalities on other family members, such as experiencing the psychological impact of the illness, reduced productivity and time costs, or reduced quality of life due to caring for the ill family member. These consequences are known as "family-spillover effects" that has been well documented (Krol et al., 2015; Rainville et al., 2016) but not thoroughly analyzed empirically (Leech et al., 2022).

This paper aims to examine how health shocks to a family member trigger changes in other family members' healthcare consumption through behavioral changes. The identifying strategy in this paper exploits an unpredictable shock, a heart attack, to a family member that allows estimating how a non-injured family member's (spouse or dependent) healthcare consumption changes after this sudden health event. Specifically, I use the spouse's heart attack as a source of exogenous variation in healthcare consumption of non-injured family members since the spouse's heart attack is relatively unpredictable and effectively random for other family members. I use an OLS regression with a dummy variable that takes a value of one for the period after the spouse's (or dependent's) heart attack and a value of zero before the heart attack to observe changes in non-injured family members' healthcare consumption, such as medical expenditures and office visits.

A health event experienced by one family member affects relatives through at least two channels; the behavioral and learning channels. The first channel occurs because people adopt behaviors after sudden health shocks due to the risks and consequences of these events. To better understand this channel, one can envision spouses (i.e., two non-blood-related family members) with almost perfect information about each other's potential health-related risk factors before and after the sudden health shock. In this picture, if a change is observed in the healthcare consumption of the family member who does not directly experience the health shock, but is indirectly affected by the consequences and fears of this event, then the observed change cannot be rationalized by the difference in the health condition of this family member. Instead, a valid explanation is that the spouse's experience of the health shock increases the other family member's attention to his own health risks. In other words, the sudden health event in this picture acts as leverage in increasing the other family member's awareness of his own health risks. The family behavior-related spillover channel is guided by the studies of Fadlon and Nielsen (2019), who estimate the causal impact of a health shock to an individual on their family members' consumption of preventive care. Using a long panel of administrative data covering the Danish population, they found that spouses immediately increase their health investments and improve their health behaviors in response to shocks (Fadlon and Nielsen, 2019).

The learning spillover channel operates in several ways. First, a sudden health event causes information transfer. To better illustrate this channel, I will continue the same scenario provided above with an additional assumption that the spouses share the same insurance plan. In this picture, information transmission occurs after the sudden health event because both family members gain more knowledge about the administrative work, logistics, and healthcare providers. This new information lowers search-time costs not only for the injured family member but also for non-injured family members, who also gain information about the plan's cost structure and how it operates. For instance, the non-injured family member can learn how to file a claim or how the payment process works. As suggested by Levy and Janke (2016), the more individuals gain health literacy, the less likely they delay getting care or routine screenings.

This paper focuses on the first channel (i.e., behavioral spillover channel)[1] and empirically studies the spillover effect by leveraging detailed claims data provided by a southern healthcare payor in the U.S. This dataset makes it suitable for studying behavioral family spillovers because it makes it possible to identify family members who share the same health insurance plan, i.e., spouses or dependents. The data provide detailed information on the healthcare consumption of those family members whose dependents' experienced a heart attack. This rich data also makes it possible to control for individual differences such as gender, age, race, chronic conditions, and income.

This study makes several contributions to the literature. First, to the best of my knowledge, this paper is the first to analyze family-spillover effects using administrative claims data rather than experimental data in the U.S. The second contribution of this paper is that it uses a wide array of control variables including the Social Vulnerability Index (SVI) and healthcare cost risk score, which were not used in the literature before. Finally, this paper also contributes to the literature by providing a clearer picture of the role of family-spillover effects in medical expenditure changes by looking at its effect on different subgroups. In particular, I explore the differences in medical expenditure changes after the health shock between people with and without chronic conditions, females and males, different race categories, the lowest and highest income quartiles, and finally, different education levels.

The remainder of the paper is organized as follows. Section 2 describes the features of the claims data provided by the southern healthcare payor, which made it possible to study family spillovers. Section 3 details the sample selection, methodology, and descriptive statistics. Section 4 describes the empirical strategy and presents the main results. Finally, Section 5 concludes the paper.

[1] It is challenging to observe which channel is causing the estimated changes. However, all the explanations in this paper are based on the behavioral spillover channel.

2 Data

The claims data from a southern healthcare payor in the U.S. is the source of information for the analysis provided in this paper. The claims data includes information on the employees of a large American retail corporation who purchase health insurance from this healthcare payor. This healthcare payor, a not-for-profit mutual insurance company, is one of the largest health insurers in its region. It offers health insurance policies for individuals and families who purchase their insurance directly and those whose insurance coverage is provided through their employer.

The data includes the period from 2019 to 2021. There are three main advantages of this data. First, it allows me to obtain information about family members who share the same insurance plan. Second, it is rich claims data that makes it possible to obtain information on specific healthcare services utilized, allowing me to identify the diagnosis. Third, it includes various member-level characteristics, such as demographic and socioeconomic characteristics, chronic conditions, and income. These characteristics allow me to control for differences between members. These three advantages of the data enable me to study family health spillovers and hence offer an opportunity for the current research.

I use a spouse's heart attack, i.e., myocardial infarction, to identify a family health shock. Heart attack is one of the most common health events used in the literature to identify family health shocks (Gupta et al., 2015; Johanna, 2017; Fransoo, 2018; Hodor, 2021). That is due to this disease's limiting and disabling nature, which occurs at unpredictable timing and affects patients' quality of life in various ways (Doyle, 2011; Hodor, 2021). Therefore, I follow the literature and use a heart attack as a health shock to analyze whether behavioral family health spillovers exist. This study aims to analyze if there is a significant effect of a heart attack on non-injured spouses' healthcare consumption. It also aims to examine the direction and the magnitude of this spillover effect that occurs through the behavioral channel.

To estimate family health spillovers, I use two outcome variables representing healthcare consumption; medical expenses and office visits. The first outcome includes the expenses covered and reimbursed by the insurance company. The second outcome–office visits–is a dummy variable that takes one for visits to healthcare providers at locations other than a healthcare facility where a health professional routinely provides health examinations, diagnosis, and treatment of illness or injury on an ambulatory basis. These outcomes are constructed based on non-injured spouses' claims for various treatments.

I also utilize a wide array of control variables including demographic characteristics and some indicator variables. These include a categorical variable denoting patients' relationship with the company—subscriber, spouse, or dependent—income, age, and dummy variables for gender, race, COVID-19 diagnosis, diabetes diagnosis, hypertension diagnosis, and dialysis treatment.

I also control for local levels of social vulnerability by using the Social Vulnerability Index (SVI) provided by the Centers for Disease Control & Prevention (CDC). Social Vulnerability Index (SVI) is a categorical variable that assigns an index to every U.S. census tract[2] in order to measure the relative social vulnerability of a given population in that tract. SVI was developed by the Centers for Disease Control & Prevention (CDC) and its subagency, the Agency for Toxic Substances and Disease Registry (ATSDR), in 2011 to identify communities that may need support during public health emergencies. The Centers for Disease Control & Prevention (CDC) indicates:

> The degree to which a community exhibits certain social conditions, including high poverty, low percentage of vehicle access, or crowded households, may affect that community's ability to prevent human suffering and financial loss in the event of a disaster. These factors describe a community's social vulnerability. (2010)

Therefore, CDC uses the Social Vulnerability Index (SVI) to identify areas that need relatively more help during emergencies, such as disease outbreaks and chemical exposure, which is vital for public health officials and emergency response planners for better preparedness. SVI ranks the tracts on 15 social factors[3] and groups these factors into four related themes[4]. Each

[2] U.S. Census tracts are subdivisions of counties for which the Census collects statistical data.

[3] Below poverty, unemployment, income, no high school diploma, aged 65 or older, aged 17 or younger, civilian with a disability, single-parent household, minority, speak English "less than well", multi-unit housing structures, mobile homes, crowding homes, no vehicle household, and group quarters.

[4] Socioeconomic status, household composition and disability, minority status and language, and housing and transportation.

tract receives a ranking for each factor, each of the four themes, and an overall vulnerability ranking. Controlling for the differences between populations with different vulnerability levels is essential to eliminate any variations in individuals' health consumption that may arise from external factors such as differences in their socioeconomic status, income, and living conditions. Thus, I include SVI as a control variable in the regression analysis, which takes four categorical values; low SVI barriers, moderate SVI barriers, high SVI barriers, and very high SVI barriers. The higher the barriers are, the higher the vulnerability.

The last control variable I include in the analysis is a healthcare cost risk score that assesses each patient's underlying medical risk conditions and demographic characteristics to predict the patient's potential medical and pharmaceutical costs associated with those risks. A healthcare cost risk score is an effective tool to understand how patient profiles may change their future health risks and consumption. This risk score is calculated by grouping each individual's diagnostic and procedural services as well as their demographic characteristics and using predetermined specific risk weights assigned to each group to estimate an overall risk score for each individual. For example, a patient with chronic or recurring conditions whose age group is 55-59 takes a higher healthcare cost risk score than a patient with acute incidents of minor skin problems whose age group is 45-49. Controlling for the differences between patients' expected healthcare costs is important to eliminate any variations in their health consumption that may arise from differences in their clinical and demographic profiles. Therefore, I include this variable as a control variable in the regression analysis that assigns a healthcare cost risk score for each individual in my sample. Higher scores indicate a greater level of healthcare cost risk.

3 Sample Selection, Methodology, and Descriptive Statistics

The sample comprises residents of one of the southern states in the U.S. from 2019 to 2021. First, I identified those individuals who had a heart attack between 2019 and 2021 from the claims data. This rich claims data provide detailed information with diagnoses, which enabled identifying patients with myocardial infarction or heart attack. The data also includes a rich set of information about these individuals, including their families with the same health insurance plan. By leveraging this information, I linked the individuals who had a heart attack and the date they had it with their dependents or spouses. Secondly, I constructed a variable journey month that shows the difference between the monthly claims of non-injured family members and the month in which the sudden health event (heart attack) occurred. Thirdly, I summed the non-injured family members' medical expenses and the number of office visits over the journey month.

I define pre-shock and post-shock periods as the 6 months before and after the spouse's heart attack. Therefore, I restrict the data to journey month greater than or equal to -6 and lower than or equal to 6. After restricting the dataset, I am left with a sample whose claims are not longer than 6 months before or after their spouse's (or dependent's) heart attack. From the dataset, I cannot distinguish between the reason why an individual does not have healthcare expenses before (or after) the heart attack is either because they do not utilize benefits during this period or because they were not in the plan (or terminated). To circumvent this, I pose the following assumption. I assume that people who have a claim any month before and after the heart attack stayed in the insurance plan. This assumption implies that if an individual does not have any claims during a specific month either in the pre- or post-period, this must be because the individual did not utilize benefits in that month. Therefore, fifthly, I identified those who had medical expenses both before and after the heart attack and assigned 0s for their medical expenditures in the missing months. Finally, I summed these individuals' monthly medical expenses over the pre- and post-period and divided them by the total number of months in each period to find their average medical expenses in the pre-period and post-period. I followed the same steps to obtain the average number of office visits in the pre-period and post-period. The average medical expenses and the average number of visits obtained after this process constitute this paper's main outcomes–the dependent variables.

After following the above steps, I am left with 1316 observations, including the average medical expenses and the average number of office visits of non-injured family members during the pre- and post-shock periods. Specifically, the final sample includes 658 individuals, along with their average medical expenses, average number of office visits before and after their spouses' heart attack period, and all other relevant member-level characteristics.

Table 1 provides summary statistics for the sample of 658 individuals (or 1316 observations that show both the pre- and post-period information of these individuals) with the outcome and control variables. On average, people spend 805$ for their medical procedures six months before and after their spouses' (or dependents') heart attack. The average number of office visits during this period, six months before and after the heart attack, is relatively small, with a value of 1.3. The table also shows that 73% of the sample are females. In other words, selecting people whose spouses (or dependents) had a heart attack left us with a sample where the ratio of females is higher than the males. One of the potential explanations for this is that men are more likely to have experienced a heart attack than females[5] (Hamil-Luker et al., 2007; Zhang et al., 2022; Jenkinson, 1997). Another possible explanation is that females are more likely to utilize their health insurance benefits than men. On the other hand, Table 1 shows that the White population constitutes the majority of the sample. This is due to the demographics of this state. According to the US Census of 2022, 78.6% of the population in the state I focus on in this paper is White. Finally, the table shows the average age of the sample as 47.6.

Table 1: Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min.	Max.
Average Medical Expense	1316	804.793	4179.05	0	102031.513
Average Number of Office Visit	1316	1.367	2.033	0	26.5
Post Heart Attack	1316	0.5	0.5	0	1
Female	1316	0.731	0.444	0	1
Relation Category	1316				
Spouse	362	27.5%			
Spouse or Dependent	316	24%			
Subscriber	638	48.5%			
Healthcare Cost Risk Score	1316	2.716	3.266	0	23.884

[5]The dataset I initially obtained that consists of members with a heart attack has a men to women ratio of 56%.

Table 1 continued

Variable	Observations	Mean	Std. Dev.	Min.	Max.
Race	1316				
Asian	12	0.9%			
Black	24	1.8%			
Hispanic	76	5.8%			
White	1038	78.9%			
Other	166	12.6%			
Estimated Annual Income	1316	52311.546	21083.334	0	147000
SVI Category	1316				
Low	196	14.9%			
Moderate	392	29.8%			
High	448	34%			
Very High	280	21.3%			
Age	1316	47.6	16.576	18	82
Covid-19	1316	0.21	0.407	0	1
Hypertension	1316	0.31	0.463	0	1
Dialysis	1316	0.003	0.055	0	1

Note: Post heart attack is a binary variable that takes a value of 1 for the post-period and 0 for the pre-period. There are three individuals in the sample with 0 estimated annual income whose ages are 18, 22, and 25, whose relation category is Spouse or Dependent. These individuals are likely to be students with no job and hence no reported annual income.

4 Empirical Strategy and Results

I employ an OLS regression with control variables to compare the average health consumption in the pre- and post-period of a spouse's (or dependent's) heart attack. In practice, my research design leverages the two main advantages of the data that I have. These are (i) the data has detailed information on specific healthcare services utilized, allowing me to identify both the diagnosis and the value of healthcare consumption, and (ii) the data makes it possible to link people who experienced a heart attack with their families. Thanks to these two advantages of the data, I can utilize variation in a sudden health shock timing to study the effect of family health spillovers on non-injured family members' healthcare consumption.

The following OLS regression framework is employed for this purpose:

$$Y_i = \alpha + \beta D_i + \gamma X_i + \delta_t + u_i, \tag{1}$$

where D_i is the main parameter of interest. It is defined as a binary variable equal to unity if the time period is after the spouse's heart attack month. Conversely, it takes a value of 0 if the time period is before the sudden health shock in the family. The coefficient of D_i identifies the effect of the sudden family health shock, i.e., heart attack, on healthcare consumption in the post-event period relative to the pre-period. Y_i denotes the dependent variable of interest, such as the average medical expenses and the average number of office visits. X_i is a vector of control variables that observes individual-level characteristics such as age, income, social vulnerability index, etc. Finally, δ_t and u_i denote monthly time fixed effects and the disturbance term, respectively.

The identification strategy in this setup is that the timing of the health shock is relatively unpredictable and effectively random for the non-injured family members. In other words, non-injured family members cannot alter their healthcare consumption based on anticipation of the sudden health event. There are, however, some factors that may change individuals' healthcare consumption, such as chronic conditions, underlying health risks, income, and the communities they live. I eliminated the effect of these incidents by including a wide range of individual-level control variables.

Table 2 report the estimation of Eq. 1 for the outcomes of average medical expense and average office visit. Both estimations control for monthly time-fixed effects. The results indicate that the family spillover effect has a statistically significant impact on non-injured family members' healthcare consumption. The coefficient of "Post Heart Attack" shows that after a sudden health event in a family, non-injured family members increased their healthcare consumption. In particular, non-injured family members increased their average medical expenses by $571 in the post-period of their spouses' heart attack compared to their average expenses in the pre-period of the heart attack. Similarly, non-injured family members increased their average number of office visits after their spouses' heart attack by 0.5 times compared to their average number of office visits before the heart attack.

Table 2: The Effect of Heart Attack on Spousal Healthcare Consumption

	Average Medical Expense	Average Office Visit
Post Heart Attack	571.204***	0.550***
	(0.005)	(0.000)
Female	−203.792	0.287**
	(0.386)	(0.023)
Relation Category Spouse or Dependent	−154.992	0.383
	(0.771)	(0.180)
Relation Category Subscriber	−150.374	0.042
	(0.550)	(0.757)
Healthcare Cost Risk Score	198.291***	0.134***
	(0.000)	(0.000)
Race Black	590.740	0.013
	(0.650)	(0.985)
Race Hispanic	827.629	0.577
	(0.475)	(0.352)
Race Other	1,319.186	0.601
	(0.236)	(0.314)
Race White	922.682	0.548
	(0.394)	(0.345)
Estimated Annual Income	0.007	0.000
	(0.197)	(0.190)
Age	5.473	0.006
	(0.681)	(0.396)
SVI Category Low	−486.273	−0.190
	(0.137)	(0.278)

Table 2 continued

	Average Medical Expense	Average Office Visit
SVI Category Moderate	−225.343	−0.084
	(0.383)	(0.546)
SVI Category Very High	−315.558	0.077
	(0.266)	(0.614)
Covid-19	−181.260	−0.092
	(0.477)	(0.500)
Hypertension	−761.321***	0.240*
	(0.003)	(0.072)
Dialysis	32,290.120***	−2.923***
	(0.000)	(0.005)
Diabetes	−100.472	0.298**
	(0.718)	(0.046)
Cancer	88.068	0.200
	(0.831)	(0.364)
Constant	−160.009	−0.737
	(0.915)	(0.357)
Observations	1,316	1,316
R^2	0.263	0.105
Adjusted R^2	0.245	0.084
Residual Std. Error	3,627.629	1.945
F Statistic	15.274	5.009

Note: P-values are shown in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

These significant and positive results support the hypothesis that people adopt behaviors after sudden health events because of the risks and consequences of these events. In particular, the $571 increase in the average medical expenses after the health event relative to the pre-period shows that family members who did not directly experience the health shock became more aware of their own health risks. As a result, they increase their healthcare expenditures. Similarly, the significant and positive impact on the average office visits can be explained by the fact that people increased their routine visits to healthcare providers either to discuss existing health issues, concerns, and symptoms or to prescribe medications. In short, it can be concluded that people's awareness of their own health risks increases after a sudden health event that they were exposed to but did not directly experience.

Figure 1 visualize the significant positive increase in average medical expenses after the sudden health shock in the family. On average, people spend 61% more on healthcare after their dependents experience a heart attack.

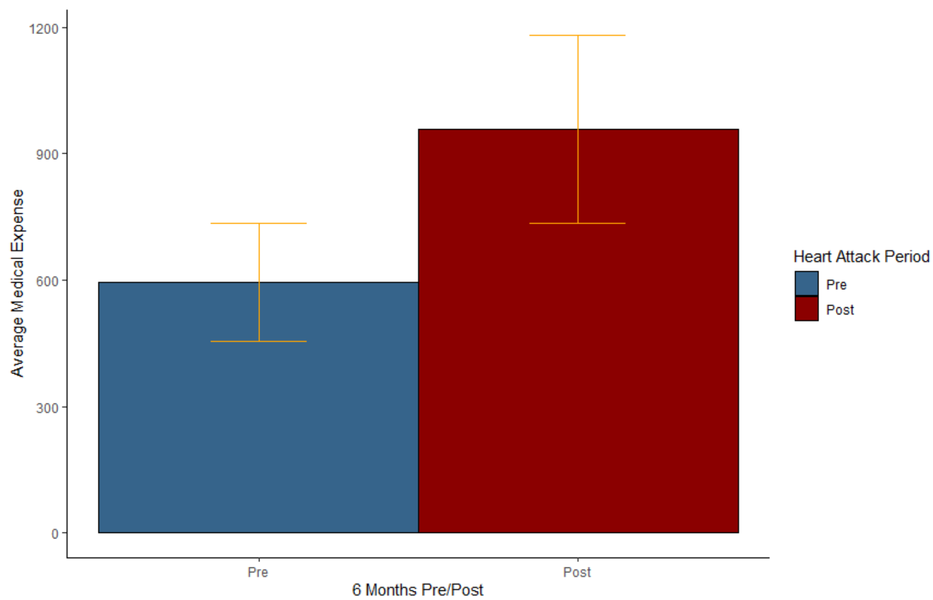

Figure 1: Average Medical Expense, 6 Months Pre/Post. The bar graph with 95% confidence interval error bars shows the average medical expenditures in pre-shock and post-shock periods.

To investigate this effect further on different subgroups, I restrict the sample to patients who have chronic conditions such as diabetes, cancer, hypertension, or patients who are in end-stage renal (kidney) failure or on dialysis treatment[6]. I then compare the changes in average medical expenditures of patients with either of the above underlying conditions with patients

[6]End-stage renal failure occurs when chronic kidney disease—the gradual loss of kidney function—reaches an advanced state. In end-stage renal disease, kidneys no longer remove enough wastes and fluids from the blood. Due to the loss of filtering, wastes, electrolytes, and dangerous fluid levels build up in the body. Patients who are

who do not have any of these chronic conditions. Figure 2-B shows that adopting behaviors after sudden health events is significant for those who do not have underlying conditions. In contrast, the effect of the dependent's heart attack does not significantly affect the average medical expenses of patients with chronic conditions (Figure 2-A).

These results imply that a sudden health shock in a family significantly increases the fears of people without chronic conditions, as those often wait for symptoms to appear to go to the doctor. Therefore, the spouse's heart attack acts as a 'nudge' (Thaler & Sunstein, 2008) to raise awareness of these people and remind them of the importance of not avoiding or delaying treatment. On the other hand, the insignificant result for people with chronic conditions is expected because these patients are more likely to meet and maintain long-term relationships with multiple healthcare providers due to their health conditions. In other words, those people consume healthcare services more frequently and hence have higher medical expenditures than those without chronic conditions. The differences in average medical expenses between the two groups in Figure 2 also validate these thoughts. Therefore, it is not surprising that the spouse's experience of the health shock does not significantly change the awareness of other family members with chronic conditions, as those are the patients who are already aware of their conditions and go to the doctor regularly to get their treatment.

To explore whether there is heterogeneity across race and gender among people without chronic conditions—who significantly increased their average medical expense after their dependent had a heart attack—I plotted the pre/post average medical expense by race and gender. Figure 3-A shows that the race difference in increasing average medical expense after the health shock in the family is significant only for White people among other race groups. This finding implies that Whites are the only people who became more conscious about their health risks and hence increased the utilization of their insurance benefits after the sudden health event in the family. One potential concern about this result is that Whites might have a higher income on average than the other race categories–Asian, Black, and Hispanic. Thus, they might be the only group that could afford to increase the average medical expenditures after the health shock. In order to check for the concern that the race gap may be due to in-

in end-stage renal failure need dialysis or a kidney transplant to stay alive. Dialysis is a procedure to remove waste products and excess fluid from the blood when the kidneys can no longer perform these functions naturally.

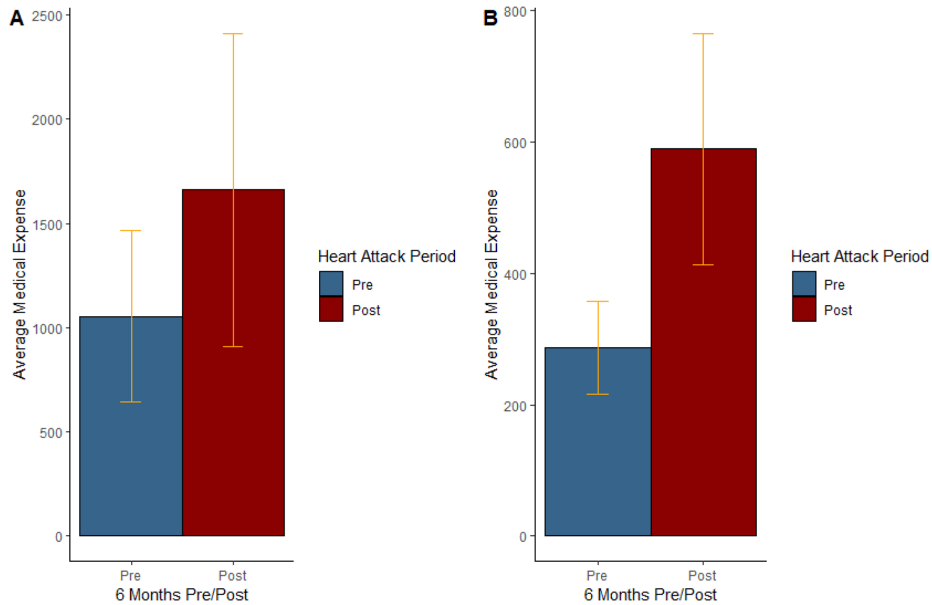

Figure 2: Average Medical Expense, 6 Months Pre/Post, Chronic Conditions Subgroup. The bar graphs with 95% confidence interval error bars show the average medical expenditures in pre-shock and post-shock periods. Figure A on the left plots the sub-sample with either diabetes, cancer, hypertension, or end-stage kidney failure. Figure B plots the sub-sample who do not have any of these chronic medical conditions.

come, I looked at the average income by the race groups. The average income for Asian, Black, Hispanic, and White populations in the sample are $67,500, $43,111, $49,961, and $52,830, respectively. Since the average income of Whites is not the highest of all and is not substantially higher than the others, I can conclude that the race difference cannot only be explained by income differences.

Figure 3-B shows that females significantly increase their average medical expense after the health shock, whereas the effect is insignificant for males. This result implies that gender significantly differs in assessing severe health events experienced by someone else in the family. It shows that a sudden health event significantly triggers family health spillovers for females, who are less likely to take health risks than men. Hence, they are more likely to be triggered to invest in their health after a health shock to avoid potentially serious health problems. This finding is consistent with large literature documenting that women are more health-conscious than men (Barebring et al., 2020; Stefan, 2015; Fagerli et al., 1999). It

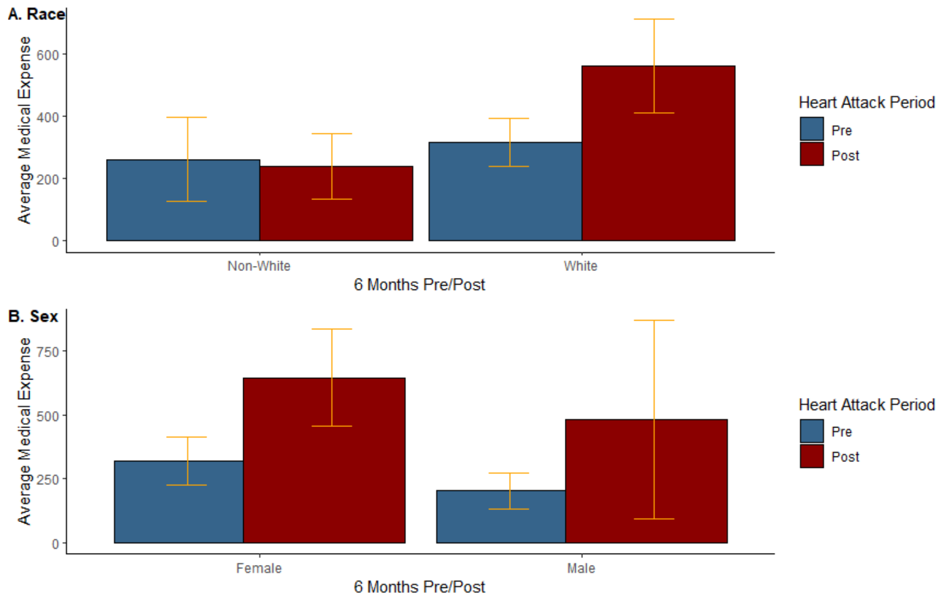

Figure 3: Average Medical Expense, 6 Months Pre/Post, Chronic Conditions Subgroup by Race and Gender. The bar graphs with 95% confidence interval error bars show the average medical expenditures in pre-shock and post-shock periods. Figure A on the top plots the sub-sample without diabetes, cancer, hypertension, or end-stage kidney failure by race. 'Non-White' includes Asian, Black, and Hispanic race groups. Figure B at the bottom plots the same sub-sample, who do not have chronic conditions, by gender.

is also consistent with the literature on gender differences in risk assessment. The studies demonstrate that women perceive higher risks than men and are less likely to engage in risky activities compared to men (Byrnes et al., 1999; Weber, 2002; Harris et al., 2006). Harris et al. (2006), using a survey of the University of California undergraduate psychology students and focusing on the health domain[7], find that females consider potential adverse outcomes more likely to occur and assess these potential adverse outcomes as significantly more severe than men.

[7]There are four questions used in this study to analyze gender differences in risk assessment in the health domain: exposing yourself to the sun without using sunscreen; not wearing a seat belt when being a passenger in the front seat; not wearing a helmet when riding a motorcycle; and walking home alone at night in a somewhat unsafe area of town.

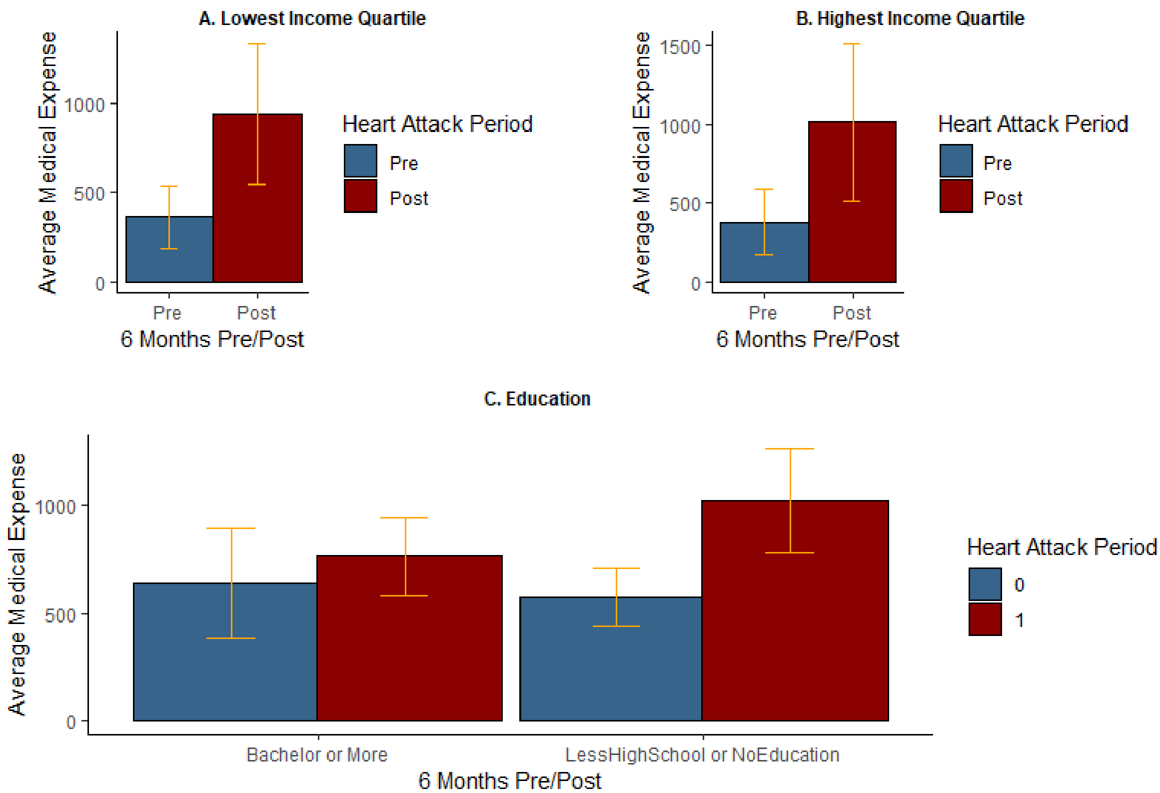

Figure 4: Average Medical Expense, 6 Months Pre/Post, Subgroups by Different Income Groups and Education. The bar graphs with 95% confidence interval error bars show the average medical expenditures in the pre-shock and post-shock periods. Figures A and B on the top plot the average medical expense of the lowest and highest income quartiles. The lowest income quartile includes individuals whose income is lower than $36,000. On the other hand, the highest income quartile includes individuals whose income is higher than $67,000. Figure C at the bottom plots the final sample by education. 'Bachelor or More' includes individuals with a graduate degree, bachelor's degree, and some college degree. Some college degree refers to individuals with a high school diploma and at least three hours of college credit but no completion or who are dropped out. 'LessHighSchool or NoEducation' includes individuals with no high school diploma or no education.

Finally, I analyze whether there is heterogeneity in average medical expenditures between different income groups and education categories. Figure 4-A and Figure 4-B plot the pre/post average medical expense for the lowest and highest income groups, respectively. These figures show that the lowest and highest income groups exhibit similar patterns in average medical expenditures both before and after the sudden health event in the family. Both income quartiles increase their expenses after the spouse's heart attack, but this increase is more significant for the lowest income quartile. On the other hand, Figure 4-C shows that differences between education levels in increasing average medical expense after the health shock in the family are driven by individuals with no high school diploma and no education. The story is similar in explaining this significant positive change in average medical expense; the spouse's heart attack nudges less educated members to become more aware of their health risks and reminds them of the importance of timely medical treatment. However, the results are insignificant when we look at more educated individuals[8]. This result implies that more educated individuals are more likely to invest in their health, so the spouse's heart attack does not have the same nudging effect for those individuals.

5 Conclusion

This paper studies how a sudden health event triggers family health spillovers through the behavioral spillover channel. My hypothesis is that the perceived risks and habits are shared and transmitted between family members. Therefore, individuals who do not directly experience health shocks but are exposed to them can alter their healthcare consumption due to changes in their behavior after the health shock.

I use claims data from a southern healthcare payor in the U.S. to analyze this impact empirically. The data is based on the employees of a large American retail corporation who purchase health insurance from the southern healthcare payor. The data provides detailed information about healthcare services utilized, various member-level demographic and socioeconomic characteristics, chronic conditions, and income. It also allows me to identify individuals who share the same insurance plan, which made it possible to study family spillovers. The dataset covers the period from 2019 to 2021.

I use a spouse's heart attack to identify a family health shock. I analyze the family health

[8]More educated individuals consist of those with a graduate degree, bachelor's degree, and some college degree.

spillovers using an OLS regression with a dummy variable showing if the period is before or after the spouse's heart attack. By utilizing variation in spouse's heart attack timing, I study the effect of family health spillovers on non-injured family members' healthcare consumption. Two outcome variables are used to measure healthcare consumption; the average medical expenses and the average number of office visits. The analyses generate two primary conclusions. First, I find a statistically significant change in the healthcare consumption of non-injured family members after a sudden health event in a family. Second, after the sudden health event, non-injured family members increase their average medical expenses and the average number of office visits. For example, the average medical expense in the post-shock period is $571 higher relative to the pre-shock period. These two results imply that health shocks increase individuals' awareness of their own health risks. Hence, people increase their routine office visits and consumption for medical procedures.

Furthermore, I explore the effect of the health shock on different subgroups. The subgroup analyses generate five primary conclusions. First, I find that individuals without chronic conditions, such as diabetes, cancer, hypertension, and kidney failure, significantly increase their average medical expenses after a sudden health event in the family. However, the effect is insignificant for patients with chronic conditions as these individuals already maintain long-term relationships with multiple healthcare providers due to their underlying health conditions.

Second, I find that among those people who significantly increase their average medical expense after a health shock, i.e., individuals without chronic conditions, Whites increase the utilization of insurance benefits after a family health shock. However, the effect is insignificant for the non-White population. Third, I find a statistically significant increase in the average medical expense of females after the health shock, whereas the effect is insignificant for males.

Fourth, I find no significant difference between the average medical expenses of the lowest and highest-income quartile groups as they both significantly increase their healthcare consumption after the spouse's heart attack. This increase also follows the same pattern for both income groups. Lastly, I find that the differences between education levels in increasing average medical expenses after the spouse's heart attack are driven by less educated individuals who have no high school diploma or education.

This paper finds that people increase their healthcare consumption after a spousal heart attack because the sudden health event increases non-injured members' awareness of their own health risks. The policy implication of the findings is that if the government aims to minimize serious illnesses before people experience these problems, it can take proper initiatives toward increasing people's awareness of their own health risks. For instance, the government can implement incentives that encourage people with a family health history of chronic diseases to see their healthcare provider regularly. For example, diabetes is one of the most expensive chronic diseases in the U.S., which can usually be kept under control with regular health examinations and prescriptions. The government can also design different nudging techniques for certain groups, such as less educated individuals.[9] Lastly, the government can offer financial incentives to encourage people to get routine preventive care services, which would increase the expenses in the short run but avoid possibly larger healthcare expenses in the future.

[9] This paper finds that less educated individuals increase awareness of their own health risks after the family health shock and hence increase their healthcare consumption.

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