Learning Spillovers About Insurance Benefits and Healthcare Utilization: Evidence from the Identified Poor Households in China

Haotian Zhang, Yi (Kitty) Yao, Justin Sydnor, and Wei Zheng

October 2024

Abstract

This paper examines how learnings through the health insurance payout experience spill over to healthcare utilization within a family. We base our analysis on the entire population of disadvantaged households in one county in China that are automatically eligible for the poverty-alleviation health insurance system, which covers about 95% of their medical expenditures. Exploiting an event-study approach, we show that after a large health insurance payout experience of one member, the medical expenditure of other family members increases promptly and remains high over one year. We find evidence consistent with the learning of insurance benefits behind these spillovers, and they mainly correspond to increased demand for medical treatments of life-threatening diseases, which may have been previously underutilized. We suggest positive welfare implications of within-family learning spillovers about insurance benefits, combined with subsidized insurance provision among the disadvantaged population.

Contact information: Zhang: School of Economics, Peking University, zhanghaotian@stu.pku.edu.cn. Yao: School of Economics, Peking University, yao.yi@pku.edu.cn. Sydnor: Wisconsin School of Business, University of Wisconsin-Madison, justin.sydnor@wisc.edu. Zheng: School of Economics, Peking University, wzheng@pku.edu.cn.

1. Introduction

Underutilization of healthcare is common among low-income populations around the world (Dror et al., 2005; Mwabu et al., 1993). To shield individuals from risks and promote allocative efficiency in medical care usage, many governments exercise great efforts in developing the insurance system, including free or highly subsidized health insurance for the disadvantaged population (Finkelstein et al., 2012; Miller et al., 2013). However, in both developing and developed countries, time constraints, and cognitive limitations prevent individuals from gathering and processing complete information on insurance programs (Cai and Song, 2017; Kruse et al., 2010), and they display imperfect use of insurance benefits (Choi et al., 2005; McCall, 1995). Although studies have shown that learning through personal experience could promote understanding and take-up of insurance (Cai et al., 2020; Kamiya and Yanase, 2019; Shai, 2022), little is known about how learning acts as an amplifier of benefit utilization following increased insurance generosity.

This paper estimates how learnings through a health insurance payout experience spill over to healthcare utilization among other members within the household, where all households are identified as poor and automatically covered by a generous health insurance system. To be specific, we aim to answer the following questions: First, after a large health insurance payout experience of a member, are there any spillovers to the medical expenditures of other family members in the short term? Second, what are the possible mechanisms behind these spillover effects? Third, do these spillovers correspond to over-utilization of medical services? These investigations help to understand the insurance learning process and have important implications for increasing the utilization of necessary healthcare services among the disadvantaged.

We use detailed information on both medical expenditure records in 2017 and family characteristics of Identified Poor Households (IPHs) in County X from Jiangxi Province, China. All individuals from these households were eligible for the poverty-alleviation health insurance system fully paid for by the government after 2016, and the average proportion of their out-of-pocket hospitalization expenditures decreased to approximately 5% in 2017. This setting is suitable to answer the above questions for the following reasons: First, this generous poverty-alleviation health insurance system has just been established since 2016, making it possible to study the learning effects in response to new insurance policies within the initial several years. Besides, this system

has been in operation for a year before our sample period, mitigating the harvesting effect that potentially occurred when it was first implemented. Second, these IPHs are automatically covered by this health insurance system for at least three years, eliminating issues such as adverse selection and strategic timing of enrollment. Third, we have obtained information on the full population from IPHs during 2015−2017 and detailed medical expenditure records in 2017, allowing us to accurately identify family relationships as well as the date and cost of each medical expenditure. Fourth, we study the learning spillovers based on poor households lacking financial literacy and insurance knowledge, and the results are largely generalizable to other disadvantaged populations.

We begin by documenting the spillovers in healthcare expenditures within a family after a health shock and the corresponding insurance payout experience. Exploiting an event-study framework that relies on the exogenous timing of shocks following Fadlon and Nielsen (2019) and Hodor (2021), we primarily estimate the effect of an adverse health shock experienced by one individual on the medical expenditures of other family members. We find that both the total and out-of-pocket medical expenditures of other family members significantly increase promptly in one month after the shock experience, and remain at a higher level over the one-year horizon, indicating the existence of spillover effects. Heterogeneous analysis shows that these spillover effects are more pronounced for the health shocks that incur larger amounts of insurance payout. We further introduce a treatment status into the event-study model and show that after a large health shock, the medical expenditures of other family members display a large and persistent increase, compared with the households that experienced smaller health shocks. These patterns are consistent with an attention effect where higher medical expenditures lead to more attention being given to information generated by the shock experience (Cai et al., 2020).

Next, we investigate the potential mechanisms underlying these spillover effects among family members. We show two pieces of evidence consistent with learning spillovers about the benefits of health insurance, i.e., the information on insurance benefits spills over within the family through a large payout experience of one member. First, we examine households that experienced health shocks in the previous one year and find that subsequent shocks no longer generate spillover effects, suggesting a one-time learning effect from the previous claim. Second, we show that the spillovers are not driven by the increase in medical expenditures on similar types of diseases as the health shock itself, and the effects largely spill over to other types of diseases, consistent with the

widespread nature of insurance benefits learning effects.

In addition, we discuss other possible explanations behind these spillover effects. The main alternative mechanism is through the correlation of health status and health risks between family members. We address this possibility from three aspects. First, although the heritability of human disease is especially pronounced for parents, children, and siblings of the family member directly exposed to the health shock (Tenesa and Haley, 2013), the observed spillover patterns do not significantly differ between these more genetically related members and other relatives. Second, healthcare spillovers occur across various types of diseases, not just those similar to the disease that causes the health shock, indicating that the correlation between similar diseases is not a major factor. Third, we find no significant changes in the diagnosis and detection rates of chronic and critical diseases among other family members following a large shock, indicating that the healthcare spillovers are not driven by a sudden deterioration in their state of health. Another potential mechanism is the increase in salience of health among other family members, which may translate to changes in their healthcare-related behaviors. Although it cannot be completely ruled out, we show that increased salience of health cannot explain the differential spillover trends observed from County Z, another county within the same city that provides slightly less comprehensive poverty-alleviation health insurance coverage for IPHs.

Finally, we explore whether the spillover effects primarily arise from the fulfillment of necessary healthcare demands or an increase in elective medical expenditures. Based on diagnostic information corresponding to each medical expenditure, we show that an important part of these spillovers comes from treatments of some commonly studied necessary and severe diseases (such as treatments for cancer and pneumonia), rather than overutilization of medical services for discretionary and less serious conditions such as diseases of the genitourinary and the upper respiratory systems. In addition, we find no evidence of any increase in the likelihood of being diagnosed with chronic diseases, critical diseases, and disabilities among other family members after a large health shock, suggesting increased medical demand for pre-existing conditions instead of the increase in new disease diagnosis behind the healthcare spillovers. Put these results together, they collectively point to potential welfare improvements from increased treatments of life-threatening diseases among other members, after information about insurance benefits spillovers within the family through a large payout experience.

Consistent with theories of bounded rationality, existing literature has agreed that individuals lack understanding of insurance products (Bhargava et al., 2017; Reschovsky et al., 2002; Samek and Sydnor, 2020) and display imperfect use of the benefits (Choi et al., 2005; McCall, 1995), while learning about insurance through personal experience and financial education help to improve individual decision-making (Cai et al., 2020; Cai and Song, 2017). Specifically for health insurance, empirical research has mainly examined learnings and consumer choices between health insurance plans (Abaluck and Gruber, 2016; Kaufmann et al., 2018; Ketcham et al., 2012). This paper is further expanded to study the learning process that occurs within a specific insurance plan through the payout experience. With a special focus on poor households that tend to have worse health status, poorer insurance literacy, and tighter resource constraints, we find evidence of learning spillovers that increase healthcare utilization within the family and point to positive welfare implications[1].

We also add to the evidence on the short-term spillover effects of adverse health shocks. The direct consequences of health shocks are well documented by existing studies, including increased out-of-pocket medical spending and reduced employment and income (Dobkin et al., 2018; García-Gómez, 2011; García-Gómez et al., 2013; Vaalavuo, 2021). Furthermore, their spillover effects on other family members are increasingly recognized, from the perspective of consumption (Islam and Maitra, 2012; Wagstaff, 2007), health conditions (Lavelle et al., 2014; Quanjer et al., 2023), labor supply behaviors (Eriksen et al., 2021; Fadlon and Nielsen, 2021; Heath et al., 2022; Jeon and Pohl, 2017; Vaalavuo et al., 2023; Wen and Huang, 2024), and child education (Bratti and Mendola, 2014). Most related to this paper but in a long-term setting, Fadlon and Nielsen (2019) find that health shocks to Danish individuals significantly increase the consumption of preventive care and health-related behaviors of their family members; Hodor (2021) use families from the RAND Health Insurance Experiment and further documents a persistent increase in elective care such as wellness dental treatments, but no increase in the demand for chronic treatments and hospital visits. We add to the short-term evidence on increased treatment of severe diseases based on the setting of disadvantaged households from the largest developing country, which tend to exhibit underutilization of necessary medical services compared with developed countries and are more

[1] Chetty (2008) highlights the importance of distinguishing between liquidity and moral hazard effects of insurance because of their divergent implications for the welfare consequences, and Gross et al. (2022) provide evidence that more complete insurance allows recipients to consume healthcare when needed.

generalizable to other less-developed areas (Flores and O'Donnell, 2016).

Finally, we speak to the literature on social and family interactions in determining healthcare-related behaviors. Existing studies document the impacts of social networks or family spillovers on health insurance demand (Cai et al., 2015; Du et al., 2023), medical expenditure (Debnath and Jain, 2020; Deri, 2005; Hodor, 2021), and preventive care participation (Bouckaert et al., 2020; Humlum et al., 2024). These long-term spillover effects are mainly through the diffusion of knowledge on health insurance and the effectiveness of medical treatment, acquisition of new information about one's own health risks, and the salience of health. We focus on the short-term spillover effects on healthcare utilization within a family and find evidence consistent with the learning spillovers about insurance benefits through a large payout experience.

2. Data

2.1 The Identified Poor Households (IPHs) in County X, China

After the year 2012, China accelerated the process of the Targeted Poverty Alleviation (TPA) program, which was designed to elevate the income of extremely disadvantaged households above the national poverty line through a comprehensive social welfare benefits package. Part of this initiative was to provide access to health care services to poor households at lower costs by constructing a generous poverty-alleviation health insurance system. The poor households–evaluated based on their recent earnings, household assets, and other indicators by the government–that are eligible for the TPA package are referred to as Identified Poor Households (IPHs).

City A in Jiangxi province was a prime example which offers fully subsidized poverty-alleviation health insurance to IPHs. We acquire information on the full population of individuals from all IPHs in County X, City A from the National Rural Revitalization Administration of China.[2] This dataset tracks approximately 160,000 individuals from around 38,000 IPHs during 2015−2017, including their gender, age, education level, health status, and schooling or working status as well as household information including their population size, current earnings, and the cause of poverty. After merging with the medical expenditure data introduced in the following subsections through

[2] County X is one of the top ten counties in Jiangxi Province and the largest county in City A in terms of population size, with a population of approximately 1.1 million people. In 2017, County X had a gross product of approximately 21 billion Yuan (US $3 billion), the third highest in City A.

the unique household and individual identifiers, we keep the IPHs with at least one individual who experienced critical diseases (i.e., the medical expenditures met the conditions for public critical illness insurance payment) in 2017 as the main study sample.

2.2 The poverty-alleviation health insurance system

City A has constructed the poverty-alleviation health insurance system since 2016. According to the city government, this system generally consists of four layers: The first two layers include public basic medical insurance and public critical illness insurance, available to the national population regardless of their poverty status. The third layer is the poverty-alleviation commercial health insurance, which was provided by a commercial insurer and was fully paid for by the government. The fourth layer consists of social assistance from the Ministry of Civil Affairs, providing assistance for out-of-pocket medical expenses for individuals in extreme poverty. Among these four layers of the poverty-alleviation health insurance system, creative practice in City A was the extension of the third layer of supplementary commercial health insurance coverage to the IPHs: In 2016, the city government paid a commercial insurer to cover 1.16 million individuals from all IPHs and in 2017, the number increased to 1.48 million insureds at a premium of 260 Yuan (US $39.2) per person. This whole poverty-alleviation health insurance system in City A generally ensured that the out-of-pocket hospitalization expenditures for the IPHs would be approximately 10% of their total expenditures.

Besides this standardized four-layer health insurance system for the IPHs of City A, its affiliated County X has further constructed the fifth layer with a contribution of 30 million RMB in 2017, so that IPHs who did not meet the requirements of the fourth layer of social assistance could also receive further compensation for medical expenditures. By the end of 2017, the average proportion of out-of-pocket hospitalization expenditures in County X was decreased to approximately 5%, which further reduced the risk of incurring large out-of-pocket medical expenses of IPHs.

2.3 Health shocks and medical expenditures

For data on health shocks, we employ a claim dataset that contains the medical expenditure records for individuals in County X whose medical expenditures met the conditions for public

critical illness insurance payment in the whole year of 2017, which can be merged with the IPHs dataset through the unique household and individual identifiers. This dataset consists of detailed information on each inpatient and outpatient expenditure record of these individuals, including the type of medical service, total expenditure per record, and the date of discharge for inpatient care. Approximately 80% of these records can be matched with a diagnosis from the doctor. We classify these diagnoses into the 22 standardized category codes in the International Classification of Diseases, 10th Revision (ICD-10), see Appendix Table A1 for the statistics on disease categories corresponding to these health shock diagnoses[3]. We restrict the analysis sample to the IPHs with at least one individual who met the conditions for critical illness insurance payment in 2017 and identified approximately 3,400 IPHs that experienced adverse health shocks.

We keep the medical records from this critical illness insurance claim dataset, sum these expenditures to the individual-month level, and identify the health shocks and time of shocks among these directly affected individuals. Specifically, we define a health shock to be a "large medical shock" if the total medical expenditure for an individual in a month exceeds a certain threshold amount, i.e., the average amount of annual minimum guarantee for households in our sample, which equals to 29,574 yuan (US$4,101) in 2017. Correspondingly, we define the time of this large medical shock as the month that the family first experienced a monthly medical expenditure that exceeded the threshold amount in a month, and the individual who experienced this large medical expenditure is identified as the member directly affected by the shock. For households with at least one individual who met the conditions for critical illness insurance payment but no individuals experienced a "large medical shock" in 2017, we define the time it experienced a "small medical shock" as the month that it experienced the largest amount of medical expenditure from a single individual within the year 2017, and this individual is identified as the member directly affected by the health shock. Furthermore, since County X adopted the instant billing system for poverty-alleviation health insurance, medical expenses, and insurance claims are incurred at the same time. Therefore, it is reasonable to identify the time of experiencing a health shock and receiving the corresponding insurance payout to be in the same month.

For the medical expenditures of other individuals (i.e., household members that were not

[3] We use the ICD-10 published by the World Health Organization (WHO) as the standard for classifying and coding diseases. It contains 22 major categories. Please refer to https://icd.who.int/browse10/2019/en for more details.

directly affected by the shock in 2017), we employ a dataset that includes about 27,000 detailed records of medical expenditures (both inpatient and outpatient) for individuals from all IPHs from May 2017 to January 2018, which can be merged with previous datasets through the unique household and individual identifiers. This dataset includes per-record information on the diagnosis, total medical expenditure, out-of-pocket medical expenditure, and the date of medical service utilization. Once again, we classify their detailed diagnoses into the standardized ICD-10 codes. At the household level, we aggregate the medical expenditures of all individuals at the monthly level (excluding the previously identified individual who was directly affected by the health shock in 2017) and construct the main outcome of interest in this paper, i.e., total and out-of-pocket medical expenditures of other family members. To avoid the effect of extreme values, we shrink the tails of the total and out-of-pocket medical expenditures, i.e., 0.01% of the observations in the right tail are replaced by the next value counting inwards from the extremes.

Table 1 presents the summary statistics for households that experienced large and small medical shocks, respectively. In our sample, approximately one-quarter of the households have experienced a "large medical shock", and the medical cost of their health shock is 48,643 yuan (US$6,814) higher than households that experienced a "small medical shock". However, if we take into account the generous poverty-alleviation health insurance system that decreases out-of-pocket hospitalization expenditures to approximately 5% of the total expenditures, the difference in out-of-pocket expenditures incurred by the health shock is approximately 2,432 yuan (US$347), which is lower than the average per-capita income in 2016 within our sample. Rows 2 and 3 in Table 1 present the overall medical expenditures from May 2017 to January 2018 for households that experienced health shocks, excluding the expenditures of individuals directly affected by the health shocks. During these nine months, total medical expenditures for other household members were significantly higher in households that experienced large health shocks, with an average value of 2,509 yuan (US$358), compared with an average of 1799 yuan (US$257) for households that experienced smaller health shock. Out-of-pocket medical expenditures account for approximately 4% of the total medical expenditures on average.

Table 1 Summary Statistics of Sample Households

	Health Shock in 2017						
	Large Expenditure Shock			Small Expenditure Shock			Difference
Household Characteristics	Obs	Mean	St Dev	Obs	Mean	St Dev	
Medical Expenditure of Health Shock	905	59,161.76	37,044.91	2,514	10,518.89	8,220.75	-48,642.87***
							(787.58)
Total Medical Expenditure of Other Members	905	2,508.74	9,078.44	2,514	1,798.90	5,756.06	-709.84***
							(263.41)
Out-of-Pocket Medical Expenditure of Other Members	905	110.58	519.69	2,514	64.22	232.54	-46.36***
							(12.93)
Non-poor in 2016	848	0.2783	0.4484	2,472	0.2989	0.4579	0.0206
							(0.0181)
Household Per Capita Income in 2016	848	3,518.00	1,646.99	2,471	3,676.69	1,899.11	158.68**
							(73.15)
Household Population in 2016	848	4.7052	1.7542	2,472	4.7067	1.8624	0.0015
							(0.0730)
Proportion of Healthy Member in 2016	848	0.7260	0.2273	2,470	0.7278	0.2350	0.0018
							(0.0093)
Any Member Working Out-Province in 2016	848	0.4776	0.4998	2,472	0.4753	0.4995	-0.0023
							(0.0199)

Significance: * significant at 10%; ** significant at 5%; *** significant at 1%.

2.4 Supplementary data from IPHs in County Z, China

To explore the mechanism of spillover effects, we supplement our analysis with data on demographic information and medical expenditure records of IPHs in County Z, which is located in the same city (i.e., City A, Jiangxi Province) as County X. County Z established the four-layer structure with an average of 10% out-of-pocket medical expenditures for IPHs during 2016−2017. Similar to County X, we also obtain two datasets from County Z: First, information on the full population of individuals from all IPHs in County Z from the National Rural Revitalization Administration of China. This dataset tracks approximately 25,000 individuals from around 8,000 IPHs during 2015−2017, including their gender, age, education level, health status, and schooling or working status as well as household information including population size, current earnings, and the cause of poverty. Second, regarding the healthcare expenditure data for IPHs in County Z, we only have the medical expenditure records for individuals whose medical expenditures met the conditions for public critical illness insurance payment in the whole year of 2017, while lacking records of individuals who incurred only small medical expenditures. In this context, we are still able to identify family health shocks using the same approach, but with a focus on spillovers to the large medical expenditures of other household members.

3. Empirical strategies and basic results

3.1 Dynamic event study

The short-term spillover effects of adverse health shocks on the healthcare utilization of other members within the family are ambiguous. Theoretically, the family faces tighter liquidity constraints after a shock that incurs a large medical expenditure and tends to spend less on the healthcare expenditures of other members. On the other hand, the health shock may trigger spillovers through insurance knowledge learning and behavioral responses that promote their healthcare utilization, leaving an uncertain overall effect on other members. Empirical investigation into the short-term spillover effects among medical expenditure is scarce, especially in developing countries.

To examine the dynamic effects of spillovers on other family members' healthcare expenditures, we first follow Fadlon and Nielsen (2019) and Hodor (2021) to utilize a quasi-experimental research design that exploits the potential randomness of the timing of a health shock within a short period. Specifically, our estimating equation is a dynamic event study specification of the following form:

$$y_{ht} = \sum_{\tau=-6}^{-2} \beta_\tau \boldsymbol{I}(t - t_{Shock} = \tau) + \sum_{\tau=0}^{12} \beta_\tau \boldsymbol{I}(t - t_{Shock} = \tau) + \gamma_h + \delta_t + \varepsilon_{ht} \quad (1),$$

where y_{ht} denotes the healthcare utilization of other individuals in household h in calendar month t, t_{Shock} denotes the calendar month that the household experienced a health shock and the corresponding insurance payout. $\tau = 0$ denotes the current month of the health shock event, $\tau = 1, \dots 12$ refers to the relative month that denotes post-shock periods, and $\tau = -6, \dots -2$ is the relative month that denotes pre-shock periods. We omit indicators of two time periods: the most negative relative time period $\tau = -7$ and the period prior to treatment $\tau = -1$, which refer to the first and seventh months before the shock, respectively.[4] γ_h are household fixed effects, δ_t are calendar month indicators absorbing time trends, and ε_{ht} is the error term, clustered at the household level.

We first estimate the dynamic effects on the likelihood of incurring positive medical expenditures, total medical expenditure, and out-of-pocket medical expenditure of other household

[4] We follow Sun and Abraham (2021) and Hodor (2021) in this step, i.e., when no never-treated units exist in the analysis sample, two relative time indicators should be omitted to avoid under-identification as a result of perfect collinearity. Correspondingly, the coefficients of the relative time indicators can be viewed as the mean differences from the average value of the outcomes in the two omitted relative periods.

members, see the results in Figure 1. Although the likelihood that other household members incur positive medical expenditures does not show an increasing pattern, both the total and out-of-pocket medical expenditures significantly increase promptly in one month after the health shock, and remain high over the one-year horizon.[5] These results indicate that an adverse health shock experienced by one individual generates spillover effects on other members within the family and increases their healthcare expenditures in the short term, which echoes and complements the results of Hodor (2021) based on a long-term setting. On the one hand, these spillover effects may reflect health correlations or the deterioration in the health status among other family members after the health shock. On the other hand, the health shock and its corresponding insurance payout experience may transmit new information to the family, including (i) learning of the insurance benefits, (ii) the salience of health, and (iii) learning about one's own health risks, which increase healthcare utilization of other family members.

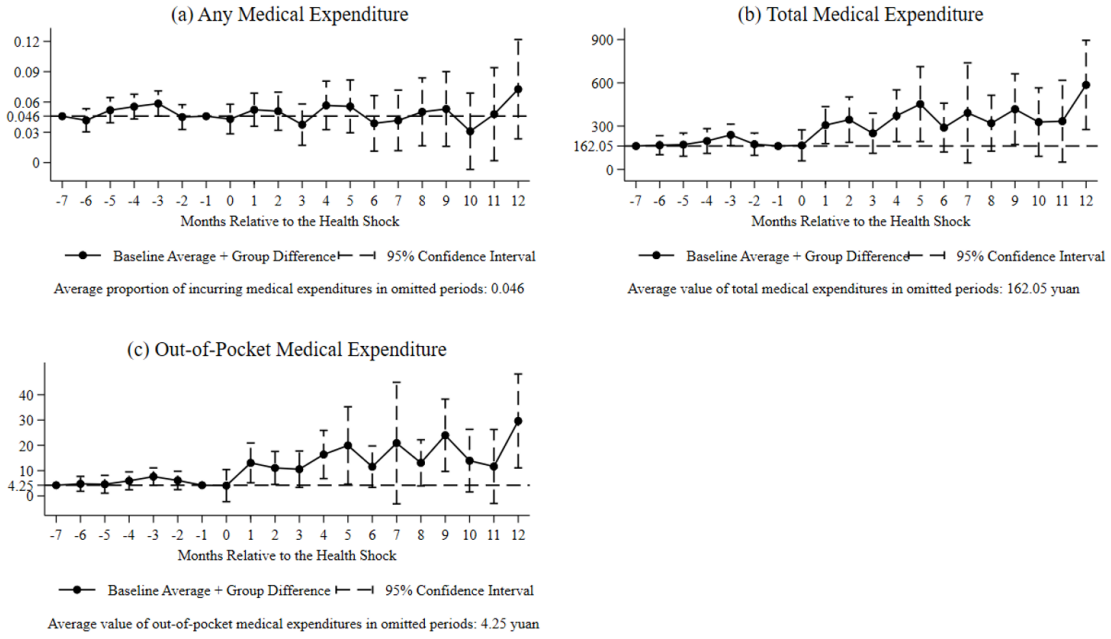


Figure 1 Effects of health shocks on other family members' medical expenditures using an event study model

Figure 2 reports the heterogeneous spillover effects for households that experienced large and small medical shocks, respectively. The left two subgraphs of Figure 2 display the effects of small

[5] One potential concern is that the two-way fixed effect estimates may not be valid in staggered DID designs, and we check the robustness of our results by using the method proposed by De Chaisemartin and D'Haultfœuille (2020), see Figure 3.

medical shocks on the healthcare expenditures of other household members. After a health shock with larger medical expenditures (as well as larger amounts of insurance payout), both the total and out-of-pocket medical expenditures significantly increase promptly after the health shock, and remain high over several months. In contrast, the right two subgraphs of Figure 2 display the effects of small medical shocks, showing a tiny increase that is not significantly different from zero for each period. Although the estimates are much noisier due to smaller sample sizes, these results indicate that the spillovers to medical expenditures of other family members are more pronounced for the health shocks that incur larger medical expenditures.

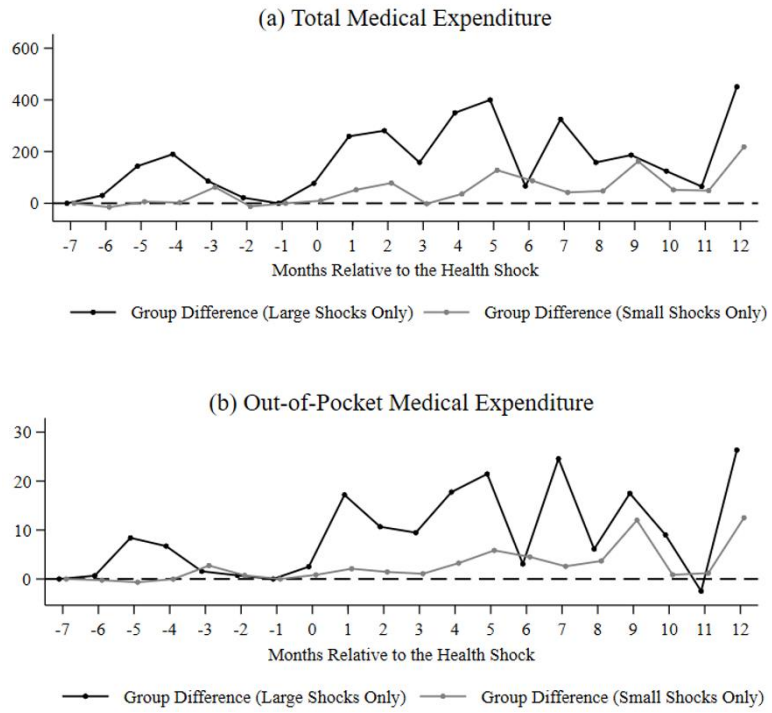


Figure 2 Effects of large/small health shocks on other family members' medical expenditures

The identification of the baseline results primarily relies on variations in other household members' medical expenditures of the treatment group relative to the control group before and after the health shock. In practice, the control group includes two cases, i.e., observations before the health shock of households who experienced a shock in a later period of the sample, and observations after the health shock of households who have already experienced a shock. Goodman-Bacon (2021) and Sun and Abraham (2021) noted that in the latter case, if the effects of the event are not homogeneous, the estimation results of the event study can be biased. As a robustness test,

we present results based on the method proposed by De Chaisemartin and D'Haultfœuille (2020), which focuses on instantaneous treatment effects and is valid even if the treatment effect is heterogeneous over time or across groups. In Figure 3, we show that the estimates for the short-term effects of large medical shocks are mostly robust to accounting for treatment heterogeneity across groups and time, except that some estimates become less precise. Instead, the estimates for the short-term effects of small medical shocks are much smaller in magnitude and close to zero. These estimates demonstrate the robustness of our main results.

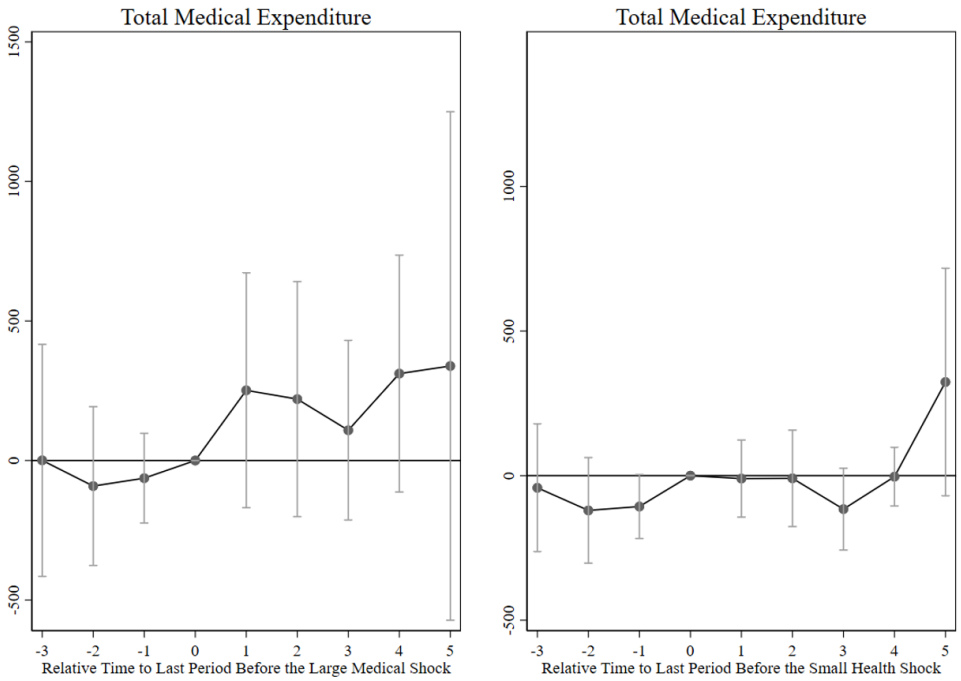


Figure 3 Robustness checks for the spillover effects: heterogeneity in the treatment effect over time

3.2 Dynamic event study with large medical shocks as treatment

Based on the results that the medical expenditures of other family members are more responsive to large medical shocks, we further introduce a treatment status into the event-study model that denotes whether the household has experienced a health shock that incurs large medical expenditure. We estimate the following equation:

$$y_{ht} = \sum_{\substack{\tau=-6 \\ \tau\neq-1}}^{12} \mu_\tau \boldsymbol{I}(t - t_{Shock} = \tau) \times Large\ Shock_h + \sum_{\substack{\tau=-6 \\ \tau\neq-1}}^{12} \rho_\tau \boldsymbol{I}(t - t_{Shock} = \tau) + \gamma_h + \delta_t + \varepsilon_{ht} \quad (2),$$

where $Large\ Shock_h = 1$ if the household has experienced a health shock that incurs a large

medical expenditure in 2017, while $Large\ Shock_h = 0$ if the household has experienced a health shock event that a small medical expenditure in 2017. Other settings are the same as equation (1). The key parameters of interest here are the coefficients of the indicators, μ_τs, which identify the effect of a larger health shock on healthcare expenditures of other family members at a given period τ.

We estimate the effects on the total medical expenditure and out-of-pocket medical expenditure of other family members. The results displayed in Figure 4 show that after a large health shock of a family member, both the total and out-of-pocket medical expenditures of other members show a large and persistent increase, relative to the increase observed for households that only experienced small health shocks. These results point to an attention effect where a higher medical expenditure related to the family health shock leads to more attention being given to information generated by the claim experience, but the specific kinds of information conveyed, i.e., the salience of health, learning of insurance benefits and health risks, remain indistinguishable.

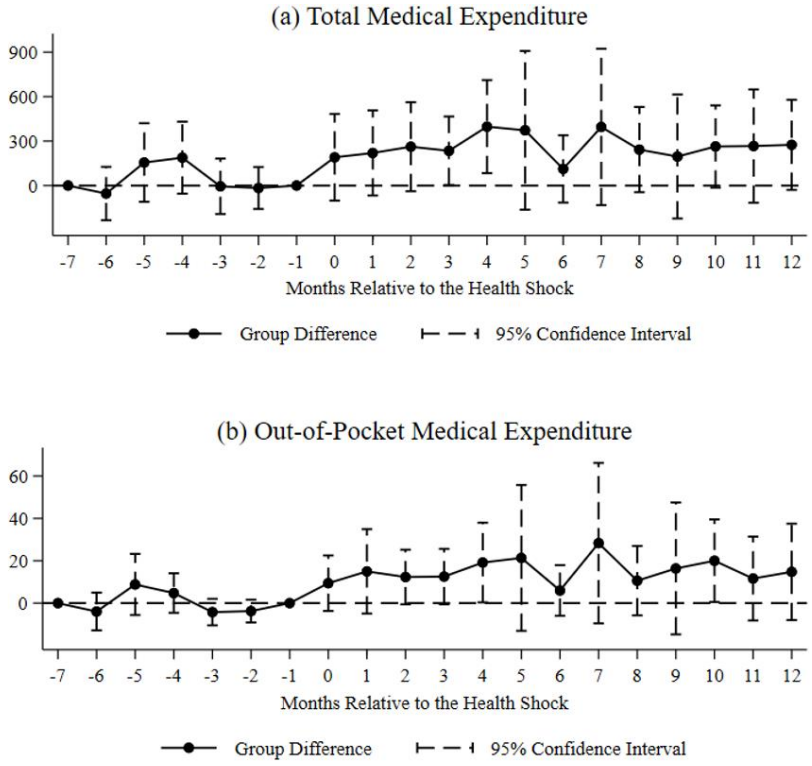


Figure 4 Effects of health shocks on other family members' medical expenditures: using an event-study model with households experienced large medical shocks as the treatment group

3.3 Difference-in-difference estimates

Besides the monthly dynamic effects, we also estimate the average magnitude of the spillover effects. Table 2 presents the difference-in-difference estimates for the impact of family health shocks on other members' healthcare utilization. Columns 1, 3, and 5 estimate equations of the following form:

$$y_{ht} = \beta Post_{ht} + \gamma_h + \delta_t + \varepsilon_{ht} \quad (3),$$

where $Post_{ht} = 1$ represents that the monthly period t is later than the month in which household h experienced a health shock, while $Post_{ht} = 0$ represents that the monthly period t is earlier than or the same as the month in which household h experienced a health shock. Other settings are the same as equation (1). The key parameter of interest here is β, which identifies the average effects of having experienced a health shock on the healthcare utilization of other family members for all monthly periods. The results in column 1 show that the likelihood of incurring medical expenditures for other household members does not increase following the health shock. This is consistent with our event-study estimates, which show no spillover patterns at the extensive margin. The results in column 3 show that the total medical expenditure of other household members significantly increases after one member experienced a health shock, which is equivalent to 68.5% $(= 123.969 \div 200.43)$ of the average medical expenditures in the pre-shock months. Similarly, the results in column 5 show a significant increase in out-of-pocket medical expenditure of other household members after the health shock, equivalent to 106.5% $(= 6.412 \div 6.01)$ of the average value in the pre-shock months. These results indicate that an adverse health shock experienced by one individual generates spillover effects on other family members and increases their healthcare expenditures to a large extent.

Columns 2, 4, and 6 estimate equations of the following form:

$$y_{ht} = \rho Post_{ht} \times Large\ Shock_h + \beta Post_{ht} + \gamma_h + \delta_t + \varepsilon_{ht} \quad (4),$$

where $Large\ Shock_h = 1$ if household h has experienced a health shock that incurs a large medical expenditure in 2017, while $Large\ Shock_h = 0$ if household h has experienced a health shock event with a smaller medical expenditure in 2017. Other settings are the same as equation (3). The key parameter of interest here is ρ, which identifies the average effects of having experienced a larger health shock on the healthcare utilization of other family members for all monthly periods.

The results in column 2 show that compared with households that only experienced small health shocks, the likelihood of incurring medical expenditures for other household members increases to some extent after a large health shock experienced by a family member. More notably, the results in columns 4 and 6 show a 3.12 times $(= 187.011 \div 59.891)$ increase in total medical expenditure and a 6.06 times $(= 12.627 \div 2.085)$ increase in out-of-pocket medical expenditure of other household members after a large health shock, relative to households that only experienced small health shocks.

Table 2 Effects of health shocks on other family members' medical expenditures: DID estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variables	Any Medical Expenditures		Total Medical Expenditures		Out-of-Pocket Medical Expenditures	
Post	0.004	-0.001	123.969**	59.891*	6.412**	2.085
	(0.005)	(0.006)	(49.183)	(33.659)	(3.054)	(1.722)
Large Shock × Post		0.014*		187.011**		12.627**
		(0.008)		(87.304)		(5.874)
Average for Pre-Shock Periods	0.055	0.055	200.43	200.43	6.01	6.01
Observations	30,681	30,681	30,681	30,681	30,681	30,681
R-Squared	0.214	0.215	0.194	0.195	0.159	0.159

Notes: The sample consists of all IPHs exposed to health shocks in 2017. All regressions include household fixed effects and month fixed effects. Standard errors are clustered at the household level.
Significance: * significant at 10%; ** significant at 5%; *** significant at 1%.

4. Learning spillovers about health insurance benefits

4.1 Evidence consistent with the learning of health insurance benefits

If the spillovers of insurance knowledge and information on insurance benefits drive the observed patterns, we expect that the households that experienced health shocks in the previous year of 2016 are likely already exposed to the knowledge, so later health shocks would play a much-limited role. Thus, we repeat the estimation of equation (1), limiting the study sample to households with at least one individual who experienced large medical expenditures and met the conditions for critical illness insurance payment in 2016. Figure 5 reports the effects of health shocks experienced in 2017 on the total medical expenditure of other family members. The results indicate that further experiencing health shocks in 2017 no longer generates spillover effects on the medical expenditure of other family members among households that already experienced health shocks in the previous year. These patterns are largely consistent with an insurance benefit learning effect: the former payout experience provides a one-time learning experience and increases households' understanding of the benefits as well as healthcare utilization persistently, while subsequent shocks and claim experiences hardly convey effective information on insurance benefits anymore.

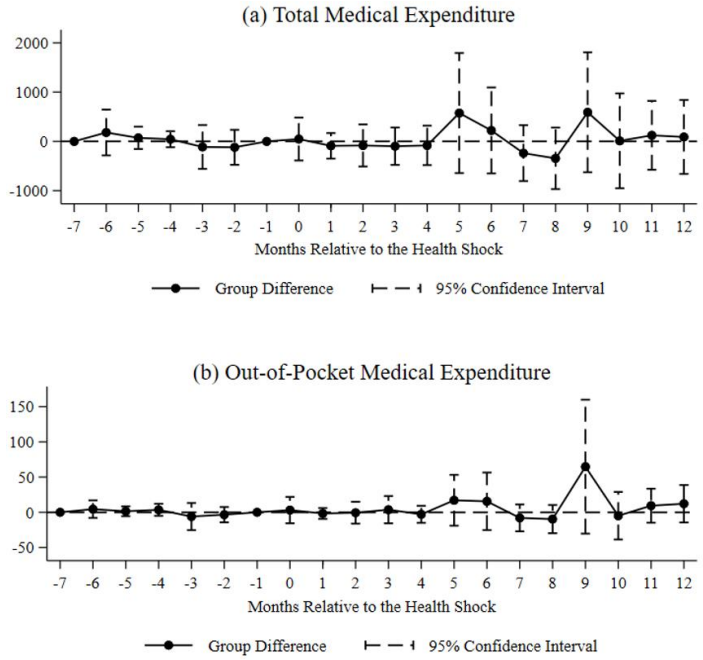


Figure 5 Effects of family health shocks on other members' medical expenditures for households that experienced health shocks in the previous year

In addition, we employ the diagnosis information and separately examine the spillover effects on the medical expenditures of other household members that belong to the same and different disease types in ICD-10 as the health shock itself. We re-estimate equation (1) under this setting. Figure 6 displays the spillover patterns on the total and out-of-pocket medical expenditures for both the same and different types of diseases, indicating a larger magnitude of spillover effects on different types of diseases. These results indicate that the basic results are not driven by the increase in medical expenditures on similar types of diseases as the health shock itself; Instead, the effects largely spill over to medical expenditure on other types of diseases. This is consistent with the insurance knowledge spillover effect, which is not limited to medical expenditure incurred by the diseases directly related to the health shock itself (Hodor, 2021).

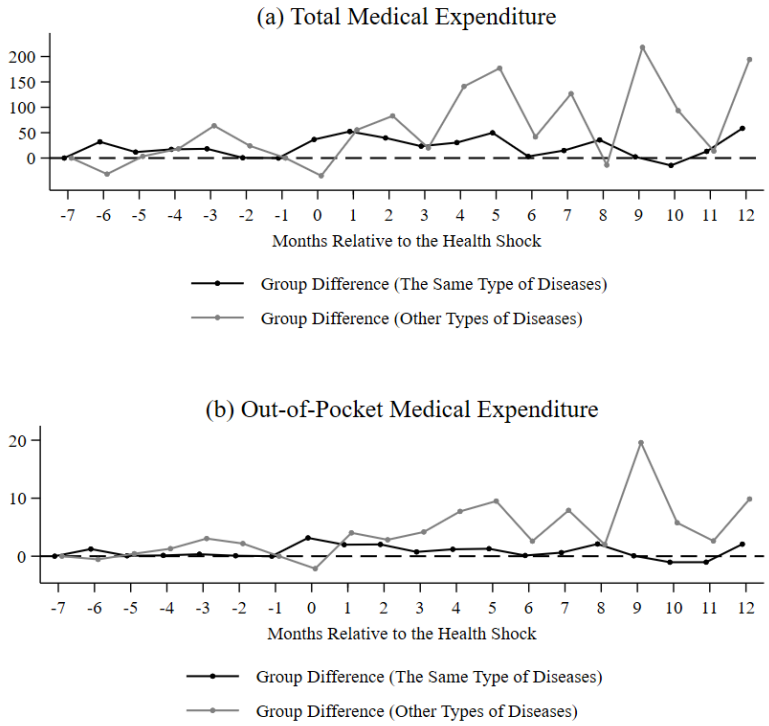


Figure 6 Effects of family health shocks on other members' medical expenditure by ICD-10 types

4.2 Evidence consistent with increased necessary healthcare demands

We next explore what kinds of disease expenditures health shocks mainly spill over into. To do this, we first classify diseases with different ICD-10 codes from the medical expenditure dataset into three main categories according to their average monthly expenditures (conditional on positive values). We test the heterogenous spillover effects for each of the three categories of diseases, and the results are reported in Figure 7. We find that the spillover effects following the family health shock are largely driven by diseases that generally incur higher medical expenditures.[6] After one family member experienced a health shock, both the likelihood that other members have positive medical expenditure and their total medical expenditure on high-cost diseases show large and significant increases. In contrast, there are no clear spillover patterns on medium-cost diseases, and on low-cost diseases, we find somewhat negative spillover effects regarding the likelihood that other members have positive medical expenditure. There are two possible explanations behind these

[6] This category includes six types of diseases in the standardized ICD-10 category, including Neoplasms, Mental and behavioural disorders, Injury, poisoning and certain other consequences of external causes, Diseases of the musculoskeletal system and connective tissue, Certain conditions originating in the perinatal period, and Factors influencing health status and contact with health services.

patterns: First, the increase in spending on high-cost diseases is crowding out utilization related to low-cost diseases for these disadvantaged households; Second, during treatment of more serious illnesses, some minor illnesses were also treated, but their detailed diagnosis was not recorded.

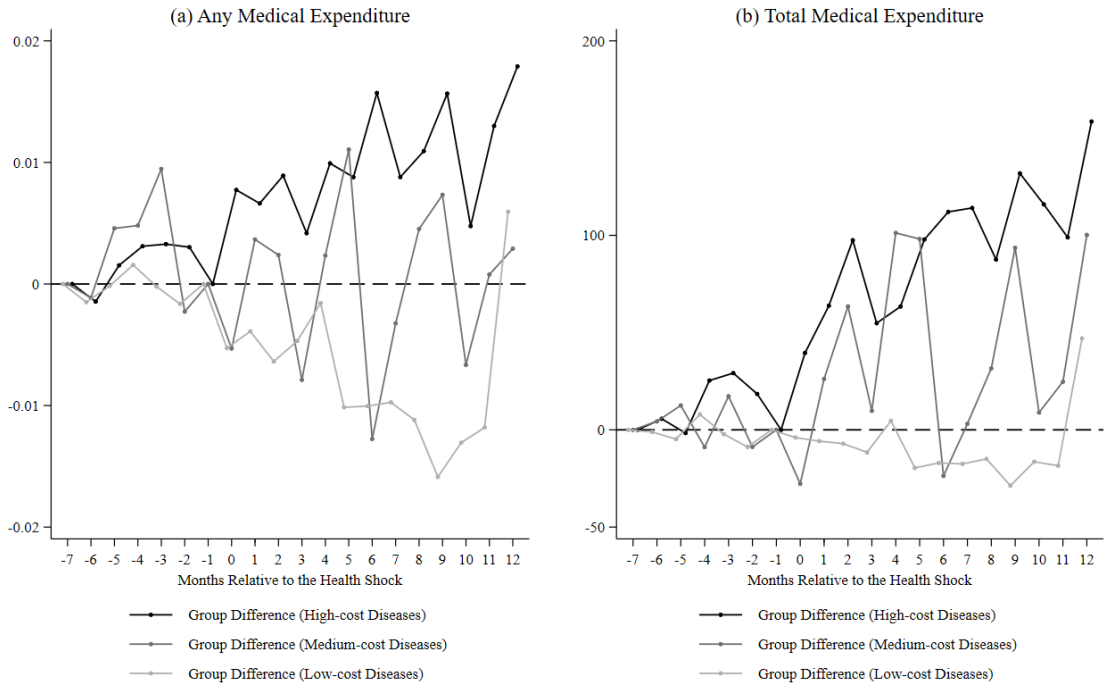


Figure 7 The spillover effects of family health shocks on other members' healthcare utilization for diseases with different levels of medical expenditure

Furthermore, we extract some commonly studied pervasive diseases. We first focus on neoplasms, one of the leading causes of mortality and morbidity, which have relatively large observations within our sample and are generally severe (Jeon and Pohl, 2017). The results in Figure 8 show that after a health shock within a family, the total medical expenditure on neoplasms significantly increase and remain high over the one-year horizon for other members within the family. These patterns indicate that an important part of these spillover effects on medical expenditures come from treatments of necessary and severe diseases, which possibly require expensive procedures and would be life-threatening if left untreated.

Next, we consider diseases of the genitourinary system, which are generally not life-threatening diagnoses and probably require treatment to enhance the quality of life (Shigeoka, 2014). We find no spillover patterns for total medical expenditures on genitourinary system diseases of other family members after the health shock, indicating that the majority of large increases are not

likely to be for these discretionary and less serious diseases.

We also conduct similar analyses for some types of respiratory diseases of different severity. One is pneumonia, which is commonly used to refer to all types of inflammation of the lung, characterized by sudden onset, high fever, and severe malaise among previously healthy individuals (Lazuka, 2020). In 20–30 percent of untreated cases, the contagion by pneumonia leads to death (Brachman and Abrutyn, 2009). The other is the upper respiratory disease (generally known as the common cold), including rhinopharyngitis and infection of the upper respiratory system, which is considered a trivial disease that can also be cured by self-medication (Thönnes, 2019). The results in Figure 8 show that the majority of large spillovers are likely to be driven by treatments of more serious diseases such as pneumonia, for which proper and early medical treatment reduces subsequent severe deterioration. Instead, we do not observe clear spillover patterns for trivial ailments, once again suggesting little evidence of healthcare overutilization of discretionary and trivial diseases.

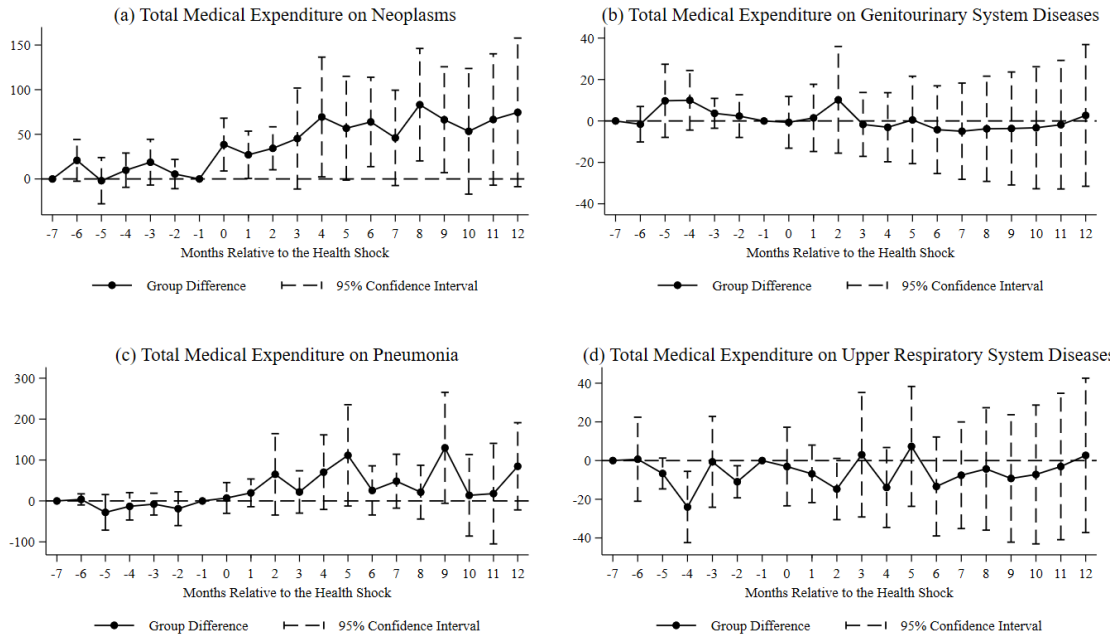


Figure 8 The spillover effects of family health shocks on other members' medical expenditure for four specific types of diseases

Next, we explore whether these spillover effects arise from increased healthcare demand for newly diagnosed diseases or pre-existing diseases. We estimate the following equation to examine the correlations between experiencing a large medical shock and the changes in outcomes of other

members within the family around the shock:

$$y_{iht} = \beta Large\ Shock_h + \gamma_v + \delta_t + \varepsilon_{ht} \quad (5),$$

where y_{iht} denotes the outcomes of interest for individual i who was not directly exposed to the identified health shocks in 2017 from an IPH h at the end of year t ($t = 2016,2017$). $Large\ Shock_h = 1$ if household h has experienced a health shock that incurs a large medical expenditure in 2017, while $Large\ Shock_h = 0$ if household h has experienced a health shock with a small medical expenditure in 2017. γ_v are village fixed effects, δ_t are calendar year indicators, and ε_{ht} is the error term, clustered at the household level. The key parameter of interest here is β, which identifies the correlation between the large medical shock and the change in outcomes of other family members before (at the end of 2016) and after the shock (at the end of 2017).

Columns 1−4 in Table 3 present the estimates for health outcomes of other members within the family, including the likelihood of being diagnosed with chronic diseases, critical diseases, and disabilities, as well as in healthy status (i.e., not diagnosed with chronic diseases, critical diseases, or disabilities). Within this one-year horizon, neither of these health indicators of other members within the households that experienced large medical shocks shows any significant change, compared with households that experienced small medical shocks. These results suggest that the previous spillover effects on medical expenditures are more likely to be driven by the release of healthcare demand for pre-existing conditions, rather than the increase in newly diagnosed diseases. Combined with the evidence that an important part of the spillover effects comes from treatment of necessary and severe diseases, which requires expensive procedures and may have been previously underutilized in this group of individuals on the edge of the poverty line. These results suggest potential welfare improvements from increased treatments of life-threatening diseases among other members, after information about insurance benefits spillovers within the family through a large payout experience.

Columns 5−8 in Table 3 present the estimates for out-of-town employment status, per-capita income, and the poverty status of other family members. The results suggest that individuals from households that experienced large medical shocks slightly reduce the possibility and duration of working outside their hometown. However, the estimates are tiny in magnitude and statistically insignificant, indicating that increased medical expenditure is not driven by the return of more

family members who previously worked outside. Besides, these households are more likely to fall into poverty status and suffer from higher income loss. These patterns are consistent with the well-documented economic consequences of adverse health shocks (Dobkin et al., 2018).

Table 3 Large Medical Shocks and the Outcomes of Other Household Members

Dependent Variables	(1) In Healthy Status (Yes=1)	(2) Chronic Diseases (Yes=1)	(3) Critical Diseases (Yes=1)	(4) Dis-ability (Yes=1)	(5) Work Outside (Yes=1)	(6) Work Outside (Months)	(7) Per-Capita Income (Logarithm)	(8) In Poverty Status (Yes=1)
Large Shock	-0.002	0.003	0.000	-0.001	-0.005	-0.024	-0.071***	0.080***
	(0.006)	(0.005)	(0.002)	(0.004)	(0.008)	(0.080)	(0.024)	(0.021)
Observations	25,444	25,444	25,444	25,444	25,444	25,444	25,441	25,444
R-Squared	0.032	0.034	0.036	0.033	0.058	0.059	0.134	0.137

Notes: The sample consists of individuals not directly exposed to the identified medical expenditure shocks in 2017 from all IPHs. The outcomes are measured with the IPH dataset in 2016 and 2017. All regressions include village fixed effects and year fixed effects. Standard errors are clustered at the household level.
Significance: * significant at 10%; ** significant at 5%; *** significant at 1%.

5. Alternative explanations

There are other possible explanations behind the observed spillover effects on family healthcare expenditures. For example, these spillover effects on healthcare expenditures after an adverse health shock may reflect the correlation of health status among family members. Also based on this kind of health relevance, a health shock may transmit new information about the health risks to other family members and thus increase their preventive and diagnostic behaviors for related diseases. We address this possibility from three aspects. First, compared with other relatives, the heritability of human disease is especially pronounced for parents, children, and siblings of the family member directly exposed to the health shock (Tenesa and Haley, 2013). If the health correlation due to genetic factors drives the main results, the spillover patterns would be noticeably higher for parents and children compared to other family members. We report the estimates of equation (1) using the difference in health care expenditures between parents/children/siblings of the individual who experienced the health shock and family members with other relationships as the outcomes of interest. Figure 9 shows no evidence of significant differences in spillover effects between the two groups of members, indicating that health correlations may not be the main factor behind healthcare spillovers. Second, health correlations are more likely to exist between similar disease conditions. However, the results in Figure 6 show that the spillover effects are not driven by the increase in medical expenditures on similar types of diseases as the health shock itself, and the

effects largely spill over to other types of diseases, further illustrating that the correlation between similar diseases is not a major factor. Third, the results in Table 3 show no significant changes in the diagnosis and detection rates of chronic and critical diseases of other family members following a large medical shock experienced by one member, indicating that the healthcare spillovers are not driven by a sudden deterioration in their state of health.

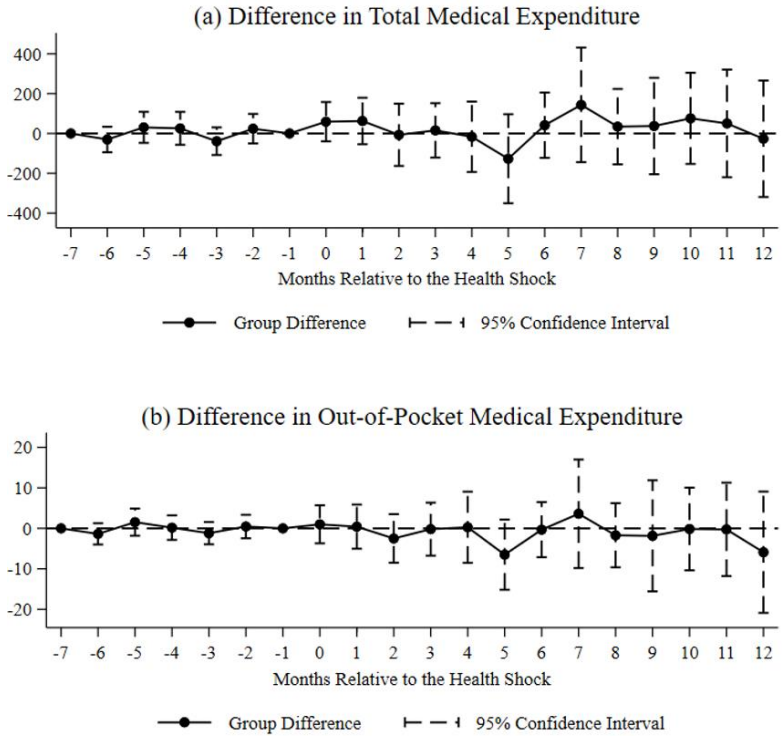


Figure 9 Differences in spillover effects on medical expenditures between parents/children/siblings and other family members

In addition, an adverse health shock is likely to increase the salience of health among other family members, which may translate to changes in their healthcare-related behaviors. Although it cannot be completely ruled out, there has been no sufficient evidence in support of this interpretation. For example, Figure A2 in the Appendix separately reports the effects of the adverse health shock on large medical expenditures of other household members for Counties X and Z, where the proportion of coverage under the poverty-alleviation health insurance system in County X is about 5% higher than that in County Z. Salience of health, if anything, should lead to greater spillover effects in County Z, where out-of-pocket expenditures are higher for IPHs due to a slightly lower reimbursement rate and thus would generate higher attention effects conditional on the same total

medical expenditures. However, based on the estimation of equation (2), we find that larger health shocks generate more pronounced spillover effects in County X, compared with small health shocks. In contrast, this difference is never significant and much smaller in magnitude for County Z. From this perspective, increased salience of health cannot explain the differential spillover trends between the two counties.

6. Conclusions

Based on the detailed information on detailed medical expenditure records in 2017 and family characteristics of Identified Poor Households (IPHs) in County X, China, this paper estimates the short-term spillover effects of a large health insurance payout experience of one individual on the medical expenditures of other members within the family. Exploiting a dynamic event study approach, we show that after a large insurance payout experience of a member, both the total and out-of-pocket medical expenditures of other family members increase promptly in one month and remain high over the one-year horizon. These spillover effects are more pronounced for the health shocks that incur larger medical expenditures.

We find evidence consistent with learning spillovers about the benefits of the newly-constructed poverty-alleviation health insurance behind these patterns, i.e., the information on insurance benefits spillovers within the family through a large payout experience of one member. Based on diagnostic information corresponding to medical expenditures, we show that an important part of the spillover effects comes from increased treatment of necessary and severe diseases, rather than overutilization of medical services for discretionary and trivial illnesses. In addition, we find no evidence of an increase in diagnosed diseases of other family members after the health shock, suggesting released healthcare demand for pre-existing conditions instead of the increase in new disease diagnoses behind the healthcare spillovers.

Our results suggest that this kind of family spillover of knowledge on insurance benefits after a large payout experience has positive welfare implications: other family members show a significant increase in medical treatments of life-threatening diseases, which require expensive procedures and may have been previously underutilized for this group of individuals on the edge of the poverty line. These findings indicate that, beyond the provision of generous health insurance to

disadvantaged populations, it remains essential to promote program awareness and insurance knowledge education to mitigate their imperfect utilization of insurance benefits.

References

Abaluck, J., Gruber, J., 2016. Evolving Choice Inconsistencies in Choice of Prescription Drug Insurance. American Economic Review 106, 2145–2184. https://doi.org/10.1257/aer.20130778

Bhargava, S., Loewenstein, G., Sydnor, J., 2017. Choose to Lose: Health Plan Choices from a Menu with Dominated Option. The Quarterly Journal of Economics 132, 1319–1372. https://doi.org/10.1093/qje/qjx011

Bouckaert, N., Gielen, A.C., Van Ourti, T., 2020. It runs in the family – Influenza vaccination and spillover effects. Journal of Health Economics 74, 102386. https://doi.org/10.1016/j.jhealeco.2020.102386

Brachman, P.S., Abrutyn, E. (Eds.), 2009. Bacterial Infections of Humans: Epidemiology and Control. Springer US, Boston, MA. https://doi.org/10.1007/978-0-387-09843-2

Bratti, M., Mendola, M., 2014. Parental health and child schooling. Journal of Health Economics 35, 94–108. https://doi.org/10.1016/j.jhealeco.2014.02.006

Cai, J., de Janvry, A., Sadoulet, E., 2020. Subsidy Policies and Insurance Demand. American Economic Review 110, 2422–2453. https://doi.org/10.1257/aer.20190661

Cai, J., Janvry, A.D., Sadoulet, E., 2015. Social Networks and the Decision to Insure. American Economic Journal: Applied Economics 7, 81–108. https://doi.org/10.1257/app.20130442

Cai, J., Song, C., 2017. Do disaster experience and knowledge affect insurance take-up decisions? Journal of Development Economics 124, 83–94. https://doi.org/10.1016/j.jdeveco.2016.08.007

Chetty, R., 2008. Moral Hazard versus Liquidity and Optimal Unemployment Insurance. Journal of Political Economy 116, 173–234. https://doi.org/10.1086/588585

Choi, J.J., Laibson, D., Madrian, B.C., 2005. $100 Bills on the Sidewalk: Suboptimal Saving in 401(k) Plans. NBER Working Paper.

De Chaisemartin, C., D'Haultfœuille, X., 2020. Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects. American Economic Review 110, 2964–2996. https://doi.org/10.1257/aer.20181169

Debnath, S., Jain, T., 2020. Social connections and tertiary health-care utilization. Health Economics 29, 464–474. https://doi.org/10.1002/hec.3996

Deri, C., 2005. Social networks and health service utilization. Journal of Health Economics 24, 1076–1107. https://doi.org/10.1016/j.jhealeco.2005.03.008

Dobkin, C., Finkelstein, A., Kluender, R., Notowidigdo, M.J., 2018. The Economic Consequences of Hospital Admissions. American Economic Review 108, 308–352. https://doi.org/10.1257/aer.20161038

Dror, D.M., Soriano, E.S., Lorenzo, M.E., Sarol, J.N., Azcuna, R.S., Koren, R., 2005. Field based evidence of enhanced healthcare utilization among persons insured by micro health insurance units in Philippines. Health Policy 73, 263–271. https://doi.org/10.1016/j.healthpol.2004.11.018

Du, X., Zheng, W., Yao, Y., 2023. The peer effect in adverse selection: Evidence from the micro health insurance market in Pakistan. Journal of Risk and Insurance 90, 1063–1100. https://doi.org/10.1111/jori.12447

Eriksen, T.L.M., Gaulke, A., Skipper, N., Svensson, J., 2021. The impact of childhood health shocks

on parental labor supply. Journal of Health Economics 78, 102486. https://doi.org/10.1016/j.jhealeco.2021.102486

Fadlon, I., Nielsen, T.H., 2021. Family Labor Supply Responses to Severe Health Shocks: Evidence from Danish Administrative Records. American Economic Journal: Applied Economics 13, 1–30. https://doi.org/10.1257/app.20170604

Fadlon, I., Nielsen, T.H., 2019. Family Health Behaviors. American Economic Review 109, 3162–3191. https://doi.org/10.1257/aer.20171993

Finkelstein, A., Taubman, S., Wright, B., Bernstein, M., Gruber, J., Newhouse, J.P., Allen, H., Baicker, K., Oregon Health Study Group, 2012. The Oregon Health Insurance Experiment: Evidence from the First Year. The Quarterly Journal of Economics 127, 1057–1106. https://doi.org/10.1093/qje/qjs020

Flores, G., O'Donnell, O., 2016. Catastrophic medical expenditure risk. Journal of Health Economics 46, 1–15. https://doi.org/10.1016/j.jhealeco.2016.01.004

García-Gómez, P., 2011. Institutions, health shocks and labour market outcomes across Europe. Journal of Health Economics 30, 200–213. https://doi.org/10.1016/j.jhealeco.2010.11.003

García-Gómez, P., Kippersluis, H.V., O'Donnell, O., Doorslaer, E.V., 2013. Long-Term and Spillover Effects of Health Shocks on Employment and Income. Journal of Human Resources 48, 873–909. https://doi.org/10.1353/jhr.2013.0031

Goodman-Bacon, A., 2021. Difference-in-differences with variation in treatment timing. Journal of Econometrics 225, 254–277. https://doi.org/10.1016/j.jeconom.2021.03.014

Gross, T., Layton, T.J., Prinz, D., 2022. The Liquidity Sensitivity of Healthcare Consumption: Evidence from Social Security Payments. American Economic Review: Insights.

Heath, R., Mansuri, G., Rijkers, B., 2022. Labor Supply Responses to Health Shocks: Evidence from High-Frequency Labor Market Data from Urban Ghana. J. Human Resources 57, 143–177. https://doi.org/10.3368/jhr.57.1.0618-9584R2

Hodor, M., 2021. Family health spillovers: evidence from the RAND health insurance experiment. Journal of Health Economics 79, 102505. https://doi.org/10.1016/j.jhealeco.2021.102505

Humlum, M.K., Morthorst, M.O., Thingholm, P.R., 2024. Sibling spillovers and the choice to get vaccinated: Evidence from a regression discontinuity design. Journal of Health Economics 94, 102843. https://doi.org/10.1016/j.jhealeco.2023.102843

Islam, A., Maitra, P., 2012. Health shocks and consumption smoothing in rural households: Does microcredit have a role to play? Journal of Development Economics 97, 232–243. https://doi.org/10.1016/j.jdeveco.2011.05.003

Jeon, S.-H., Pohl, R.V., 2017. Health and work in the family: Evidence from spouses' cancer diagnoses. Journal of Health Economics 52, 1–18. https://doi.org/10.1016/j.jhealeco.2016.12.008

Kamiya, S., Yanase, N., 2019. Learning from extreme catastrophes. J Risk Uncertain 59, 85–124. https://doi.org/10.1007/s11166-019-09310-8

Kaufmann, C., Müller, T., Hefti, A., Boes, S., 2018. Does personalized information improve health plan choices when individuals are distracted? Journal of Economic Behavior & Organization 149, 197–214. https://doi.org/10.1016/j.jebo.2018.03.013

Ketcham, J.D., Lucarelli, C., Miravete, E.J., Roebuck, M.C., 2012. Sinking, Swimming, or Learning to Swim in Medicare Part D. American Economic Review 102, 2639–2673. https://doi.org/10.1257/aer.102.6.2639

Kruse, D., Freeman, R.B., Blasi, J.R. (Eds.), 2010. Shared capitalism at work: employee ownership, profit and gain sharing, and broad-based stock options, National Bureau of Economic Research conference report. The University of Chicago Press, Chicago ; London.

Lavelle, T.A., Wittenberg, E., Lamarand, K., Prosser, L.A., 2014. Variation in the Spillover Effects of Illness on Parents, Spouses, and Children of the Chronically Ill. Appl Health Econ Health Policy 12, 117–124. https://doi.org/10.1007/s40258-014-0079-8

Lazuka, V., 2020. Infant Health and Later-Life Labor Market Outcomes: Evidence from the Introduction of Sulfa Antibiotics in Sweden. J. Human Resources 55, 660–698. https://doi.org/10.3368/jhr.55.3.0817-9016R

McCall, B.P., 1995. The Impact of Unemployment Insurance Benefit Levels on Recipiency. Journal of Business & Economic Statistics 13, 189–198. https://doi.org/10.1080/07350015.1995.10524593

Miller, G., Pinto, D., Vera-Hernández, M., 2013. Risk Protection, Service Use, and Health Outcomes under Colombia's Health Insurance Program for the Poor. American Economic Journal: Applied Economics 5, 61–91. https://doi.org/10.1257/app.5.4.61

Mwabu, G., Ainsworth, M., Nyamete, A., 1993. Quality of Medical Care and Choice of Medical Treatment in Kenya: An Empirical Analysis. The Journal of Human Resources 28, 838. https://doi.org/10.2307/146295

Quanjer, B., Van Dijk, I.K., Rosenbaum-Feldbrügge, M., 2023. Short Lives: The Impact of Parental Death on Early-Life Mortality and Height in the Netherlands, 1850–1940. Demography 10421550. https://doi.org/10.1215/00703370-10421550

Reschovsky, J.D., Hargraves, J.L., Smith, A.F., 2002. Consumer Beliefs and Health Plan Performance: It's Not Whether You Are in an HMO but Whether You Think You Are. Journal of Health Politics, Policy and Law 27, 353–378. https://doi.org/10.1215/03616878-27-3-353

Samek, A., Sydnor, J.R., 2020. Impact of Consequence Information on Insurance Choice. NBER Working Paper.

Shai, O., 2022. Out of time? The effect of an infrequent traumatic event on individuals' time and risk preferences, beliefs, and insurance purchasing. Journal of Health Economics 86, 102678. https://doi.org/10.1016/j.jhealeco.2022.102678

Shigeoka, H., 2014. The Effect of Patient Cost Sharing on Utilization, Health, and Risk Protection. American Economic Review 104, 2152–2184. https://doi.org/10.1257/aer.104.7.2152

Sun, L., Abraham, S., 2021. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. Journal of Econometrics 225, 175–199. https://doi.org/10.1016/j.jeconom.2020.09.006

Tenesa, A., Haley, C.S., 2013. The heritability of human disease: estimation, uses and abuses. Nature Reviews Genetics 14, 139–149. https://doi.org/10.1038/nrg3377

Thönnes, S., 2019. Ex-post moral hazard in the health insurance market: empirical evidence from German data. Eur J Health Econ 20, 1317–1333. https://doi.org/10.1007/s10198-019-01091-w

Vaalavuo, M., 2021. The unequal impact of ill health: Earnings, employment, and mental health among breast cancer survivors in Finland. Labour Economics 69, 101967. https://doi.org/10.1016/j.labeco.2021.101967

Vaalavuo, M., Salokangas, H., Tahvonen, O., 2023. Gender Inequality Reinforced: The Impact of a

Child's Health Shock on Parents' Labor Market Trajectories. Demography 60, 1005–1029. https://doi.org/10.1215/00703370-10828906

Wagstaff, A., 2007. The economic consequences of health shocks: Evidence from Vietnam. Journal of Health Economics 26, 82–100. https://doi.org/10.1016/j.jhealeco.2006.07.001

Wen, J., Huang, H., 2024. Parental health penalty on adult children's employment: Gender differences and long-term consequences. Journal of Health Economics 95, 102886. https://doi.org/10.1016/j.jhealeco.2024.102886

Appendix

Table A1 presents the statistics on disease categories corresponding to health shocks in our sample. Approximately 80% of the health shocks can be matched with a diagnosis from the doctor, and we classify the health shocks into the 22 standardized ICD-10 categories according to the disease diagnoses. 23.82% of the IPHs in our sample experienced Diseases of the respiratory system, which has the highest frequency among the various categories of diseases. In addition, a higher percentage of households experienced neoplasms, diseases of the musculoskeletal system and connective tissue, diseases of the genitourinary system and diseases of the circulatory system. These five broad disease categories accounted for more than 70 percent of all types of health shock.

Table A1 Statistics on disease categories corresponding to health shock diagnoses

ICD-10	**Frequency**	**Percent**
Diseases of the respiratory system	656	23.82
Neoplasms	478	17.36
Diseases of the musculoskeletal system and connective tissue	316	11.47
Diseases of the genitourinary system	276	10.02
Diseases of the circulatory system	272	9.88
Diseases of the digestive system	171	6.21
Injury, poisoning and certain other consequences of external causes	148	5.37
Mental and behavioural disorders	98	3.56
Diseases of the nervous system	72	2.61
Diseases of the blood and blood-forming organs and certain disorders involving the immune mechanism	71	2.58
Certain infectious and parasitic diseases	66	2.4
Symptoms, signs and abnormal clinical and laboratory findings, not elsewhere classified	49	1.78
Endocrine, nutritional and metabolic diseases	36	1.31
Pregnancy, childbirth and the puerperium	13	0.47
Factors influencing health status and contact with health services	13	0.47
Diseases of the eye and adnexa	11	0.4
Diseases of the skin and subcutaneous tissue	3	0.11
Certain conditions originating in the perinatal period	3	0.11
Diseases of the ear and mastoid process	2	0.07
Congenital malformations, deformations and chromosomal abnormalities	0	0
External causes of morbidity and mortality	0	0
Codes for special purposes	0	0
Total	**2754**	**100**

Notes: The table presents the disease type according to the ICD-10 categories corresponding to disease diagnosis of health shocks in our sample households. Approximately 80% of the health shocks can be matched with the diagnosis information, therefore the number of health shocks used for disease classification is less than the number of health shocks experienced by all IPHs in the main sample.

We also explore whether poverty-alleviation health insurance with different levels of generosity is associated with differential spillover trends. To do this, we make use of the setting that only County X further constructed the fifth layer of the poverty-alleviation health insurance system and the average proportion of out-of-pocket hospitalization expenditures for IPHs has been decreased to approximately 5% in 2017. As a comparison, other regions (for example, County Z) in City A remained a four-layer structure with an average of 10% out-of-pocket medical expenditures for IPHs. Figure A1 displays the distribution of large medical expenditures for individuals from Counties X and Z within our sample. We find that individuals in County X systematically incur higher medical expenditures, with the highest value of monthly expenditures in our sample roughly 100,000 yuan (US$13,827) higher than in County Z. This may be related to the higher reimbursement rate in County X, which constructed the fifth layer of the poverty-alleviation health insurance system.

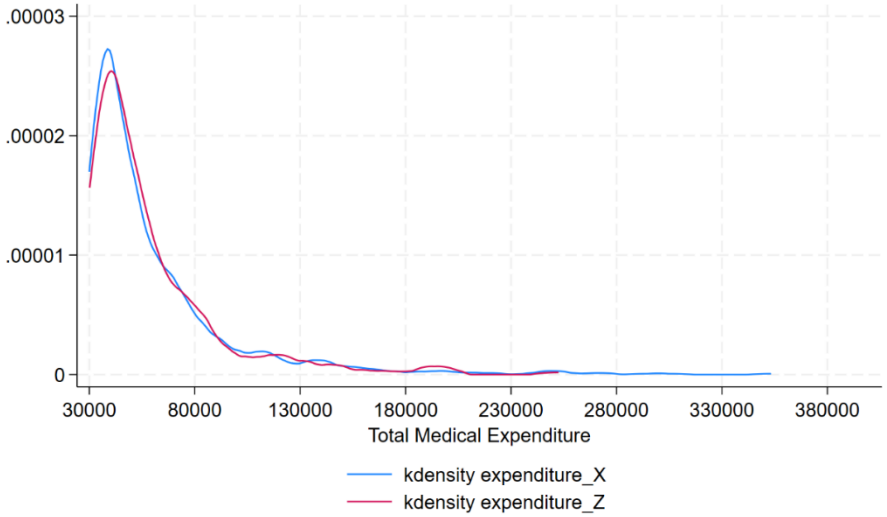


Figure A1 Distribution of monthly medical expenditures over 30,000 yuan (US$4,148) for individuals from our sample in Counties X and Z

Based on these policy contexts, we next conduct similar analyses of the spillover effects of a health shock based on the IPHs in County Z and compare the results with County X. However, regarding the healthcare expenditure data for IPHs in County Z, we only have the medical expenditure records for individuals whose medical expenditures met the conditions for critical illness insurance payment in the whole year of 2017, and lack records of individuals who incurred only small medical expenditures. In this context, we can still identify family health shocks using the same approach, but with a focus on spillovers to the large medical expenditures of other household

members. To ensure comparability, we also re-estimate equations (1) and (2) for County X in this setting, i.e., by keeping only the medical expenditure records of other family members who incurred large expenditures and met the conditions for public critical illness insurance payments in 2017.

The dynamic effects on large medical expenditures of other household members for Counties X and Z are reported in Figure A2. The top two graphs report the estimation of equation (1), and we find that medical expenditures of other family members show large and persistent increases after the health event, and the estimates are largely comparable between the two counties. This is consistent with the fact that both counties offer relatively comprehensive coverage for the IPHs and may both generate strong learning effects after a payout experience. The bottom two graphs report the estimation of equation (2), i.e., the spillover effects of a larger health shock on the healthcare expenditures of other family members. We find that after a large health shock by a family member, the total medical expenditures of other members show significant and persistent increases in County X. In contrast, these estimates are never significant and much smaller in magnitude for County Z. These results provide supportive evidence for the insurance benefit learning channel behind the healthcare spillovers: in County X with a slightly higher percentage of insurance coverage, there is a stronger learning effect from the claim experience, and this small difference in coverage is multiplied when experiencing large medical expenditures related to the shock. This is also consistent with an attention effect where a higher insurance payout leads to more attention being given to the insurance benefits. By comparison, increased salience of health and transmission of health risk information cannot explain these distinctive spillover trends between the two counties, as both factors, if anything, should lead to greater spillover effects in County Z, where out-of-pocket expenditures are higher for IPHs due to a slightly lower reimbursement rate and thus the attention effects would be higher.

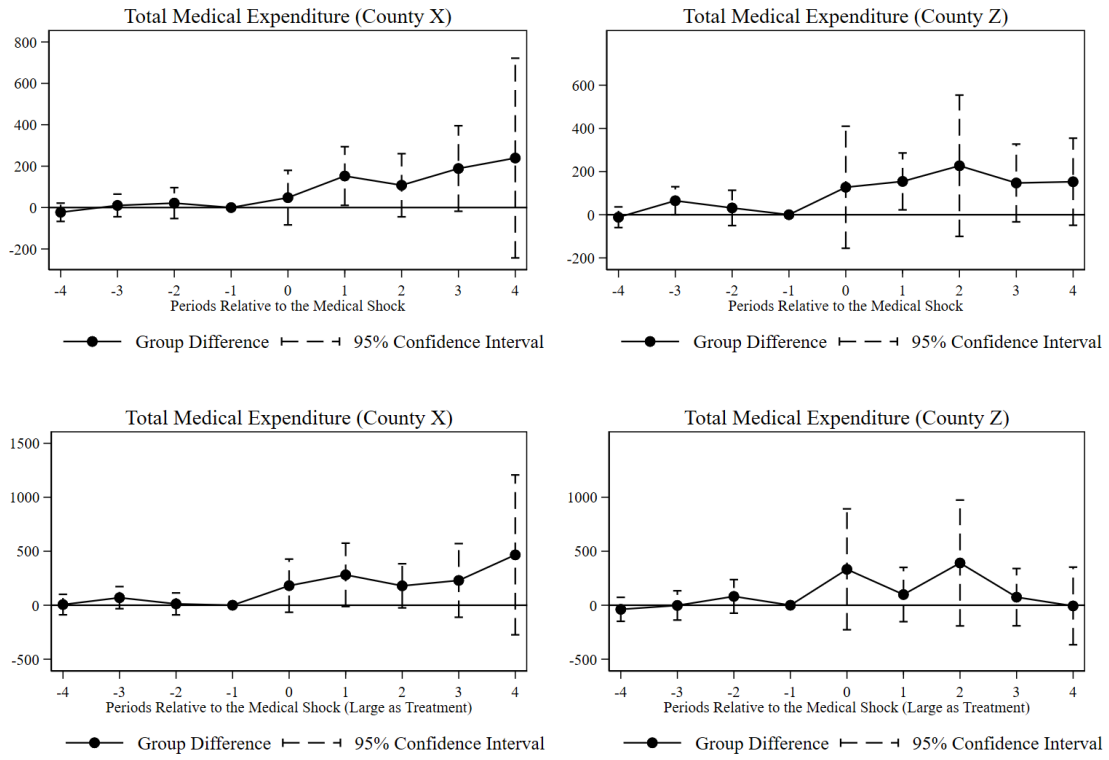


Figure A2 Effects of health shocks on other family members' large medical expenditures: a comparison between Counties X and Z[7]

[7] Due to the smaller size of the sample observations in County Z, we estimate and report the coefficients by combining two months into one period.