Universidad del Rosario | Facultad de Economía

SERIE DOCUMENTOS DE TRABAJO

No. 303

Junio de 2023

Expenditure Responses to Adverse Health Shocks: Evidence from a Panel of Colombian Households

Darwin Cortés

Andrés Gallegos-Vargas

Jorge Pérez Pérez

Universidad del Rosario, Facultad de Economía
Cl. 12c #4-59. Bogotá, D. C., Colombia
PBX: (031) 2970200 ext. 4163

facultadeconomia@urosario.edu.co
https://www.urosario.edu.co/Facultad-de-Economia/Inicio/
https://repository.urosario.edu.co/handle/10336/20291

Expenditure Responses to Adverse Health Shocks: Evidence from a Panel of Colombian Households*

Darwin Cortés† Andrés Gallegos-Vargas‡ Jorge Pérez Pérez§

June 15, 2023

Abstract

We analyze the effect of adverse health shocks on households' expenditure shares in different good categories using a fixed-effects approach and a structural approach based on microeconomic theory. We find that households substitute health and food expenditure in response to adverse health shocks. We find substantial heterogeneity in this trade-off between current and future health mediated by access to social protection, job contract type, and location (urban-rural). Households from rural areas –where household heads are more likely to hold informal jobs and lack access to safety nets– are more vulnerable than others. Our findings suggest that access to formal employment and a higher quality of local institutions can help mitigate the negative consequences of health shocks.

Keywords health shocks, household expenditure, informal labor, urban-rural

JEL Codes D12, I15, J46

*We thank Julieth Pico, Diego Mayorga, Ivonne Lara, Stephany Amaya, Gabriela Triviño-Motta, Gabriel Suárez, Jorge Meléndez, Carolina Crispín, and Sergio Rivera for research assistance. We also thank Claudia Quintero and Nicolás Fuertes for assistance with the ELCA data. We thank Seema Jayachandran, Karen Macours, Mrinal Mishra, Paul Rodríguez-Lesmes, Nicolás de Roux, Andrés Zambrano, and participants at the Economics of Informality Conference, SEHO 2021, LACEA 2022 and the Annual Congress of the Economics Researchers Network – Banrep 2022 for comments and suggestions. The views and conclusions presented in this paper are exclusively the authors' responsibility and do not necessarily reflect those of Banco de México. We acknowledge financial support from Fulbright - Colciencias and Colombia Científica - Alianza EFI #60185 contract # FP44842- 220-2018, funded by The World Bank through the Scientific Ecosystems, managed by the Colombian Ministry of Science, Technology and Innovation (MINCIENCIAS).

†*Corresponding author.* Universidad del Rosario and Alianza EFI. E-mail: darwin.cortes@urosario.edu.co. Postal Address: Calle 12c 4-69 of. 310, 111711, Bogotá, Colombia.

‡Universidad del Rosario. E-mail: german.gallegos@urosario.edu.co.

§Banco de México. E-mail: jorgepp@banxico.org.mx.

1 Introduction

How do households react to adverse shocks that may alter both their income constraint and preferences? Consumer theory suggests that agents should adjust their expenditure on different goods according to their income elasticity. However, these expenditure adjustments may change because of other circumstances surrounding households, such as their insurance degree and income sources. Understanding the origins of heterogeneity in these responses is vital for the design of social protection programs (Blundell et al., 2020).

This paper uses household data from Colombia to study the expenditure response to adverse health shocks. We document substantial differences in the expenditure response to these adverse shocks between urban and rural households. We examine the mechanisms behind these heterogeneous responses focusing on the role of labor informality and insurance. The Colombian setting is attractive, at least for two reasons. First, Colombia is an increasingly urban developing country, where the urban share of the population has grown by 9% in the last three decades. This urbanization process has led to a sizeable urban-rural divide in development indicators. In such a setting, the response to adverse health shocks may differ starkly across urban and rural areas. Second, Colombia has a high degree of labor informality. The percentage of informal workers without access to employer-financed health insurance was 56% in January 2020.

To examine the expenditure response to adverse health shocks, we use two panel data waves (2013 and 2016) on urban and rural households in Colombia. We create a harmonized dataset of household expenditure in several item categories across its two waves. In the first part of the paper, we estimate the effect of health shocks on expenditure by comparing households who experienced negative health shocks to those who did not, using a two-way fixed effects approach. Our identification assumption is that in the absence of adverse health shocks, the expenditure shares in each item category we consider would evolve in parallel across unaffected and affected households, conditional on household demographics and the occurrence of other shocks. The panel nature of the data allows us to control for time-invariant heterogeneity across households using fixed effects. The panel analysis contrasts with other studies that rely on repeated cross-section data or synthetic panel methods (Attanasio and Székely, 2004).

We then model the expenditure share on item category as a function of prices, income, and demographics, following specifications from the demand system estimation literature (Deaton and Muellbauer, 1980; Pollak and Wales, 1981; Barnett and Serletis, 2008). This specification allows us to separate the effects of the health shocks into effects on expenditure into two components: 1) Their effects on expenditure shares via changes in income, and 2) their effects on expenditure shares through changes in preferences. We do this by allowing the demand functions to shift in response to shocks and estimating these shifts. Our approach follows that of Attanasio et al. (2011), who embed a difference-in-differences analysis in consumer theory-inspired Engel curves to assess the response of food expenditure to cash transfers.

We find that health shocks induce significant expenditure adjustments that vary between household types. Both food and health expenditure react strongly to health shocks. Rural households increase their health expenditure share by around four percentage points (p.p.) and substitute away from food expenditure, reducing their budget share by about four p.p. Urban households increase their health expenditure by about one p.p. These differences across rural and urban households do not arise from different baseline expenditures or income responses to the adverse shocks. When decomposing these effects into the income-mediated and preference-change components, we find that most of the effects come from changes in preferences that shift the demand curves for food and health, not from mere income effects.

Our results contrast with those of Kinnan et al. (2020), who find that households' expenditures in categories other than health do not react to health shocks, suggesting that households can buffer health shocks. This difference may be due to our households being more liquidity-constrained or having less social insurance access. Indeed, our estimates show a substantial role of insurance and formal employment as sources of the observed heterogeneity in responses. Among urban households, those whose household heads have formal jobs do not reduce their food expenditure in response to adverse health shocks. In contrast, urban households with informally-employed heads and rural households reduce their food expenditure by four p.p. Households with access to formal safety nets, such as a conditional cash transfer program, or informal safety nets, such as risk-sharing with neighbors, do not substitute away from food expenditure to weather adverse health shocks.

This work contributes to the literature on consumption responses to health and income shocks in developing countries. Many of these papers have focused on the Indonesian case. Gertler and Gruber (2002) show that households in Indonesia cannot entirely smooth consumption against shocks arising from severe illness. Genoni (2012) shows that these illness-related shocks also reduce income in Indonesian households and that transfers act as a coping strategy. Sparrow et al. (2014) show that the negative response of income to shocks comes mostly from poor rural households, while other households can smooth consumption. Our results for the Colombian case confirm that rural households cannot level off the shocks and highlight substitution away from food expenditure as a shock response.

On coping strategies, Gertler et al. (2009) show that access to finance may help households smooth consumption against these shocks. Wagstaff (2007) shows that families with more inactive working-age members may adjust to the shock by sending these members to the labor force. In their case, rural households are more insured because they usually have more idle members. We also find that larger households can smooth their consumption when affected by a health shock. Access to formal and informal insurance also allows these households to maintain their levels of food expenditure.

Our paper also contributes to the literature on expenditure responses to income shocks that may arise because of conditional cash transfers (Attanasio et al., 2011) and transitory income shocks (Arbelaez et al., 2019; Ganong and Noel, 2019). We also contribute to the literature on household demand (Barnett and Serletis, 2008) and the role of household heterogeneity (Lewbel and Pendakur, 2009). Last, we contribute to the literature about demand analysis in Colombia (Atuesta and Paredes Araya, 2012; Cortés and Pérez Pérez, 2010; Londoño Cano et al., 2011).

The rest of the paper proceeds as follows. Section 2 describes the data and provides some descriptive statistics. Section 3 describes our empirical strategy. We show our main results on the impact of shocks on expenditure in section 4. In section 5, we discuss heterogeneous effects and mechanisms. Section 6 concludes.

2 Data and Descriptive Statistics

This section describes the data we use in detail and provides descriptive statistics about household expenditures and the prevalence of adverse shocks.

Data source. We use two waves of the Colombian Longitudinal Survey from Universidad de los Andes (ELCA) (CEDE, 2016). The ELCA is a longitudinal survey of about 5,000 urban and 4,500 rural households. We use the survey's 2013 and 2016 waves. This dataset is unique for Colombia, which lacks other longitudinal data sets for this period.

The survey has separate modules for urban and rural households and collects socio-demographic, labor markets, and expenditure data. It classifies Colombian households into six economic strata according to income levels. The urban module is representative of the four lowest strata in the urban portion of the country. The rural module is representative of low- and middle-income farm producers in four specific micro-regions that concentrate most of the agricultural production in the country.[1] The effects of shocks we estimate in section 4 are therefore not representative of the entire rural population (Solon et al., 2015). Because the rural and urban modules represent different population segments, we do not pool them in our regression models using survey weights. [2]

Income and expenditure data. The survey collects detailed household income and in-

[1] The four micro-regions are: "Atlántica Media", which covers parts of Córdoba and Sucre; "Cundiboyacense", which covers parts of Cundinamarca, Boyacá and Santander; "Eje Cafetero", which covers several municipalities in Risaralda and Quindío; and "Centro-Oriente", which includes municipalities in Tolima and Cundinamarca.

[2] We also report unweighted estimates in the Appendix to show the robustness of our results.

come data for each household member and collects data on expenditure in several categories. This expenditure data is collected directly from interviewers using the recall method. Expenditure on certain goods may have some measurement error, particularly for goods purchased at low frequencies (Battistin, 2003).

We harmonize the income and expenditure data to be comparable across waves. For income, we contrast individual-level with household-level information and real income variation through time for each household and the whole income distribution. For expenditure, we remove durable expenditures such as furniture and home appliances, education, vehicles, or real estate. We then aggregate the remaining items into nine categories: Food, Alcoholic Beverages and Tobacco, Small Furnishings, Recreation, Health, Personal Services, House Services, Transport and Communication, and Clothing.[3]

Shocks data. The ELCA data includes questions about whether the household experienced shocks in the last three years before being surveyed at each wave. Households answer questions about 19 types of shocks of diverse nature, for example, whether a crop failed or a household member passed away. A household is affected by a health shock if any household member is affected by an accident or illness.[4]

Sample selection. We restrict our analysis to households we can follow in the second and third waves of the data.[5]

We discard outliers of total household expenditure.[6] To control for household member composition changes that may change budget shares, we keep only households whose member composition did not change between waves. A household is in our sample if it did not separate between the two waves and if none of its members left, arrived, passed away, or were born between waves. In doing so, we arrive at 2,734 households maintaining the same composition from 2013 to 2016. From these, 1,198 are rural, 1,458 are urban, 67 transitioned from rural to urban between waves, and 11 transitioned from urban to rural. We finally exclude these migrant households because our identification strategy is estimated separately for rural and urban households, and in a fixed effects specification, we would not observe migrant households long enough. Our final sample consists of 1,458 urban and 1,198 rural households, 2,656 households in total.

[3] The ELCA data has an additional wave for 2010. We do not use this wave because we cannot make income and expenditure from it compatible with income and expenditure on the other two waves. The questions about different sources of income and expenditure were substantially different in 2010.

[4] Table A.1 in the Appendix catalogs the types of shocks available in the data. We classify these shocks into six categories. Arbelaez et al. (2019) also use the shocks data from ELCA and study the shocks' persistence and their effects on household consumption and income.

[5] Attrition between these two waves of data is 4.8%; 6.1% for the urban sample, and 3.4% for the rural sample.

[6] We remove the lowest 5% and the highest 5% of households in the distribution of total expenditure, as well as those remaining with no positive expenditure.

Descriptive statistics. Table 1 shows descriptive expenditure and income statistics for urban and rural households. In 2013, urban households received more than twice the monthly income of rural households and spent about 80% more. By 2016, the income gap had narrowed, but the expenditure gap remained. The expenditure amounts are usually higher for urban households, with a few exceptions. Health expenditure was higher for rural households in 2013 but declined sharply by 2016. Relative to urban households, rural households spend a more significant fraction of their total expenditure on food and smaller fractions on house services, transport, and clothing. The average number of household members is between 3 and 4, with rural households larger than urban ones. The informality of the household head, which we define as either non-affiliation to social health insurance or not contributing to the pension system, is also higher in rural households. The informal rural households' share fell from 97% in 2013 to 91% in 2016. Unlike them, the proportion of urban households with an informal head increased slightly between 2013 and 2016, from 55% to 58%.

Table 2 shows the percentage of households who experienced negative health shocks. In 2013, 26% of urban households and 22% of rural households in our sample experienced health shocks. In 2016, the percentage of urban households affected by health shocks remained the same, but the percentage of rural households affected increased to 32%. The frequency of shocks was higher for small urban and rural households in 2013 but lower in 2016. The low incidence of health shocks for rural households in 2013 seems to be related to households whose household head works with a contract (and in the retailing sector). Other shocks affected our sample in different manners. For instance, significantly more households reported having a natural disaster shock in 2016 than in 2013, and the prevalence of crime/violence shocks decreased slightly between both waves[7].

Table 3 compares budget shares among households that experienced and did not experience health shocks. The differences are substantial for some expenditure categories. The food budget share is about four p.p. higher for rural households experiencing health shocks and is significant in standardized terms. Additionally, the food budget share for shocked urban households is about one p.p. lower than for non-shocked ones. Urban households with health shocks have around a two p.p. larger share of health expenditure than their unaffected counterparts, and rural households have a 7 p.p. higher share. Across the board, rural households reduce expenditure in non-health categories in response to the shock larger than urban households.

Additional data sources. We merge the ELCA data (with private municipality identifiers) with municipality-level information on financial products from Asobancaria and information on the public services provision and health infrastructure from the CEDE municipal

[7] Appendix table A.2 shows the incidence of other types of shocks.

Table 1: Descriptive Statistics

	2013		2016	
	Urban	Rural	Urban	Rural
Household income	1140677.80	418607.36	1228853.95	616932.53
Total expenditure	927217.75	512244.83	1042673.68	543756.28
Number of members	3.46	3.68	3.46	3.68
Informal household head	0.55	0.97	0.58	0.91
Expenditure by Category				
Food	455059	298297	519433	358700
Alcoholic beverages and tobacco	9019	8227	14925	7918
Furnishings	2148	2041	1716	1222
Recreation	26659	4323	28195	5024
Health	21896	36212	20664	15505
Personal services	79619	43596	96891	44842
House services	133375	35247	120048	38472
Transport and communication	147672	70704	179533	63018
Clothing	51771	13597	61269	9054
Budget Shares				
Food share	0.508	0.596	0.524	0.682
Alcoholic beverages and tobacco share	0.010	0.018	0.013	0.015
Furnishings share	0.002	0.004	0.002	0.002
Recreation share	0.024	0.007	0.022	0.008
Health share	0.022	0.072	0.018	0.023
Personal services share	0.084	0.082	0.091	0.078
House services share	0.153	0.069	0.123	0.074
Transport and communication share	0.149	0.123	0.160	0.106
Clothing share	0.048	0.029	0.049	0.013

Note: Monetary amounts are monthly averages by household. Colombian pesos of 2008 deflated using the national yearly consumer price index. Statistics are for the estimation sample of 2,656 households, using the average of the survey weights for 2013 and 2016 by household. "Informal household head" is defined as 0 if the head is affiliated with health insurance and contributes to the pension system and 1 in any other case. In 2008, the USDollar-COP exchange rate amounted to 2066.19 COP per 1 US dollar. Then, for instance, the income of urban households in 2013 was around 570 US dollars. Source: ELCA.

Table 2: Incidence of Adverse Health Shocks

	2013			2016			2013-2016
	Urban	Rural	Overall	Urban	Rural	Overall	Overall
All households	0.26	0.22	0.26	0.26	0.32	0.26	0.26
3 members or less	0.27	0.32	0.27	0.26	0.34	0.26	0.26
4 members or more	0.26	0.14	0.26	0.27	0.31	0.27	0.26
Formal household head	0.28	0.25	0.28	0.25	0.15	0.25	0.26
Informal household head	0.26	0.22	0.25	0.28	0.34	0.28	0.27
Not in CCT program	0.28	0.31	0.28	0.26	0.47	0.26	0.27
Is in CCT program	0.18	0.12	0.18	0.30	0.16	0.30	0.24
No social capital	0.25	0.22	0.25	0.25	0.32	0.25	0.25
Has social capital	0.31	0.21	0.31	0.32	0.31	0.32	0.32
Unemployed	0.25	0.12	0.25	0.33	0.15	0.33	0.29
Employed	0.27	0.24	0.27	0.25	0.36	0.25	0.26
Unemployed	0.25	0.12	0.25	0.33	0.15	0.33	0.29
Works with contract	0.27	0.09	0.27	0.25	0.31	0.25	0.26
Works without contract	0.26	0.26	0.26	0.24	0.36	0.25	0.25
Unemployed	0.25	0.12	0.25	0.33	0.15	0.33	0.29
Other primary-secondary sectors	0.26	0.22	0.26	0.25	0.26	0.25	0.25
Agriculture	0.34	0.26	0.33	0.25	0.41	0.25	0.30
Wholesaling and retailing	0.27	0.05	0.27	0.17	0.09	0.17	0.22
Other tertiary sector	0.25	0.20	0.25	0.28	0.36	0.28	0.27

Note: A household suffers a health shock if any member has been affected by an accident or illness in the last three years. Informal households are those whose household head is either unaffiliated with social health insurance or does not contribute to the pension system. CCT stands for conditional cash transfer. The conditional cash transfer program is called *Familias en Acción*, the main program of its kind in Colombia. A household has social capital if its head participates in local groups or organizations, like political parties, guilds, or sports clubs. Labor market variables are for the household head. "Works with contract" includes households whose head has a verbal or written contract. "Other primary and secondary sectors" includes mining, manufacturing, construction, and water treatment. "Other tertiary sector" includes hotels, restaurants, public service, education, communication, health services, management, science, art, and other industries not previously classified. Source: ELCA.

Table 3: Average Budget Shares / Health Shock vs. No Health Shock

Budget share		Shock	No shock	Diff.	Std. diff.
Food	Urban	0.508	0.519	-0.011	-0.055
	Rural	0.613	0.648	-0.035	-0.156
	Overall	0.508	0.519	-0.011	-0.055
Alcoholic beverages and tobacco	Urban	0.010	0.012	-0.002	-0.051
	Rural	0.016	0.017	-0.001	-0.019
	Overall	0.010	0.012	-0.002	-0.051
Furnishings	Urban	0.002	0.002	0.000	0.000
	Rural	0.002	0.003	-0.001	-0.101
	Overall	0.002	0.002	0.000	0.000
Recreation	Urban	0.026	0.022	0.004	0.064
	Rural	0.007	0.008	-0.001	-0.034
	Overall	0.026	0.022	0.004	0.064
Health	Urban	0.034	0.015	0.019	0.273
	Rural	0.100	0.028	0.072	0.394
	Overall	0.034	0.015	0.019	0.268
Personal services	Urban	0.086	0.088	-0.002	-0.026
	Rural	0.075	0.082	-0.007	-0.112
	Overall	0.086	0.088	-0.002	-0.026
House services	Urban	0.135	0.139	-0.004	-0.036
	Rural	0.075	0.070	0.005	0.064
	Overall	0.135	0.139	-0.004	-0.036
Transport and communication	Urban	0.158	0.153	0.005	0.033
	Rural	0.100	0.120	-0.020	-0.161
	Overall	0.158	0.153	0.005	0.034
Clothing	Urban	0.041	0.051	-0.010	-0.112
	Rural	0.011	0.025	-0.014	-0.257
	Overall	0.041	0.051	-0.010	-0.112

Note: The standardized difference is calculated as $(\bar{x}_1 - \bar{x}_0)/\sqrt{\sigma_1^2 + \sigma_0^2}$, where σ_i^2 is the variance of each budget share in each group $i \in \{0, 1\}$.

panel and the Colombian Ministry of Health. We use this expanded database to explore the heterogeneous effects of the institutional environment on easing a health shock's effect on consumption.

3 Empirical Strategy

We estimate the effects of adverse health shocks on expenditure in different categories, first by using a fixed-effects approach and then by estimating the households' demand for goods in each category and allowing the shocks to shift these demand curves. Our strategies compare households that experience health shocks to those that do not. We describe the specification, the identification strategy, and the estimation below.

Fixed effects specification. We first use the standard two-way fixed effects approach to measure the total effect of the health shock (and the other measured shocks) in each budget share. Our regression specification is:

$$s_{ght} = \beta_0 + \beta_{Health} Health\ Shock_{h,t-1} + Shocks'_{h,t-1}\boldsymbol{\beta}_{\mathbf{Others}} + Z'_{ht}\boldsymbol{\beta}_{\mathbf{Z}} + \delta_h + \delta_t + \varepsilon_{ght}. \tag{1}$$

Here, $s_{ght} \equiv \frac{X_{ght}}{X_{ht}}$ is the budget share for good category $g \in \{1, \dots, G\}$ in household h at time t. The parameters δ_h and δ_t are household and time fixed-effects, respectively, and ε_{ght} is an error term. $Health\ Shock_{h,t-1}$ is one if a household experienced an adverse health shock during the three years before being surveyed, and zero otherwise. The coefficient of interest β_{Health} measures how the budget share reacts to a health shock. The vector $Shocks_{h,t-1}$ contains indicator variables for shocks in the other categories. The vector of coefficients $\boldsymbol{\beta}_{\mathbf{Others}}$ captures the effect of these other shocks. Last, Z_{ht} is a vector of covariates.

Demand specification. The total effect given by β_{Health} in equation (1) can be decomposed effects on preferences and income, following the literature on demand estimation (Barnett and Serletis, 2008). To decompose the total effect, we model household expenditure in each category of goods as a function of prices, income, and demographics. We estimate quadratic demand functions with time and household fixed effects:

$$s_{ght} = \theta_0 + P'_{ght}\boldsymbol{\theta}_{\mathbf{P}} + \theta_X \ln X_{ht} + \theta_{X^2} \ln X^2_{ht} + Z'_{ht}\boldsymbol{\theta}_{\mathbf{Z}} + \gamma_h + \gamma_t + \epsilon_{ght}. \tag{2}$$

This specification assumes that demand is linear in the logarithm of prices faced by the household, $P'_{ght} = (P_{1ht}, P_{2ht}, \dots, P_{Ght})$. It is quadratic on total household expenditure X_{ht} (it is usual in this theory to assume that consumers expend all their income and do not incur debt). Additional variables Z_{ht} can shift the level of demand.

Equation (2) is a reduced form of a demand function from a quadratic almost ideal demand system (QUAIDS) (Banks et al., 1997). We allow demographics to shift demand linearly as in Pollak and Wales (1981). We also allow for household-level taste heterogeneity through the household fixed effects γ_h (Lecocq and Robin, 2015).[8]

Estimation issues. We cannot estimate equation (2) directly because we lack price data. Instead, we follow Attanasio et al. (2011) and estimate a separate equation for each good category g, allowing for heterogeneous trends across regions. These heterogeneous trends capture regional differences in the evolution of prices. The household fixed effects absorb any cross-sectional variation in Z_{ht}. To allow for a flexible role of demographics in determining expenditure evolution, we allow for differential time trends interacted with demographics in the first period. We control for the education level of the household head in 2013. To account for the spatial correlation of prices and other unobservables at the municipality level, we cluster our standard errors at the municipality level.

An additional issue with equation (2) is the presence of division bias because X_{ht} appears both on the left- and right-hand sides. While this is a pervasive problem in cross-sectional demand estimation, it is likely less of an issue in the panel setting. On the cross-section, division bias would imply a negative mechanical correlation between X_{ht} and ε_{ght} because households with larger expenditures would have smaller budget shares. However, the fixed effects γ_h address this cross-sectional effect. Over time, budget shares would be mechanically lower for an individual household if total expenditure increases. The time effects γ_t, and the differential trends by demographics address this mechanical effect. Any remaining division bias would come from the differential evolution of expenditure not addressed by these controls.

Addressing these issues with prices and demographics, and considering that we only use two waves of data, our specification for demand in the absence of shocks is:

$$
\begin{aligned}
s_{ght} = \theta_0 + \sum_s \theta_{r(h)} 1(r(h) = s) 1(t = 2016) + \theta_X \ln X_{ht} + \theta_{X^2} \ln X_{ht}^2 \\
+ Z'_{h,2013} 1(t = 2016) \boldsymbol{\theta_{2016}} + \gamma_h + \gamma_t + \epsilon_{ght}.
\end{aligned} \tag{3}
$$

Here, $1(r(h) = s)$ is a region indicator, and $1(t = 2016)$ equals one for the second wave of data and zero otherwise.

Effect of shocks. If we allow adverse shocks in the previous three years to shift demand as covariates Z in equation (3), we get:

[8] Seeming-unrelated-regressions estimation (SUR) of these equations yields the same point estimates as estimating each equation using fixed effects because the right-hand-side variables are the same. However, we will use the SUR model in our main results estimations to consider possible correlations between the error terms ϵ_{ght}.

$$
\begin{aligned}
s_{ght} = \beta_0 + \sum_s \theta_{r(h)} 1(r(h)=s)1(t=2016) + \theta_X \ln X_{ht} + \theta_{X^2} \ln X_{ht}{}^2 + \gamma_h + \gamma_t \\
+ \theta_{Health} Health\ Shock_{h,t-1} + Shocks'_{h,t-1}\boldsymbol{\theta_{\mathbf{Others}}} + Z'_{ht} 1(t=2016)\boldsymbol{\theta_{\mathbf{2016}}} + \epsilon_{ght}.
\end{aligned} \tag{4}
$$

Since all the shocks are idiosyncratic and specific to each household, we do not expect them to alter prices through general equilibrium effects. Still, households may respond to a shock by modifying their total level of expenditure (be it through the shock affecting their income or their savings behavior). Therefore, if we assume that $\ln X_{ht}$ depends linearly on the shocks, we can estimate the following auxiliary equation:

$$
\begin{aligned}
\ln X_{ht} = \varphi_0 + \sum_s \varphi_{r(h)} 1(r(h)=s)1(t=2016) + \varphi_{Health} Health\ Shock_{h,t-1} \\
+ Shocks'_{h,t-1}\boldsymbol{\varphi_{\mathbf{Others}}} + Z'_{ht} 1(t=2016)\boldsymbol{\varphi_{\mathbf{2016}}} + \phi_h + \phi_t + \nu_{ht}.
\end{aligned} \tag{5}
$$

Based on equations (4) and (5), we can find the following decomposition of the total effect from the reduced form in (1) that the health shock has on each budget share:

$$
\frac{ds_{ght}}{dHealthShock_{h,t-1}} = \frac{\partial s_{ght}}{\partial HealthShock_{h,t-1}} + \frac{\partial s_{ght}}{\partial \ln X_{ht}} \frac{\partial \ln X_{ht}}{\partial HealthShock_{h,t-1}} + \frac{\partial s_{ght}}{\partial \ln X_{ht}{}^2} \frac{\partial \ln X_{ht}{}^2}{\partial \ln X_{ht}} \frac{\partial \ln X_{ht}}{\partial HealthShock_{h,t-1}}, \tag{6}
$$

which we can in terms of the equations' parameters as:

$$
\beta_{Health} = \underbrace{\theta_{Health}}_{\text{Direct Effect}} + \underbrace{\theta_X \varphi_{Health} + 2\theta_{X^2} \varphi_{Health} \ln X_{ht}}_{\text{Indirect Effect}}. \tag{7}
$$

The direct and indirect effects have geometrical interpretations for the Engel curves of each good category. Allowing shocks to affect the demand curve linearly implies that these shocks shift Engel curves up or down but do not change demand's price or income elasticities. In contrast, the indirect effect does not shift the Engel curve but allows the consumer to move on it through the effect on total expenditure. This decomposition of the total effect β_{Health} is relevant because it helps us understand if the health shock modifies the household's preferences (by shifting the Engel curve) or if it moves the household along the same Engel curve by affecting their income or total consumption. In addition to estimating (1), (4), and (5) using the aforementioned quadratic Engel curve specification, we estimate unconditional non-parametric Engel curves for households that experience and do not experience health shocks. We do this through local polynomial regressions. The visual evidence on shifts of these demand curves helps us validate the estimations and the adequacy of the assumption of quadratic Engel curves.

Heterogeneous responses. We examine different expenditure responses to health shocks for households with different characteristics by interacting the shock indicators in equation (4) and (5) with several household characteristics. We consider different responses for rural and urban households, households with heads working in the formal or informal sectors, households with access to safety nets, and households whose heads work in different economic sectors.

4 Effects of Health Shocks on Expenditures

In this section, we outline our main results. We show that health shocks affect food and health budget shares differently across urban and rural households. Conditional on total expenditure, rural households adjust their food and health expenditures more sharply in response to shocks. Formal households, households with social capital and whose heads have jobs with contracts, are more likely to adjust to the health shock without substantial expenditure changes.

Overall effect of health shocks on food and health expenditure. Table 4 shows the coefficients on health shocks from the estimation of equations (1), (4) and (5). We find significant food and health expenditure changes in response to the health shocks, with stark differences across urban and rural households. Focusing on the columns marked OLS, which correspond to specification (1), we find that urban households increase their health budget share by 1.3 p.p. In contrast, the reaction of the food expenditure share is not statistically significant. For their part, rural households adjust their expenditure more heavily. Their health expenditure share increases by four p.p. while their food expenditure share decreases by 3.8 p.p.

Analyzing the decomposition results (the columns marked SUR in Table 4), we find evidence that urban and rural households increase their total expenditure after experiencing a health shock. In particular, urban households' consumption increases by 8% while rural households' consumption increases by 6.5%. We also find evidence for the food Engel curve being quadratic for both urban and rural households, while the health Engel curve is quadratic only for rural households.

Regarding shifts in the Engel curves due to the health shock (i.e., the direct effect from (6)), we find that most of the increase in the health budget share comes from this direct effect. In the case of urban households, 1.1 p.p. of the increase in the health share comes from the direct effect, which is 85% of the total effect. For rural households, the direct effect corresponds to 90% of the total effect, that is, 3.6 p.p.

We also find changes in rural consumers' preferences for food after a health shock, although

Table 4: Decomposition of the effect of Health Shocks on Food and Health expenditure

	Urban			Rural		
	OLS	SUR		OLS	SUR	
Panel 1:	Food Expenditure share	Food Expenditure share	ln(Total expenditure)	Food Expenditure share	Food Expenditure share	ln(Total expenditure)
Health shock	-0.007	-0.004	0.080***	-0.038**	-0.030*	0.065***
	(0.006)	(0.007)	(0.031)	(0.015)	(0.016)	(0.024)
ln(Total expenditure)		0.756***			2.197***	
		(0.139)			(0.475)	
ln(Total expenditure)^2		-0.029***			-0.088***	
		(0.005)			(0.018)	
Observations	2916	2916	2916	2396	2396	2396
R^2	0.045			0.419		
Mean dep. var.	0.534	0.534	13.626	0.625	0.625	13.096
Household F. E.	✓	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Panel 2:	Health Expenditure share	Health Expenditure share	ln(Total expenditure)	Health Expenditure share	Health Expenditure share	ln(Total expenditure)
Health shock	0.013***	0.011***	0.080***	0.040***	0.036***	0.065***
	(0.003)	(0.003)	(0.031)	(0.012)	(0.011)	(0.024)
ln(Total expenditure)		0.069			-0.995***	
		(0.101)			(0.242)	
ln(Total expenditure)^2		-0.002			0.040***	
		(0.004)			(0.010)	
Observations	2916	2916	2916	2396	2396	2396
R^2	0.037			0.492		
Mean dep. var.	0.024	0.024	13.626	0.035	0.035	13.096
Household F. E.	✓	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓

Note: The table shows the coefficients on the health shock, total expenditure, and total expenditure squared from estimates of equations (1), (4) and (5) using OLS and SUR. Standard errors clustered at the municipality level are in parentheses. A household suffers a health shock if any member has been affected by an accident or illness in the last three years. Controls are region-specific trends, and the education level of the household head in 2013 interacted with the trend. *: p<0.1, **: p<0.05, ***: p<0.01.

this effect is only significant at the 10% level. We find that rural households' food budget share decreases by three p.p. directly after a health shock, which is almost 80% of the total effect.

Several channels may be at work behind these findings. Rural households may be less insured than urban ones and unable to smooth the health shock –and incur additional health expenditure– without reducing their expenditure in other categories. This reduced insurance may be due to several characteristics, such as labor informality or access to financial markets. We turn to these mechanisms in section 5.

Engel curves. To show more evidence of the role of health shocks in shifting demand for food and health goods and to justify our regression specification, we show non-parametric evidence of the adjustments of demand to health shocks. We estimate non-parametric Engel curves through local polynomial regression and obtain separate estimates for health-shock-affected and unaffected households.[9]

Figures 1 and 2 show Engel curves for food. These are approximately linear for urban households spending over 300.000 pesos a month and for all rural households but are concave for the 2013 urban sample that experienced a health shock. For both waves and urban and rural households, the estimated food Engel curves for households affected by the health shock tend to be below those unaffected by it. The gap between Engel curves is larger for mid-expenditure rural households and negligible for mid-expenditure urban households. These gaps are consistent with our main findings, where the direct effect of a health shock is not statistically significant for urban households, contrary to rural ones.

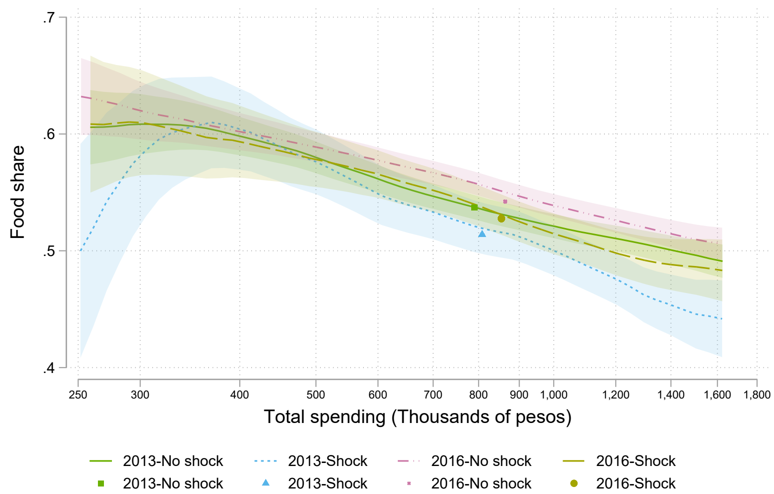
Figures 3 and 4 show the equivalent estimates for the health Engel curve. Once again, the Engel curves are approximately linear (except for low-expenditure urban households) and slightly convex. The Engel curves of shocked households are consistently above that of unaffected households.

The figure for rural households shows some evidence of a change in slope between the curve for unaffected and affected households. This slope change would invalidate our specification in equation (4), which only allows for level shifts in response to shocks. In Appendix table A.6, we estimate specifications that enable the health shock to change the slope of the Engel curves. Our estimates for the marginal effect of the health shock on the average household's expenditure shares are virtually identical to those of table 4.

Additional Regression Results and Robustness. In the appendix, we show four pieces of additional evidence on food and health expenditure responsiveness to shocks. First, we show results for item categories besides food and health in appendix table A.7. Urban households seem to increase their expenditure on recreation in response to the health shock and

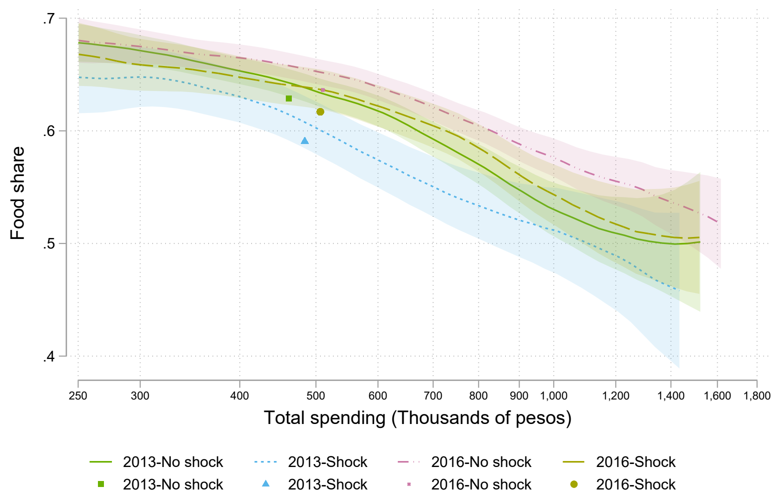
[9] Our estimates are not conditional to other shocks. The conditional and unconditional Engel curves are similar given the low impact of other shocks on demand shown in Appendix table A.3.

Figure 1: Food Engel Curves, for Urban Households with/without a Health Shock.



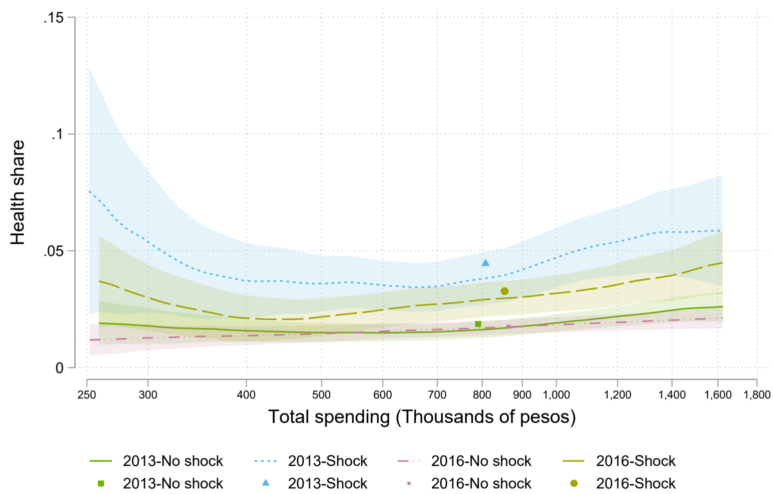
Note: Each line corresponds to an Engel curve for a different year and sample. Local polynomials are estimated using a triangular kernel, where the bandwidths minimize the conditional weighted mean integrated squared error. Points represent the average household in each of the four samples. The shared areas are 95% confidence intervals.

Figure 2: Food Engel Curves, for Rural Households with/without a Health Shock.



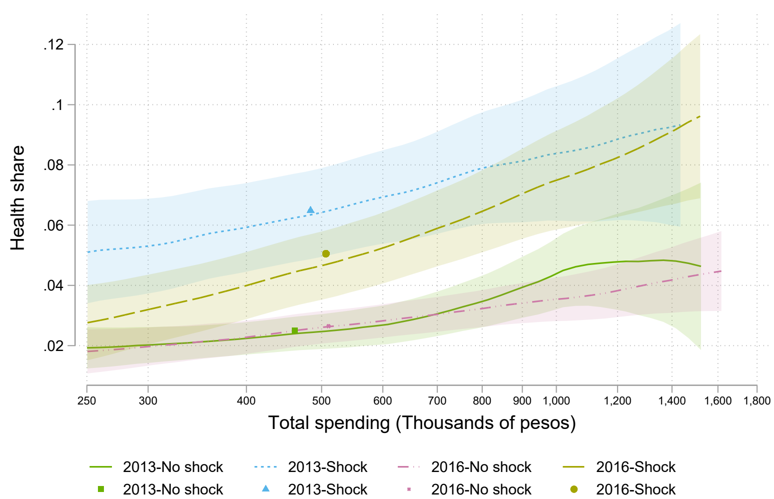
Note: Each line corresponds to an Engel curve for a different year and sample. Local polynomials are estimated using a triangular kernel, where the bandwidths minimize the conditional weighted mean integrated squared error. Points represent the average household in each of the four samples. The shared areas are 95% confidence intervals.

Figure 3: Health Engel Curves, for Urban Households with/without a Health Shock.



Note: Each line corresponds to an Engel curve for a different year and sample. Local polynomials are estimated using a triangular kernel, where the bandwidths minimize the conditional weighted mean integrated squared error. Points represent the average household in each of the four samples. The shared areas are 95% confidence intervals.

Figure 4: Health Engel Curves, for Rural Households with/without a Health Shock.



Note: Each line corresponds to an Engel curve for a different year and sample. Local polynomials are estimated using a triangular kernel, where the bandwidths minimize the conditional weighted mean integrated squared error. Points represent the average household in each of the four samples. The shared areas are 95% confidence intervals.

steer away from alcohol and clothing purchases. There are few changes in other budget shares for rural households except for transport and clothing purchases. An increase in transport spending makes sense if rural households are far from health service providers. Food and health expenditures are the most reactive for rural households, and we will continue to focus on them from now on.

We also show the response of food and health expenditure to other types of shocks in appendix table A.3, which includes full estimation results for table 4. Food and health expenditures seem most responsive to health shocks, although other shocks may also induce adjustments. Family shocks reduce (increase) food expenditure in rural (urban) households. These findings are corroborated by appendix figure A.1, which shows the predicted change in average budget shares stemming from a health shock. We build these predicted shares using estimates of equation (1) for each expenditure category.

As robustness exercises, we carry out estimations without controls and region trends (Table A.4) and without survey weights (Table A.5) in the appendix. We still find significant changes in health expenditure in the uncontrolled regressions; however, we prefer our baseline estimates that control for trends to account for price changes. Our estimates without survey weights are statistically significant and similar to our baseline results.

Equation (3) assumes that in the absence of shocks, expenditure in the different categories would have a similar evolution across households that experienced shocks and households that did not, after conditioning on demographics and total expenditure. Such an assumption may be invalid for households that experience shocks and have differences in observables that may lead to differences in future expenditure. To restrict our estimation further to households similar in observables, we estimate logistic models for the probability of receiving a household shock between wave $t-1$ and t using observed variables from $t-1$ and calculate an estimated propensity score. Then, we exclude households with estimated propensity score values outside the common support of the estimated propensity score distribution across households with and without shocks. This step amounts to using the propensity score as a pre-processing step before estimating equations (1) and (4) (Ho et al., 2007).

We estimate separate propensity scores for the probability of experiencing adverse shocks in 2013 and 2016 for urban and rural households. We use lags of expenditure as demographics as covariates. Figures A.2 and A.3 in the Appendix show distributions of the estimated propensity score for urban and rural households. There are few observations outside the common support of the distributions.

Appendix Table A.9 shows estimates of the effects of health shocks on expenditure, excluding households outside the common support of the estimated propensity score distributions. The results are similar to those in table 4.

Additionally, our estimates assume that attrition is not an issue in the estimation. Still, we face two potential sources of attrition: a) households included in ELCA that left in 2016, and b) households excluded from our sample because of changing household composition between waves. Both attrition sources are potentially dependent on receiving health shocks or other observed characteristics of the household (missing at random). Appendix Table A.8 shows estimates of equation (4) using inverse probability weights (IPW) to tackle this issue. First, we estimate logit models to predict the probability of each type of attrition, including all the shocks, the same controls of the main specification, and the categorical characteristics used in Table 2, as variables. Afterward, we predict the probabilities of each attrition source and multiply their inverse values with the original survey weight to obtain the new weight for the estimation. Appendix Table A.8 shows that the IPW results are not qualitatively different from our main results in Table 4.

5 Heterogeneous Effects

This section examines heterogeneous food and health expenditure responses to shocks by types of households. First, we show how the self-reported intensity of the shock affects the magnitude of our findings. Later, we highlight the role of informality and insurance in shaping the expenditure response to health shocks. Households whose heads work in the formal sector and have access to insurance through social capital are more able to smooth the shock and reduce expenditure adjustments. Finally, we analyze if environmental factors, such as access to financial markets or health services, may help mitigate the substitution effect found.

Intensity of the health shocks. The ELCA survey asked households how important were the shocks they suffered for the economic stability of the household. They could categorize such impact as low, medium, or high. In our urban sample, 25.4% of households affected by a health shock reported a low impact, 13.9% reported a medium impact, and the remaining 60.7% reported a high impact. We observe similar proportions among rural households suffering from a health shock, with 28.7% reporting a low impact, 25.5% reporting a medium impact, and 45.8% reporting a high impact.

We divide our health-shock sample and estimate heterogeneous impacts of the health shocks according to their intensity. Table 5 shows the total and direct effect of a health shock on expenditure for each impact level compared to not having a health shock. We find an expected pattern for urban households: those who reported low impact did not significantly change their food and health budget shares. Those who reported medium impact increased their health expenditure share by 1.4 p.p but had no significant effect on their food share. Finally, those with self-reported high impact show the strongest substitution effect, with an increase in health expenditure of 1.6 p.p and a decrease in food expenditure of 1.8 p.p. We also find that the direct effect on preferences accounts for approximately 90% of the total effect in high-impact level households.

Table 5: Effect of a Health Shock on Food and Health Expenditure, by Health Shock Intensity

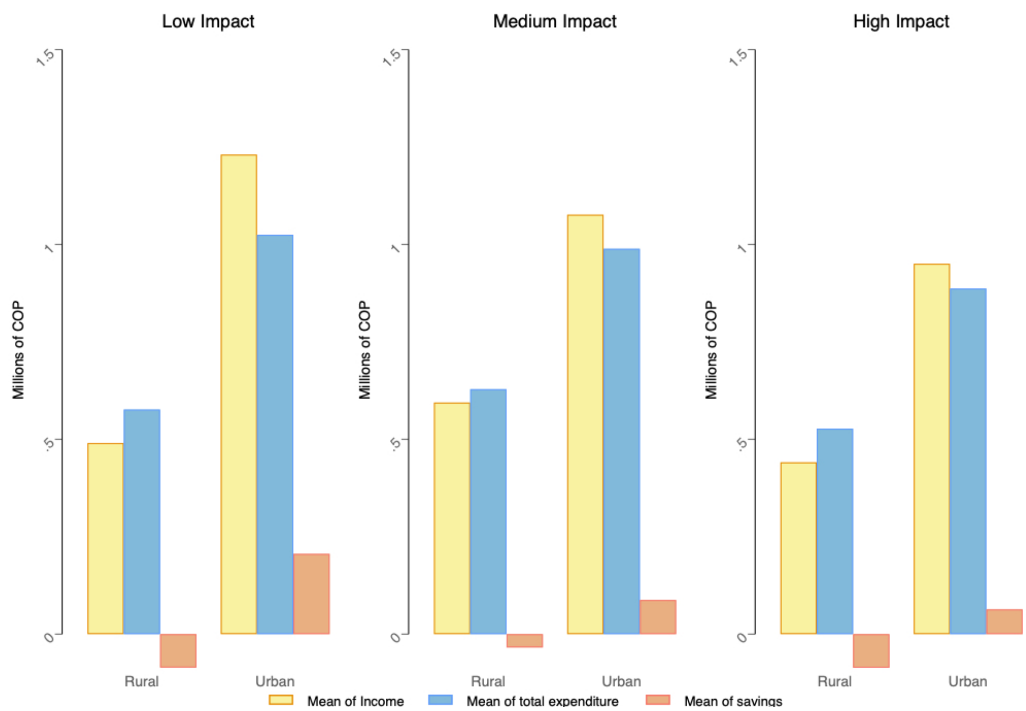
	Low impact level				Medium impact level				High impact level			
	Urban		Rural		Urban		Rural		Urban		Rural	
	Food	Health	Food	Health	Food	Health	Food	Health	Food	Health	Food	Health
Panel 1: Total effect												
Health shock	0.014	-0.001	-0.043**	0.016*	-0.011	0.015***	-0.008	0.025***	-0.020**	0.017***	-0.038***	0.026**
	(0.010)	(0.004)	(0.016)	(0.009)	(0.017)	(0.003)	(0.015)	(0.009)	(0.009)	(0.005)	(0.012)	(0.011)
Observations	2315	2315	1875	1875	2303	2303	1894	1894	2484	2484	2095	2095
Mean dep. var.	0.518	0.016	0.656	0.027	0.519	0.017	0.646	0.030	0.516	0.193	0.633	0.050
Household F. E.	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Region Trends	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Panel 2: Direct effect												
Health shock	0.017	0.000	-0.049***	0.019*	-0.007	0.014***	0.001	0.021**	-0.018**	0.016***	-0.035***	0.023**
	(0.011)	(0.004)	(0.016)	(0.010)	(0.018)	(0.004)	(0.015)	(0.010)	(0.008)	(0.004)	(0.012)	(0.011)
Observations	2315	2315	1875	1875	2303	2303	1894	1894	2484	2484	2095	2095
Mean dep. var.	0.518	0.016	0.656	0.027	0.519	0.017	0.646	0.030	0.516	0.193	0.633	0.050
Household F. E.	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Region Trends	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Note: The table shows the coefficients on the health shock from estimates of equations (1) and (4) using OLS and SUR, respectively. Panel 1 estimates are comparable to those from columns labeled OLS in Table 4, and Panel 2 estimates are comparable to those from the first columns labeled SUR in Table 4. Standard errors clustered at the municipality level are in parentheses. A household suffers a health shock if any member has been affected by an accident or illness in the last three years. Controls are region-specific trends, and the education level of the household head in 2013 interacted with the trend. *: p<0.1, **: p<0.05, ***: p<0.01.

The heterogeneous effects for rural households are more complex than those for urban households. We find substitution responses in households with low impact (a 4.9 p.p. reduction in food with a 1.9 p.p. increase in health) and high impact (a 3.5 p.p. reduction in food with a 2.3 p.p. increase in health), but not in households who reported medium impact. These households' health budget share increased by 2.1 p.p., while their food expenditure had no significant change after the health shock.

What could be a likely explanation for this puzzling result? We turn to the available information on total income and total expenditure. Figure 5 shows households' average income, expenditure, and resulting monthly savings according to the self-reported impact level. First, we note that urban households save a part of their income, while rural households consume over their monthly income. Secondly, we note an inverse relationship between the reported impact level of urban households and their average incomes, expenditure, and savings. This relationship makes sense because a health shock may affect lower-income households without enough saved funds for emergency purposes. Similarly, we find that rural households who reported a medium impact level have higher income on average compared to those with low or high impact levels. Medium-impact rural households also have a smaller gap between income and expenditure compared to high-impact and low-impact ones, which means that they may be better prepared for an upcoming health shock and, therefore, may not need to substitute food consumption as much.

Figure 5: Mean Income, Expenditure and Savings of Households by Impact Level of the Health Shock

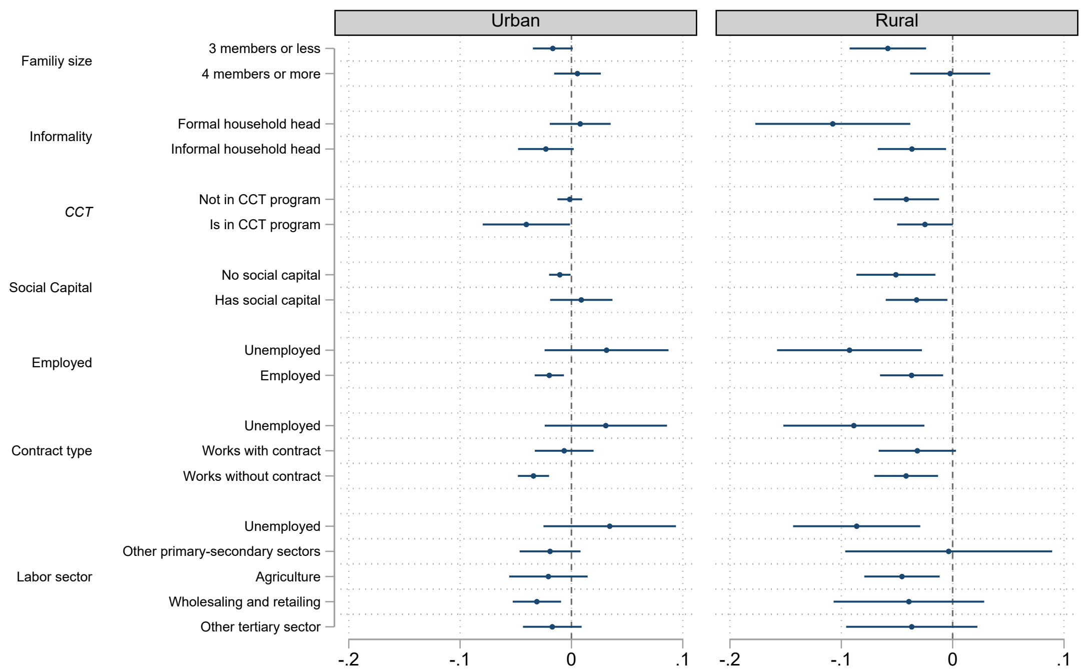


Note: Savings is the difference between income and expenditure and do not come directly from the survey.

Figure 6 shows estimates of the response of food expenditure to health shocks obtained from interacting the health shock dummy with household characteristics in equation (1). Overall, as expected from Table 4, the adjustments for rural households are more extensive. This pattern reappears in Figure 7, which shows that health expenditure increases more in rural households across groups. We now turn to each one of the categories driving heterogeneity in the consumption responses.

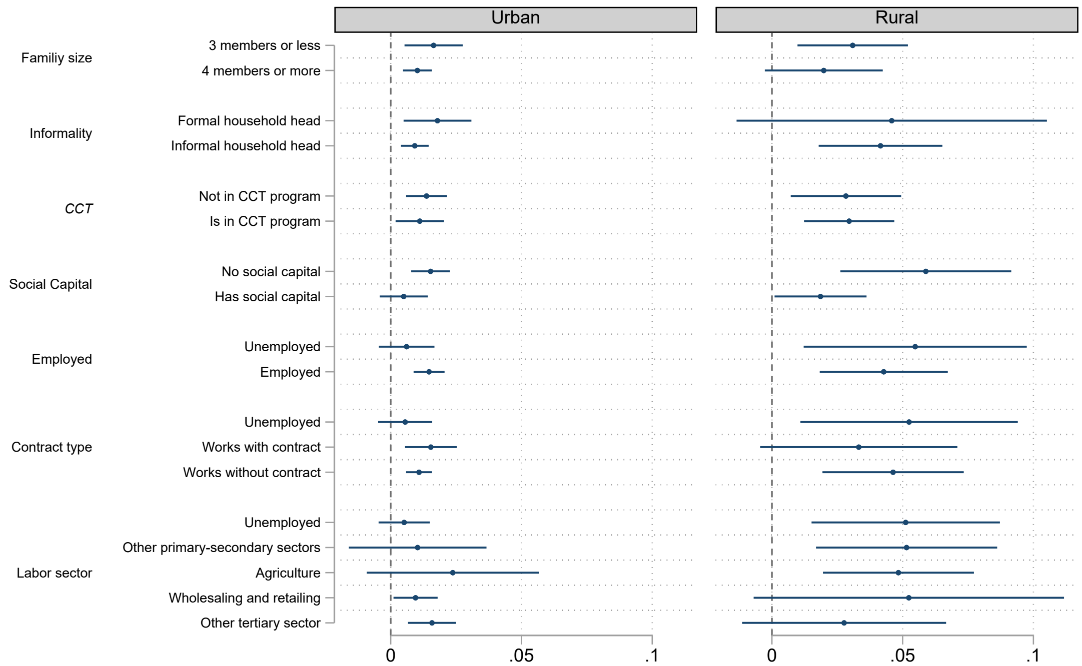
Household size. Larger households may have more trouble adjusting food expenditure because of broader caloric needs at the household level. At the same time, larger families may send more members to the labor force in response to a shock (Wagstaff, 2007). We find that small urban households reduce their food expenditure by around two p.p. and small rural households by 5.7 p.p. in response to the health shock. In contrast, large households with four or more members do not adjust food expenditure. The difference is independent of

Figure 6: Heterogeneous Effects of a Health Shock in the Share of Food Expenditure



Note: The dots are point estimates of the effect of a health shock on food expenditure for different household characteristics. Estimates are obtained from equation 1, interacting the health shock dummy with household characteristics. Horizontal bars are 95% confidence intervals from standard errors clustered at the municipality level. Informal households are those whose household head is either unaffiliated with social health insurance or does not contribute to the pension system. CCT stands for conditional cash transfer. The conditional cash transfer program is called *Familias en Acción*, the main program of its kind in Colombia. A household has social capital if its head participates in local groups or organizations, like political parties, guilds, and sports clubs. Labor market variables are for the household head. "Works with contract" includes households whose head has a verbal or written contract. "Other primary and secondary sectors" includes mining, manufacturing, construction, and water treatment. "Other tertiary sector" includes hotels, restaurants, public service, education, communication, health services, management, science, art, and other industries not previously classified.

Figure 7: Heterogeneous Effects of a Health Shock in the Share of Health Expenditure



Note: The dots are point estimates of the effect of a health shock on food expenditure for different household characteristics. Estimates are obtained from equation 1, interacting the health shock dummy with household characteristics. Horizontal bars are 95% confidence intervals from standard errors clustered at the municipality level. Informal households are those whose household head is either unaffiliated with social health insurance or does not contribute to the pension system. CCT stands for conditional cash transfer. The conditional cash transfer program is called *Familias en Acción*, the main program of its kind in Colombia. A household has social capital if its head participates in local groups or organizations, like political parties, guilds, and sports clubs. Labor market variables are for the household head. "Works with contract" includes households whose head has a verbal or written contract. "Other primary and secondary sectors" includes mining, manufacturing, construction, and water treatment. "Other tertiary sector" includes hotels, restaurants, public service, education, communication, health services, management, science, art, and other industries not previously classified.

whether the household is urban o rural, although the reduction for small urban households is not significant at the 95% level. The increases in health expenditure are also relatively more onerous for smaller households.

Informality. We classify households as informal if their household head is either unaffiliated to employer-provided health insurance or does not contribute to the pension system. We find that labor informality plays a large role in shaping the food expenditure reaction to health shocks in urban households. The increase in health expenditure is similar for formal and informal urban households (with formal households having a slightly higher increase), but only informal households decrease their food expenditure. Such heterogeneity is not necessarily a mechanical effect of access to health insurance since informal households may still have insurance through the public health system. The food share falls by about two p.p. for informal urban households. Rural households paint a different picture. Formal rural households have large food expenditure decreases in response to the health shock. However, only a small share of rural households is formal, so this result may be due to the small sample size.

CCTs and social capital. We turn to informal insurance sources and insurance from other income sources. We do not find significant differences in the health expenditure response of urban households according to whether they receive transfers from *Familias en Acción*, Colombia's flagship conditional cash transfer program. In contrast, there are vast differences in how households adjust their food expenditure. Urban households receiving the cash transfer (which amount to 16% of our sample) reduce their food budget share by four p.p., while the remaining households are unaffected. A plausible explanation behind this heterogeneity is that the CCT program clearly selects the poorest families, and they may be more prone to substitute away food consumption.

Rural households present a different pattern. Firstly, note that 49% of our sample's rural households belong to the CCT program, a significantly higher share than in the urban sample. This larger CCT share may be because rural households are poorer than urban ones, but especially because the rural ELCA survey was conducted in disadvantaged countryside regions. In this case, households not covered by *Familias en Acción* lower their food consumption by three p.p. At the same time, those benefiting from the program have a smaller and statistically non-significant reduction in their food share.

Households may also insure themselves by risk-sharing.[10] This risk-sharing may be easier if households belong to informal networks. We create a dummy variable for social capital active if the household head or their spouse participates in local groups or organizations, such as political parties, guilds, religious organizations, or sports clubs.

[10] For example, Acquah and Dahal (2018) study the Rotating Savings and Credit Associations in Indonesia. These informal financial institutions are used to access credit or increase savings and are formed by neighbors, relatives, and friends. They find evidence of risk-sharing across members of the same associations.

Regarding urban households, we only find statistically significant decreases in food expenditure in response to the health shock in households without social capital. The food expenditure response of urban households with social capital is nearly zero (and the point estimate is actually positive). The food expenditure decrease for rural households without social capital is almost twice as large as that of households with social capital.

The results for health expenditure follow the same pattern. Households without social capital increase their health budget share significantly more than those with social capital in response to the health shock. The estimate for urban households with social capital is statistically equal to zero, and the effect for rural households without social capital is three times larger than for those with social capital.

These results highlight the substantial role of social networks and risk-sharing in mitigating health shocks. Other studies have found evidence of smoothing through risk-sharing (Attanasio and Székely, 2004; Genoni, 2012; Gertler and Gruber, 2002; Sparrow et al., 2014). We highlight that access to social capital eliminates the need to reduce food expenditure when illnesses or accidents strike.

Work status, contract, and industry. This set of variables pertains to the labor market characteristics of the households.

Unsurprisingly, it seems harder to smooth consumption in response to the health shock for rural households whose heads are unemployed. Their food budget share decrease is about three times that of employed rural households, and their health expenditure share increase is about one-fourth larger. The urban households' case is surprising, with more extensive adjustments for employed households than for unemployed ones. This remarkable effect is driven by those households whose household head works without a contract and in the wholesaling and retailing sector. In contrast, urban households whose head works with a formal contract or in the service sector (apart from retailing) experience little changes in their food expenditure. Concerning their health expenditure, there are no important differences between working with or without a labor contract or between sectors.

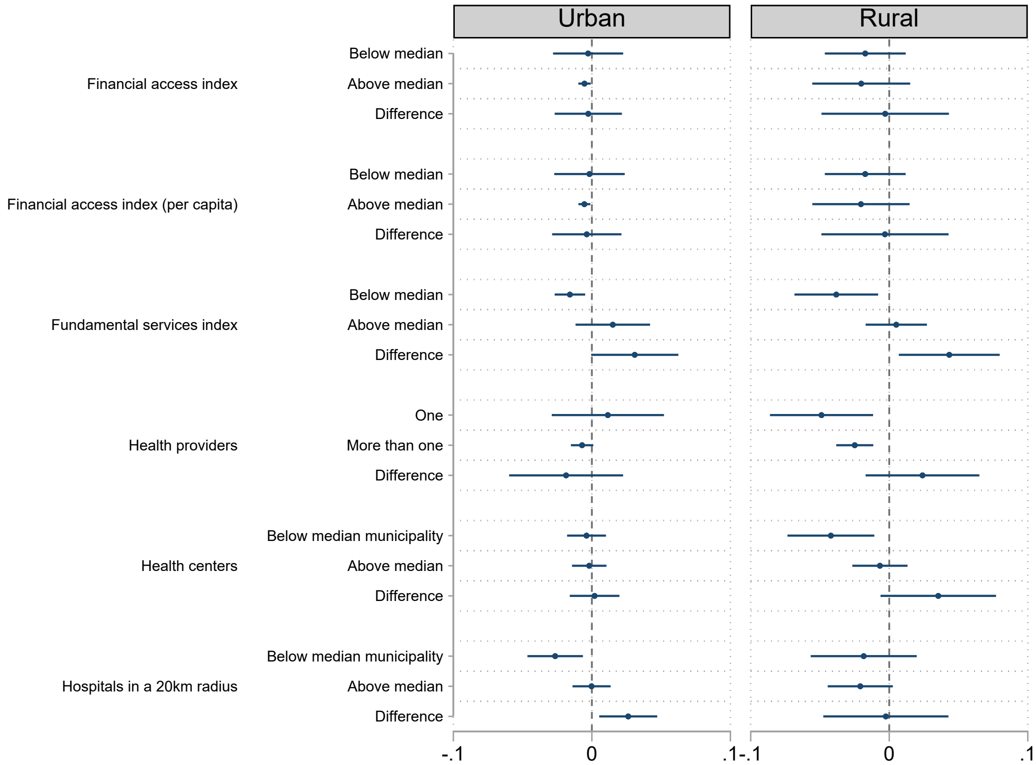
Similarly, rural households whose heads work without a contract need to make somewhat stronger adjustments than those employed with a contract. Last, we do not see substantial differences for rural households when we turn to the sector where the household head is employed. We find a statistically non-significant effect for those working in wholesaling, retailing, and other service activities, but this is mainly due to the small proportion of rural households in this sector (5%).

State capacity and access to health resources. In addition to the heterogeneous effects derived from the variables mentioned previously, we also explored the role of state capacity in the response of households to a health shock. In this particular case, "state capacity" corresponds to a) access to formal financial markets, b) an institutional environment capable of providing essential public services such as sewage and water, and c) access to health resources and facilities such as hospitals or health centers.

Coverage and access to health services are still insufficient in Colombia, despite the progress of recent decades. (Ayala García, 2014) finds significant gaps in access to health services between different regions of the country and between urban and rural zones. These access disparities are relevant to the present study because, on the one hand, households without easy access to health services may not increase their health expenditure even when needed. On the other hand, lower-income households with access to hospitals or healthcare centers tend to have access to free healthcare. Still, if the same household cannot access hospitals or government-provided healthcare, they may use costly substitutes.

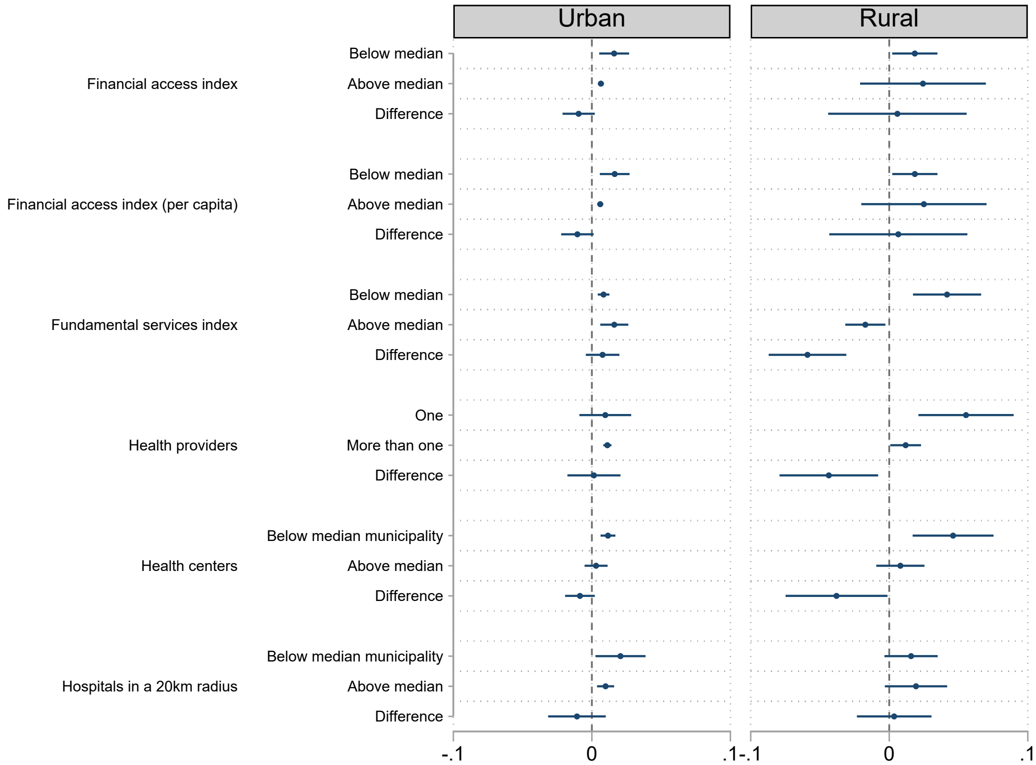
Figures 8 and 9 show the heterogeneous effect of the abovementioned variables. First, we find no significant differences between households in municipalities above the median of the financial access indexes and those below. The only pattern we see is that the estimated increase in the health budget share for those urban households below the median of the financial access indexes is more than double that of the urban households above the median. This pattern indicates that access to formal financial services may mitigate the expenditure increase in health after the health shock but does not affect the subsequent substitution effect. It also indicates that the coverage and usage of financial services in the rural domain are still low, and rural households are not yet benefiting.

Figure 8: Heterogeneous effects of state capacity in the Share of Food Expenditure



Note: The dots are point estimates of the effect of a health shock on food expenditure for different municipality services. Estimates are from equation 4, interacting the health shock dummy with each institutional variable. Horizontal bars are 95% confidence intervals from standard errors clustered at the municipality level. We created the financial access and fundamental services indexes using principal component analysis. The variables for the financial access index are the number of savings accounts, consumer loans, micro-credits, and credit cards for each municipality in 2010. The variables for the fundamental services index are the average aqueduct, sewerage, and garbage removal coverage between 2009 and 2013. Health providers are companies that provide health services within the municipality. Health centers are the average points of care in the municipality before each shock (2010 and 2013) at the per capita level. The median of health centers at the municipality level is 0.0001426. Hospitals in a 20km radius are the number of tertiary level hospitals within a 20km radius of the center of the municipality in 2005. The median of hospitals at the municipality level is 4.

Figure 9: Heterogeneous effects of state capacity in the Share of Health Expenditure



Note: The dots are point estimates of the effect of a health shock on food expenditure for different municipality services. Estimates are from equation 4, interacting the health shock dummy with each institutional variable. Horizontal bars are 95% confidence intervals from standard errors clustered at the municipality level. We created the financial access and fundamental services indexes using principal component analysis. The variables for the financial access index are the number of savings accounts, consumer loans, micro-credits, and credit cards for each municipality in 2010. The variables for the fundamental services index are the average aqueduct, sewerage, and garbage removal coverage between 2009 and 2013. Health providers are companies that provide health services within the municipality. Health centers are the average points of care in the municipality before each shock (2010 and 2013) at the per capita level. The median of health centers at the municipality level is 0.0001426. Hospitals in a 20km radius are the number of tertiary level hospitals within a 20km radius of the center of the municipality in 2005. The median of hospitals at the municipality level is 4.

Secondly, we find significant differences using the fundamental services index, constructed via Principal Component Analysis based on information on average access to water, sewerage, and garbage removal services between 2009 and 2013. We interpret this variable as a proxy for general State capacity and its ability to provide public goods. Regarding the increase in health expenditure after a health shock, we find no significant difference in urban households above and below the index's median. Still, we find a significant difference in rural households: those below the median experience a health share increase of more than four p.p. In contrast, those above the median decrease their health expenditure by 1.5 p.p.

In contrast, we do not see a similar pattern in the urban domain. Those households above the median of the fundamental services index show a slightly larger increase in health expenditure than those below the median. However, we observe in Figure 8 that those households in municipalities below the median of the fundamental services index (regardless of urban or rural domain) do substitute away food expenditure, while those above the median have no significant effect on the food share.

Finally, we find that urban households with few hospitals in their surroundings are more affected by the health shock because they increase their health expenditure share more than those households with more hospitals nearby, and their food share is significantly affected after the shock. This last result contrasts with the fact that the households above the median of hospitals in a radius of 20km do not significantly change their food expenditure after a health shock. The findings are consistent with the hypothesis that having access to hospitals and state-provided healthcare mitigates the negative effect of a health shock in the budget composition. The heterogeneity in the effects of health shocks by access to health providers and health centers is not as stark as the one driven by closeness to hospitals for urban households, which may be related to the fact that health centers and other health providers are more relevant in rural contexts.

Consequently, rural households behave similarly to urban households concerning the presence of health providers and health centers in the municipality. For instance, households in municipalities with more than one health provider have smoother food and health expenditure adjustments than those in municipalities with only one health provider. Likewise, rural households in municipalities above the median of health centers do not change their food and health budget shares with a significance of 5%, while those below the median increase their health expenditure and decrease their food expenditure as expected. Note that the presence of hospitals in a 20 km radius has no effect because of their absence in rural contexts.

In conclusion, having health centers in rural municipalities and hospitals in urban municipalities seems to moderate the effect of having a health shock.

6 Concluding Remarks

Adverse health shocks cause complex changes in households' expenditure behavior. We look at how households in Colombia behave when they face such a shock. This case is fascinating because Colombia's comprehensive health insurance system covers almost the entire population, and we show that such a system does not provide complete insurance. In particular, we find that when facing a negative health shock, on average, households substitute food expenditures with health expenditures, i.e., they substitute future health for present health. Such a substitution might be critical in disadvantaged households' development and the likelihood of overcoming poverty.

We show that increases in health expenditures (and reductions in food expenditures) are more significant for rural households. Formality (paying for health insurance and pension) attenuates this trade-off for urban households but not for rural ones. Interestingly, cash transfer programs and social capital can provide insurance for families to deal with such a shock. On top of that, the household head's labor status plays a role in the household's ability to attenuate substitution. Beyond informality, unemployed workers and workers without labor contracts are more vulnerable to adverse health shocks.

We also identify several channels that mitigate the harmful effects of health shocks on expenditure. First, having a low income and a low or negative savings rate aggravates the severity of the health shock's impact on expenditure. Secondly, we show that a state capable of providing public goods and health infrastructure plays a role in enabling households to absorb negative health shocks, even in a setting with universal health insurance.

To the extent that improving present health has the cost of deteriorating future health, informality-reducing policies appear critical (especially in the rural sector) for households to escape poverty traps. Our findings provide another mechanism for how social insurance programs might help alleviate poverty. Further research on this topic is needed.

References

Acquah, Joseph Kofi and Roshani Dahal (2018), "ROSCAs as Lenders of Last Resort After Financial Crises: Lessons from Indonesia." *Journal of International Development*, 30, 1223–1239, URL `https://doi.org/10.1002/jid.3366`.

Arbelaez, Mateo, Leopoldo Fergusson, and Andres Zambrano (2019), "Endogenous Persistent Shocks and Poverty Traps." Mimeo.

Attanasio, Orazio, Erich Battistin, and Alice Mesnard (2011), "Food and Cash Transfers: Evidence from Colombia." *The Economic Journal*, 122, 92–124, URL `https://doi.org/10.1111/j.1468-0297.2011.02473.x`.

Attanasio, Orazio P and Miguel Székely (2004), "Wage Shocks and Consumption Variability in Mexico During the 1990s." *Journal of Development Economics*, 73, 1–25, URL `https://doi.org/10.1016/j.jdeveco.2003.01.001`.

Atuesta, Laura H and Dusan Paredes Araya (2012), "A Spatial Cost of Living Index for Colombia using a Microeconomic approach and Censored Data." *Applied Economics Letters*, 19, 1799–1805.

Ayala García, Jhorland (2014), "La salud en Colombia: más cobertura pero menos acceso." Technical report, Documentos de Trabajo sobre Economía Regional, Banco de la República.

Banks, James, Richard Blundell, and Arthur Lewbel (1997), "Quadratic Engel Curves and Consumer Demand." *Review of Economics and Statistics*, 79, 527–539, URL https://doi.org/10.1162/003465397557015.

Barnett, William A and Apostolos Serletis (2008), "Consumer Preferences and Demand Systems." *Journal of Econometrics*, 147, 210–224, URL https://doi.org/10.1016/j.jeconom.2008.09.009.

Battistin, Erich (2003), "Errors in Survey Reports of Consumption Expenditures." Technical report, IFS Working Papers.

Blundell, Richard, Margherita Borella, Jeanne Commault, and Mariacristina De Nardi (2020), "Why does Consumption Fluctuate in Old Age and How Should the Government Insure It?" Technical report, NBER Working Paper 27348.

Center for Studies on Economic Development (CEDE) (2016), "Encuesta Longitudinal Colombiana de la Universidad de los Andes ELCA." Public and restricted databases. Produced and distributed by the Center for Studies on Economic Development (CEDE), School of Economics, Universidad de los Andes, Bogota, Colombia.

Cortés, Darwin and Jorge Pérez Pérez (2010), "El Consumo de los Hogares Colombianos, 2006-2007: Estimación de Sistemas de Demanda." *Desarrollo y Sociedad*, 7–44, URL https://doi.org/10.13043/dys.66.1.

Deaton, Angus and John Muellbauer (1980), *Economics and Consumer Behavior*. Cambridge University Press.

Ganong, Peter and Pascal Noel (2019), "Consumer Spending During Unemployment: Positive and Normative Implications." *American Economic Review*, 109, 2383–2424, URL https://doi.org/10.3386/w25417.

Genoni, Maria Eugenia (2012), "Health Shocks and Consumption Smoothing: Evidence from Indonesia." *Economic Development and Cultural Change*, 60, 475 – 506, URL https://doi.org/10.1257/000282802760015603.

Gertler, Paul and Jonathan Gruber (2002), "Insuring Consumption Against Illness." *American Economic Review*, 92, 51–70, URL https://doi.org/10.1257/000282802760015603.

Gertler, Paul, David I Levine, and Enrico Moretti (2009), "Do Microfinance Programs Help Families Insure Consumption Against Illness?" *Health Economics*, 18, 257–273, URL https://doi.org/10.1002/hec.1372.

Ho, Daniel E, Kosuke Imai, Gary King, and Elizabeth A Stuart (2007), "Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference." *Political Analysis*, 15, 199–236.

Kinnan, Cynthia, Krislert Samphantharak, Robert Townsend, and Diego A Vera Cossio (2020), "Propagation and Insurance in Village Networks." Working Paper 28089, National Bureau of Economic Research, URL https://doi.org/10.3386/w28089.

Lecocq, Sébastien and Jean-Marc Robin (2015), "Estimating Almost-ideal Demand Systems with Endogenous Regressors." *The Stata Journal*, 15, 554–573, URL https://doi.org/10.1177/1536867X1501500214.

Lewbel, Arthur and Krishna Pendakur (2009), "Tricks with Hicks: The EASI demand system." *American Economic Review*, 99, 827–63, URL https://doi.org/10.1257/aer.99.3.827.

Londoño Cano, Daniel, Edwar Londoño Zapata, and Andrés Ramírez Hassan (2011), "Un Sistema Casi Ideal de Demanda para el Gasto en Colombia: Una Estimación utilizando el Método Generalizado de los Momentos en el Período 1968-2007." *Ecos de Economia: A Latin American Journal of Applied Economics*, 15, 39–58.

Pollak, Robert A and Terence J Wales (1981), "Demographic Variables in Demand Analysis." *Econometrica: Journal of the Econometric Society*, 1533–1551.

Solon, Gary, Steven J Haider, and Jeffrey M Wooldridge (2015), "What are We Weighting For?" *Journal of Human Resources*, 50, 301–316, URL https://doi.org/10.3386/w18859.

Sparrow, Robert, Ellen Van de Poel, Gracia Hadiwidjaja, Athia Yumna, Nila Warda, and Asep Suryahadi (2014), "Coping with the Economic Consequences of Ill Health in Indonesia." *Health Economics*, 23, 719–728, URL https://doi.org/10.1002/hec.2945.

Wagstaff, Adam (2007), "The Economic Consequences of Health Shocks: Evidence from Vietnam." *Journal of Health Economics*, 26, 82–100, URL https://doi.org/10.1016/j.jhealeco.2006.07.001.

Appendix

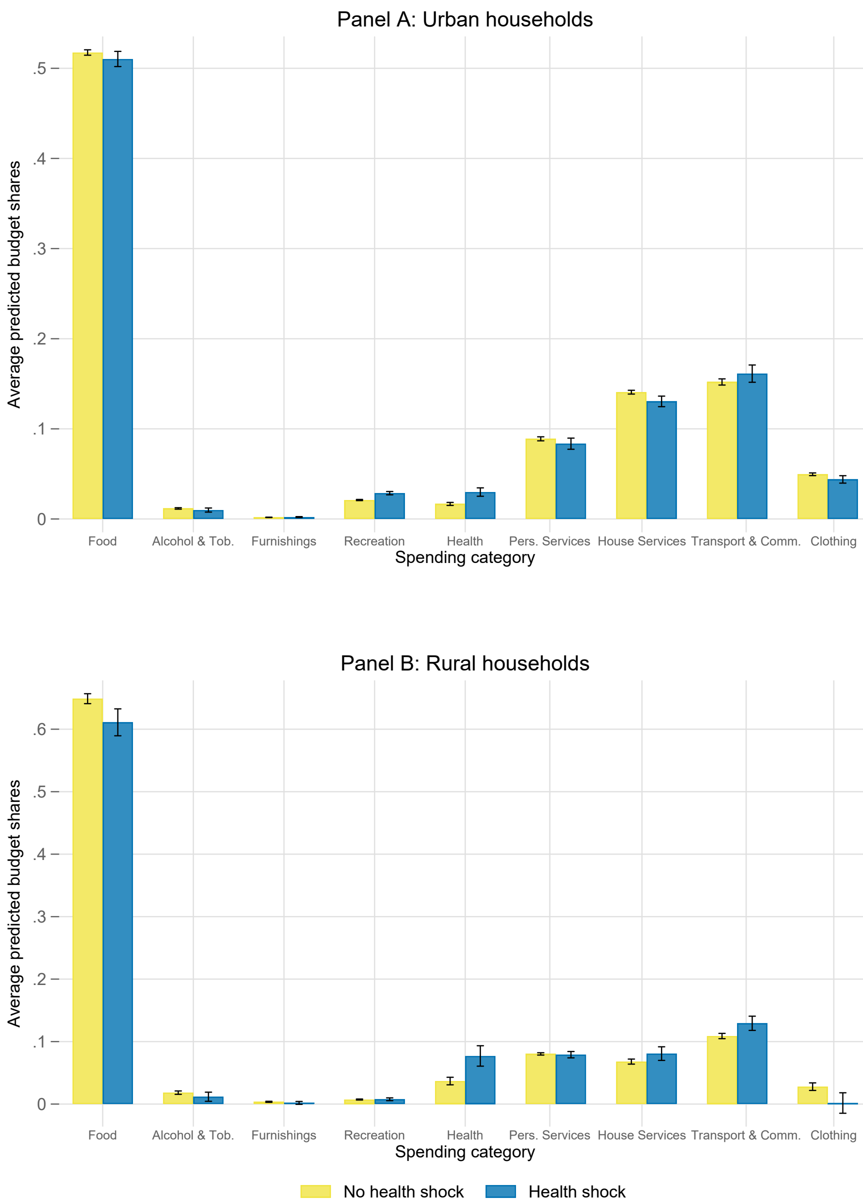
A Additional Figures and Tables

Table A.1: Types of Shocks

Individual Shock	Classification
Death of household head or their spouse Death of another household member Divorce Abandonment of their habitual residence Arrival of a relative	Family shock
Accident or illness of any household member	Health shock
Household head lost their job Household head's spouse lost their job Other member lost their job Bankruptcy of the family business Loss or reduction of remittances	Economic shock
Loss of farms, ranches or plantations Pests or loss of harvest Loss or death of animals	Farm Income shock
Theft, fire or destruction of assets Loss of dwelling Victim of the conflict	Crime shock
Floods, mudslides, landslides, avalanches or gales Earthquakes Drought	Natural disaster shock

Source: ELCA.

Figure A.1: Average Predicted Budget Shares for Urban and Rural Households Before and After a Health Shock



Note: The figure shows average predicted budget shares before and after a health shock, using estimates from equation (4). The black vertical ranges are confidence intervals at the 95% confidence level.

Table A.2: Frequency of Shocks

	Wave 2013			Wave 2016		
	Urban	Rural	Overall	Urban	Rural	Overall
Economic shock	0.26	0.07	0.25	0.27	0.24	0.27
Farm Income shock	0.00	0.36	0.00	0.00	0.37	0.00
Family shock	0.22	0.25	0.22	0.11	0.13	0.11
Natural disaster shock	0.07	0.25	0.07	0.08	0.57	0.08
Health shock	0.26	0.22	0.26	0.26	0.32	0.26
Crime shock	0.10	0.03	0.10	0.08	0.02	0.08
Any shock	0.58	0.60	0.58	0.55	0.83	0.55

Note: Source: ELCA.

Table A.3: Effects of All Types of Shocks on Food and Health Expenditures

	Urban		Rural	
	Food	Health	Food	Health
Panel 1: No controls nor region fixed effects				
Economic shock	0.005	-0.002	0.036	-0.001
	(0.010)	(0.002)	(0.037)	(0.032)
Farm Income shock	.	.	-0.050*	0.042
	(.)	(.)	(0.029)	(0.028)
Natural disaster shock	0.016	-0.009	-0.008	0.004
	(0.015)	(0.006)	(0.021)	(0.015)
Health shock	-0.006	0.012***	-0.047	0.057
	(0.007)	(0.002)	(0.032)	(0.037)
Crime shock	-0.001	0.008**	0.025	-0.011
	(0.010)	(0.004)	(0.018)	(0.018)
Family shock	0.001	0.003	-0.108	0.098
	(0.010)	(0.002)	(0.075)	(0.075)
ln(Total expenditure)	0.853***	0.041	2.097***	-0.857**
	(0.112)	(0.091)	(0.529)	(0.345)
ln(Total expenditure)^2	-0.033***	-0.001	-0.084***	0.035**
	(0.004)	(0.003)	(0.020)	(0.014)
Observations	2916	2916	2396	2396
R^2	0.983	0.421	0.984	0.408
Mean dep. var.	0.534	0.024	0.625	0.035
Panel 2: Controls and region fixed effects				
Economic shock	0.005	-0.002	0.050	-0.022
	(0.012)	(0.002)	(0.032)	(0.024)
Farm Income shock	.	.	-0.029*	0.021
	(.)	(.)	(0.015)	(0.014)
Natural disaster shock	0.018	-0.008	-0.017	0.010
	(0.012)	(0.006)	(0.020)	(0.014)
Health shock	-0.004	0.011***	-0.030*	0.036***
	(0.007)	(0.003)	(0.016)	(0.011)
Crime shock	-0.001	0.009*	-0.003	0.020*
	(0.008)	(0.005)	(0.014)	(0.012)
Family shock	0.003	0.002	-0.080**	0.069**
	(0.009)	(0.002)	(0.039)	(0.034)
ln(Total expenditure)	0.756***	0.069	2.197***	-0.995***
	(0.138)	(0.101)	(0.472)	(0.240)
ln(Total expenditure)^2	-0.029***	-0.002	-0.088***	0.040***
	(0.005)	(0.004)	(0.018)	(0.009)
Observations	2916	2916	2396	2396
R^2	0.983	0.426	0.987	0.596
Mean dep. var.	0.534	0.024	0.625	0.035

Note: The table shows estimates of equation (4) using SUR. Standard errors clustered at the municipality level are in parentheses. Panel 1 shows regressions without any controls. Panel 2 includes region-specific trends and the education level of the household head in 2013, interacted with the trend. All regressions include household and time fixed effects. $p<0.1$, **; $p<0.05$, ***: $p<0.01$.

Table A.4: Decomposition of the effect of Health Shocks on Food and Health Expenditures, Without controls

	Urban			Rural		
	OLS	SUR		OLS	SUR	
Panel 1:	Food expenditure share	Food expenditure share	ln(Total expenditure)	Food expenditure share	Food expenditure share	ln(Total expenditure)
Health shock	-0.009	-0.006	0.086***	-0.051	-0.047	0.042**
	(0.007)	(0.007)	(0.029)	(0.031)	(0.032)	(0.021)
ln(Total expenditure)		0.853***			2.098***	
		(0.112)			(0.531)	
ln(Total expenditure)^2		-0.033***			-0.084***	
		(0.004)			(0.021)	
Observations	2916	2916	2916	2396	2396	2396
R^2	0.017	.	.	0.314	.	.
Mean dep. var.	0.534	0.534	13.626	0.625	0.625	13.096
Household F. E.	✓	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓	✓	✓
Controls						
Panel 2:	Health expenditure share	Health expenditure share	ln(Total expenditure)	Health expenditure share	Health expenditure share	ln(Total expenditure)
Health shock	0.014***	0.012***	0.086***	0.059*	0.057	0.042**
	(0.003)	(0.002)	(0.029)	(0.036)	(0.037)	(0.021)
ln(Total expenditure)		0.041			-0.857**	
		(0.091)			(0.346)	
ln(Total expenditure)^2		-0.001			0.035**	
		(0.003)			(0.014)	
Observations	2916	2916	2916	2396	2396	2396
R^2	0.031	.	.	0.276	.	.
Mean dep. var.	0.024	0.024	13.626	0.035	0.035	13.096
Household F. E.	✓	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓	✓	✓
Controls						

Note: The table shows the coefficients on the health shock, total expenditure, and total expenditure squared from estimates of equations (1), (4) and (5) using OLS and SUR. Standard errors clustered at the municipality level are in parentheses. A household suffers a health shock if any member has been affected by an accident or illness in the last three years. Controls are region-specific trends, and the education level of the household head in 2013 interacted with the trend. *: $p<0.1$, **: $p<0.05$, ***: $p<0.01$.

Table A.5: Effect of Health Shocks on Food and Health Expenditures, Unweighted Estimates

	Urban			Rural		
	OLS	SUR		OLS	SUR	
Panel 1:	Food expenditure share	Food expenditure share	ln(Total expenditure)	Food expenditure share	Food expenditure share	ln(Total expenditure)
Health shock	-0.009**	-0.008**	0.051**	-0.039***	-0.033***	0.051**
	(0.004)	(0.004)	(0.022)	(0.007)	(0.007)	(0.022)
ln(Total expenditure)		0.798***			1.710***	
		(0.142)			(0.363)	
ln(Total expenditure)^2		-0.031***			-0.069***	
		(0.005)			(0.014)	
Observations	2916	2916	2916	2396	2396	2396
R^2	0.008	.	.	0.033	.	.
Mean dep. var.	0.534	0.534	13.626	0.625	0.625	13.096
Household F. E.	✓	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Panel 2:	Health expenditure share	Health expenditure share	ln(Total expenditure)	Health expenditure share	Health expenditure share	ln(Total expenditure)
Health shock	0.013***	0.012***	0.051**	0.024***	0.021***	0.051**
	(0.003)	(0.003)	(0.022)	(0.005)	(0.005)	(0.022)
ln(Total expenditure)		-0.126**			-0.440***	
		(0.064)			(0.136)	
ln(Total expenditure)^2		0.006***			0.018***	
		(0.002)			(0.005)	
Observations	2916	2916	2916	2396	2396	2396
R^2	0.022	.	.	0.026	.	.
Mean dep. var.	0.024	0.024	13.626	0.035	0.035	13.096
Household F. E.	✓	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓

Note: The table shows the coefficients on the health shock, total expenditure, and total expenditure squared from estimates of equations (1), (4) and (5) using OLS and SUR. Standard errors clustered at the municipality level are in parentheses. A household suffers a health shock if any member has been affected by an accident or illness in the last three years. Controls are region-specific trends, and the education level of the household head in 2013 interacted with the trend. *: $p<0.1$, **: $p<0.05$, ***: $p<0.01$.

Table A.6: Main Results, Marginal Effect of a Health Shock on Expenditure Shares when total expenditure interacts with the Health Shock.

	Urban		Rural	
	Food	Health	Food	Health
Panel 1: No controls nor region fixed effects				
Health Shock (Marginal effect)	-0.008	0.012***	-0.043*	0.053*
	(0.007)	(0.003)	(0.025)	(0.028)
Observations	2916	2916	2396	2396
R^2	0.050	0.060	0.362	0.296
Mean dep. var.	0.534	0.024	0.625	0.035
Panel 2: Controls and region fixed effects				
Health Shock (Marginal effect)	-0.006	0.011***	-0.031**	0.037***
	(0.006)	(0.003)	(0.013)	(0.011)
Observations	2916	2916	2396	2396
R^2	0.075	0.068	0.470	0.518
Mean dep. var.	0.534	0.024	0.625	0.035

Note: The table shows marginal effects of the health shock from estimates of equation (4) allowing the health shock to interact with total expenditure and total expenditure squared. The marginal effects are calculated at the means of ln(total expenditure) and ln(total expenditure)^2. Standard errors clustered at the municipality level are in parentheses. Panel 1 shows regressions without any controls. Panel 2 includes region-specific trends and the education level of the household head in 2013, interacted with the trend. We also control for all the other shocks, total expenditure, and total expenditure squared without interactions. *: p<0.1, **: p<0.05, ***: p<0.01.

Table A.7: Effect of Health Shocks on Other Expenditure Categories

	AlcoholT	Furnish.	Recreat.	Personal	House	TransCom	Cloth.
Panel 1: No controls nor region fixed effects							
Health shock Urban	-0.003	0.000	0.008***	-0.004	-0.005	0.010	-0.013***
	(0.002)	(0.000)	(0.001)	(0.004)	(0.005)	(0.007)	(0.004)
Observations	2916	2916	2916	2916	2916	2916	2916
R^2	0.043	0.021	0.028	0.044	0.163	0.024	0.067
Mean dep. var.	0.012	0.002	0.019	0.087	0.133	0.145	0.044
Household F. E.	✓	✓	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓	✓	✓	✓
Region Trends							
Health shock Rural	-0.010	-0.002	0.001	-0.005	0.012	0.027**	-0.032*
	(0.008)	(0.002)	(0.001)	(0.006)	(0.011)	(0.011)	(0.018)
Observations	2396	2396	2396	2396	2396	2396	2396
R^2	0.067	0.113	0.022	0.090	0.035	0.116	0.228
Mean dep. var.	0.019	0.003	0.011	0.082	0.076	0.126	0.024
Household F. E.	✓	✓	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓	✓	✓	✓
Region Trends							
Panel 2: Controls and region fixed effects							
Health shock Urban	-0.003*	0.000	0.007***	-0.004	-0.006	0.008	-0.009***
	(0.002)	(0.000)	(0.001)	(0.004)	(0.004)	(0.007)	(0.003)
Observations	2916	2916	2916	2916	2916	2916	2916
R^2	0.049	0.034	0.077	0.060	0.186	0.052	0.161
Mean dep. var.	0.012	0.002	0.019	0.087	0.133	0.145	0.044
Household F. E.	✓	✓	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓	✓	✓	✓
Region Trends	✓	✓	✓	✓	✓	✓	✓
Health shock Rural	-0.007	-0.002	-0.000	-0.001	0.013	0.018**	-0.027**
	(0.005)	(0.002)	(0.002)	(0.003)	(0.008)	(0.008)	(0.012)
Observations	2396	2396	2396	2396	2396	2396	2396
R^2	0.100	0.144	0.035	0.166	0.097	0.184	0.288
Mean dep. var.	0.019	0.003	0.011	0.082	0.076	0.126	0.024
Household F. E.	✓	✓	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓	✓	✓	✓
Region Trends	✓	✓	✓	✓	✓	✓	✓

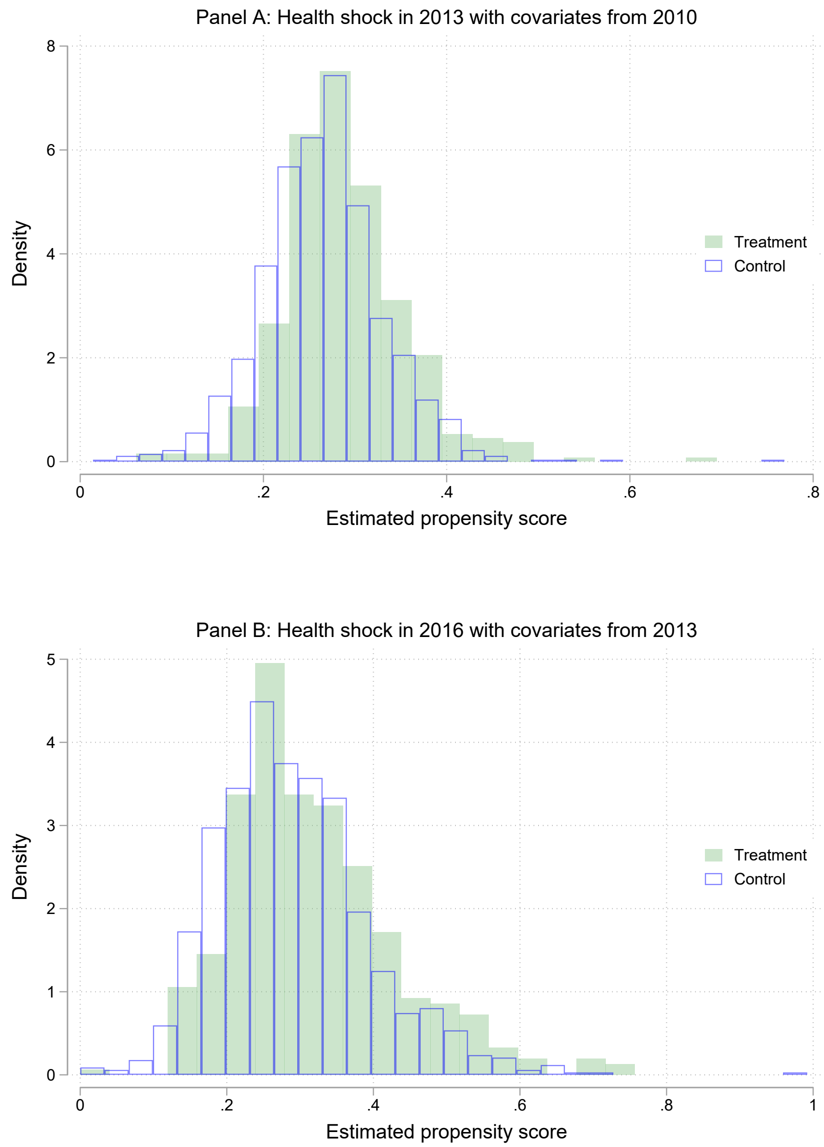
Note: The table shows the coefficients on the health shock from estimates of equation (4). Standard errors clustered at the municipality level are in parentheses. Panel 1 shows regressions without any controls. Panel 2 includes region-specific trends and the education level of the household head in 2013, interacted with the trend. We also control for all the other shocks in Appendix Table A.1, total expenditure, and total expenditure squared in both panels. *: p<0.1, **: p<0.05, ***: p<0.01.

Table A.8: Effect of Health Shocks on Food and Health Expenditures, IPW

	Urban			Rural		
	OLS	SUR		OLS	SUR	
Panel 1:	Food expenditure share	Food expenditure share	Total expenditure	Food expenditure share	Food expenditure share	Total expenditure
Health shock	-0.003	0.000	0.077***	-0.037**	-0.029*	0.052*
	(0.007)	(0.008)	(0.027)	(0.015)	(0.016)	(0.028)
ln(Total expenditure)		0.840***			2.503***	
		(0.081)			(0.446)	
ln(Total expenditure)^2		-0.033***			-0.099***	
		(0.003)			(0.017)	
Observations	2916	2916	2916	2396	2396	2396
R^2	0.052	.	.	0.394	.	.
Mean dep. var.	0.534	0.534	13.626	0.625	0.625	13.096
Household F. E.	✓	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Panel 2:	Health expenditure share	Health expenditure share	Total expenditure	Health expenditure share	Health expenditure share	Total expenditure
Health shock	0.011***	0.010***	0.077***	0.039***	0.035***	0.052*
	(0.004)	(0.003)	(0.027)	(0.010)	(0.010)	(0.028)
ln(Total expenditure)		-0.017			-0.947***	
		(0.074)			(0.301)	
ln(Total expenditure)^2		0.001			0.038***	
		(0.003)			(0.012)	
Observations	2916	2916	2916	2396	2396	2396
R^2	0.035	.	.	0.440	.	.
Mean dep. var.	0.024	0.024	13.626	0.035	0.035	13.096
Household F. E.	✓	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓

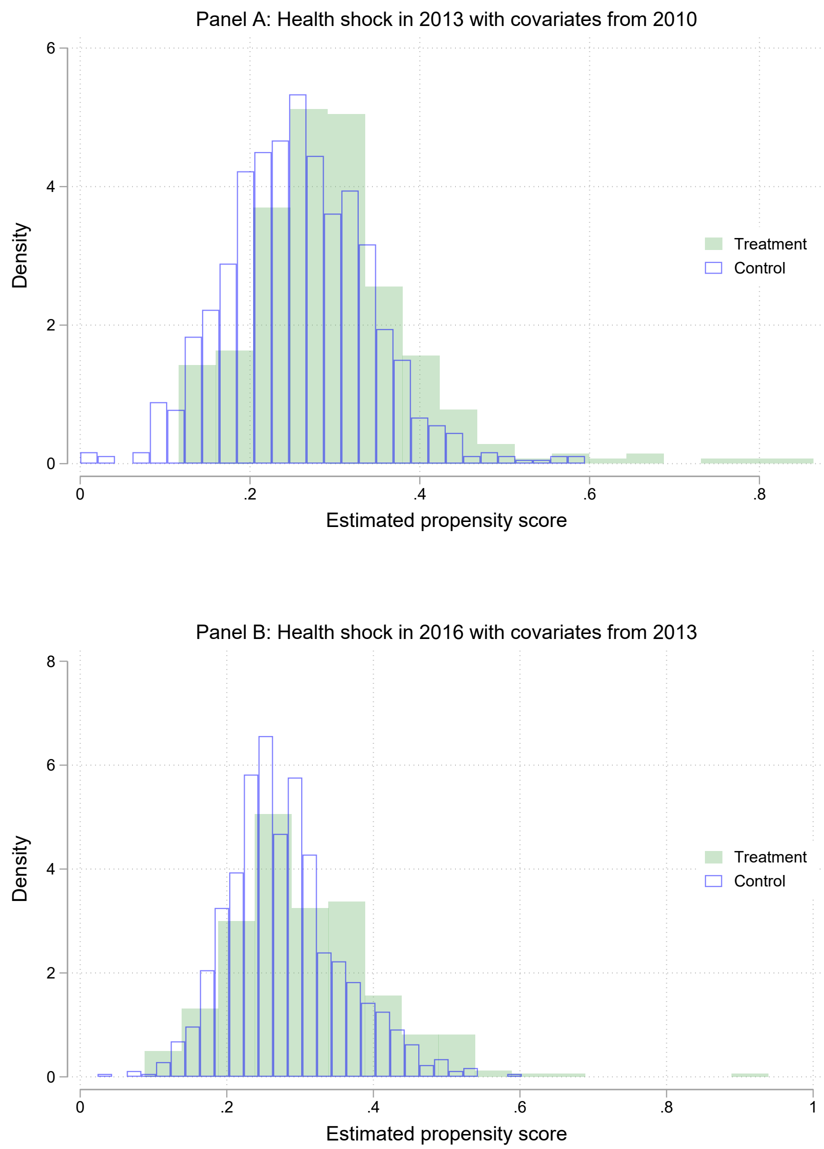
Note: The table shows the coefficients on the health shock from estimates of equations (1), (4) and (5) using FE (OLS) and SUR. Standard errors clustered at the municipality level are in parentheses. Panel 1 shows regressions without any controls. Panel 2 includes region-specific trends and the education level of the household head in 2013, interacted with the trend. We also control for all the other shocks in Appendix Table A.1, total expenditure, and total expenditure squared in both panels. *: p<0.1, **: p<0.05, ***: p<0.01.

Figure A.2: Estimated Propensity Score Distributions: Urban Households



Note: These graphs show the distribution of the estimated propensity score of getting a health shock in 2013 and 2016. The estimations only include urban households. The covariates include household characteristics (informality, number of household members, and status in the *Familias en Acción* program), total expenditure, expenditure by category. as well as these variables squared and interacted between them. All the covariates are measured in the wave before the shock occurs: for 2013, covariates are from 2010; and for 2016, covariates are from 2013.

Figure A.3: Estimated Propensity Score Distributions: Rural Households



Note: These graphs show the distribution of the estimated propensity score of getting a health shock in 2013 and 2016. The estimations only include rural households. The covariates include household characteristics (informality, number of household members, and status in the *Familias en Acción* program), total expenditure, expenditure by category. as well as these variables squared and interacted between them. All the covariates are measured in the wave before the shock occurs: for 2013, covariates are from 2010; and for 2016, covariates are from 2013.

Table A.9: Effect of Health Shocks on Food and Health Expenditures using the Propensity Score Common Support Sample

	Urban			Rural		
	OLS	SUR		OLS	SUR	
Panel 1:	Food expenditure share	Food expenditure share	ln(Total expenditure)	Food expenditure share	Food expenditure share	ln(Total expenditure)
Health shock	-0.007	-0.003	0.078**	-0.041**	-0.036**	0.047***
	(0.006)	(0.007)	(0.030)	(0.015)	(0.014)	(0.015)
ln(Total expenditure)		0.789***			2.580***	
		(0.130)			(0.491)	
ln(Total expenditure)^2		-0.031***			-0.103***	
		(0.005)			(0.019)	
Observations	2756	2756	2756	2280	2280	2280
R^2	0.049	.	.	0.425	.	.
Mean dep. var.	0.532	0.532	13.688	0.626	0.626	13.058
Household F. E.	✓	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Panel 2:	Health expenditure share	Health expenditure share	ln(Total expenditure)	Health expenditure share	Health expenditure share	ln(Total expenditure)
Health shock	0.013***	0.011***	0.078**	0.045***	0.041***	0.047***
	(0.003)	(0.002)	(0.030)	(0.012)	(0.012)	(0.015)
ln(Total expenditure)		0.091			-1.172***	
		(0.105)			(0.274)	
ln(Total expenditure)^2		-0.002			0.048***	
		(0.004)			(0.011)	
Observations	2756	2756	2756	2280	2280	2280
R^2	0.041	.	.	0.507	.	.
Mean dep. var.	0.024	0.024	13.688	0.035	0.035	13.058
Household F. E.	✓	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓

Note: The table shows the coefficients on the health shock from estimates of equations (1), (4) and (5) using OLS and SUR. Standard errors clustered at the municipality level are in parentheses. Panel 1 shows regressions without any controls. Panel 2 includes region-specific trends and the education level of the household head in 2013, interacted with the trend. We also control for all the other shocks in Appendix Table A.1, total expenditure, and total expenditure squared in both panels. *: $p<0.1$, **: $p<0.05$, ***: $p<0.01$.