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

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Abstract

We analyze the effect of adverse health shocks on different expenditure shares of households using a difference in differences approach. We find that households engage in substitution between health expenditures and food expenditures. We also find important heterogeneity in this trade-off between present health and future health mediated by access to social protection, job contract type, and location (urban-rural). We document that households from rural areas headed by persons with informal jobs are more vulnerable. We discuss several policy implications.

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1 Introduction

How do households react to negative shocks that may alter their income constraint?. Consumer theory suggests that when income changes, households should adjust their expenditure in different goods according to their income elasticity. However, these spending adjustments may change because of other circumstances surrounding households, such as their degree of insurance and their sources of income. Understanding the sources of heterogeneity in these responses is important for the design of social protection programs.

In this paper, we study the response of spending to negative health shocks using household data from Colombia. We document substantial differences in the spending response to negative 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 interesting for three 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 process of urbanization has led to a large 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, defined as those without access to employer-financed health insurance, was 56% in January 2020. Informal workers have fewer alternatives to deal with adverse shocks because they have both less access to insurance and more volatile income. Third, Colombian households often experience adverse health shocks. In our sample, 25% report experiencing adverse shocks in the previous 10 years.

To examine the response of spending to negative health shocks we use two waves of panel data on urban and rural households in Colombia from 2013 to 2016. We create a harmonized dataset of household spending in several item categories across the three waves of the dataset. We model the demand on each 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). We then compare the spending of households who experienced adverse health shocks to the spending of those who did not experience them. We do this by allowing the demand functions to shift in response to shocks, and we estimate these shifts through a two-way fixed-effects analysis. Our approach follows that of

Attanasio et al. (2011), who embed a difference-in-differences analysis in consumer theory-inspired Engel curves to estimate the response of food spending to cash transfers. Our identification assumption is that in absence of adverse health shocks, the shares of spending 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. This contrasts with other studies that rely on repeated cross-section data or synthetic panel methods (Attanasio and Székely, 2004).

We find that health shocks induce large spending adjustments that vary between household types. Food and health spending react strongly to health shocks. Rural households increase their health spending share by around 5 percentage points (p.p) and substitute away from food spending, reducing its budget share by about 3 p.p. Urban households increase their health spending by about one p.p., and reduce their food spending share by 1.8 p.p. These differences across rural and urban households do not arise from different baseline spending or different income responses to the adverse shocks.

When we turn to the potential sources of the observed heterogeneity in responses we find a substantial role of insurance and formal employment. Among urban households, those where the household heads are employed as formal workers do not reduce their food spending in response to negative health shocks. In contrast, urban households with informally-employed heads, as well as rural households, substantially reduce their food spending. 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 spending to weather adverse health shocks.

Our work contributes to the literature on the responses of consumption 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 are unable to completely 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 are used 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 are able to smooth spending. Our results for the Colombian case confirm that rural households are less able to smooth away the shocks and highlight substitution away from food spending 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 households with more inactive working-age members may adjust to the shock by sending these members to the labor force. In his case, rural households are more insured because they usually have more idle able members. We also find that larger households are able to smooth their spending when they are affected by a health shock. Access to formal and informal insurance also allows these households to maintain their levels of food spending.

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 on the role of household heterogeneity (Lewbel and Pendakur, 2009). Last, we contribute to the literature about demand analysis in Colombia (Cortés and Pérez Pérez, 2010).

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 spending in section 4. We discuss heterogeneous effects and mechanisms in section 5. Section 6 concludes.

2 Data and Descriptive Statistics

In this section we describe the data we use in detail and provide some descriptive statistics about household spending and the prevalence of adverse shocks.

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

The survey has separate modules for urban and rural households, and collects socio-demographic, labor markets, and spending data. Colombian households are classified into 6 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). We also report unweighted estimates to show the robustness of our results.

Income and spending data. The survey collects detailed data on overall household income and income for each household member. It also collects data on spending in several categories. This spending data is collected directly from interviewers using the recall method. As such, spending on certain goods may have some measurement error, particularly for goods purchased at low frequencies (Battistin, 2003).

We harmonize the income and spending data to be comparable across waves. For income, we contrast individual-level with household-level information, as well as real income variation through time for each household and for the whole distribution of incomes. For spending, we remove durable expenditures such as furniture and home appliances, education, vehicles, or real estate. We then aggregate the remaining items in nine categories: Food, Alcoholic Beverages and Tobacco, Small Furnishings, Recreation, Health, Personal Services, House Services, Transport and Communication, and Clothing.[2]

Shocks data. The ELCA data includes questions about whether the household experienced shocks in the last three years prior to being surveyed. Households answer questions about 19 types of shocks of diverse nature, for example: whether a crop failed, whether a member of the household passed away, etc. A household is affected by a health shock if any household member is affected by an accident or illness.[3]

Sample selection. We restrict our analysis to households that we can follow in the second and third waves of the data.[4]

We discard outliers of total household spending.[5] To control for changes in household

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

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

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

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

member composition, 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 in between the two waves, and if none of its members left, arrived, passed away, or were born in between waves. In doing so, we arrive at a total of 2,499 households that maintain the same composition from 2013 to 2016. From these, 1,076 households are rural, 1,346 are urban, 69 transitioned from rural to urban between waves, and 8 transitioned from urban to rural.

Descriptive statistics. Table 1 shows descriptive statistics of spending and income for urban and rural households. In 2013, urban households received more than twice the monthly income of rural households and spent about 30% more. By 2016, the income gap narrows, but the expenditure gap remains. The amounts of spending are usually higher for urban households, with a few exceptions. Health spending is higher for rural households in 2013 but declines sharply for 2016. Rural households spend a larger fraction of their total spending on food, and smaller fractions in house services, transport, and clothing. The average number of members per household is between 3 and 4, with rural households being larger than rural ones. The informality of the household head, which we define as either being unaffiliated of social health insurance or not contributing to the pension system, is also higher in rural households. Although the proportion of urban households with an informal head remained constant between 2013 and 2016, the share of informal rural households fell almost by half, from 87% in 2013 to 55% in 2016.

Table 2 shows the percentage of households who experienced negative health shocks. In 2013, 26% of urban households and 24% of rural households in our sample experienced health shocks. In 2016, the percentage of urban households affected by health shocks slightly decreased, but the percentage of rural households affected increased to 35%. The frequency of shocks is higher for small urban and large rural households. A large share of agricultural households experience shocks during 2011-2013, but this share falls to about half for 2014-2016. [6]

Table 3 compares budget shares among households that experienced and did not experience health shocks. The differences are substantial for some spending categories. The food budget share is about 9 p.p. lower for rural households that experience health shocks and is large in standardized terms. In contrast, the food budget shares for shock and non-shock urban households are similar. Urban households with health shocks

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

Table 1: Descriptive Statistics

	2013		2016	
	Urban	Rural	Urban	Rural
Household income (pesos/month)	1211854	470932	1125653	526961
Total spending (pesos/month)	951828	608719	1075463	601038
Number of members	3.48	3.75	3.48	3.82
Informal household head	0.51	0.87	0.53	0.55
Spending by Category (pesos/month)				
Food	461441	306271	520280	394636
Alcoholic beverages and tobacco	9632	13284	15868	9688
Furnishings	1970	1280	1618	955
Recreation	28530	8168	30915	3206
Health	22865	76890	21444	11596
Personal services	83851	56524	104756	43010
House services	136024	38145	123599	53701
Transport and communication	152708	81752	189664	76503
Clothing	54807	26405	67319	7743
Budget Shares				
Food	0.503	0.545	0.513	0.676
Alcoholic beverages and tobacco	0.011	0.030	0.013	0.015
Furnishings	0.002	0.003	0.001	0.002
Recreation	0.026	0.011	0.023	0.005
Health	0.022	0.099	0.018	0.017
Personal services	0.086	0.086	0.094	0.071
House services	0.151	0.066	0.120	0.085
Transport and communication	0.151	0.124	0.164	0.117
Clothing	0.049	0.037	0.053	0.012

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 2499 households, using the average of the survey weights for 2013 and 2016 by household. “Informal household head” is defined as 0 if the household head is affiliated to health insurance and if they contribute to the pension system, and 1 in any other case. Source: ELCA.

Table 2: Incidence of Adverse Health Shocks

	2013 Urban	2013 Rural	2013 Overall	2016 Urban	2016 Rural	2016 Overall	2013-2016 Overall
All households	0.26	0.24	0.26	0.24	0.35	0.24	0.25
3 members or less	0.27	0.42	0.27	0.25	0.25	0.25	0.26
4 members or more	0.26	0.11	0.26	0.24	0.41	0.24	0.25
Formal household head	0.27	0.05	0.27	0.22	0.34	0.22	0.25
Informal household head	0.25	0.27	0.25	0.27	0.36	0.27	0.26
Not in CCT program	0.26	0.23	0.26	0.24	0.47	0.24	0.25
Is in CCT program	0.28	0.24	0.28	0.26	0.14	0.26	0.27
No social capital	0.25	0.25	0.25	0.24	0.35	0.24	0.24
Has social capital	0.32	0.19	0.32	0.27	0.32	0.27	0.30
Unemployed	0.22	0.04	0.22	0.30	0.09	0.30	0.26
Employed	0.27	0.27	0.27	0.23	0.37	0.24	0.25
Unemployed	0.22	0.04	0.22	0.30	0.09	0.30	0.26
Works with contract	0.27	0.07	0.27	0.23	0.37	0.24	0.25
Works without contract	0.27	0.31	0.27	0.23	0.38	0.23	0.25
Unemployed	0.22	0.04	0.22	0.30	0.09	0.30	0.26
Other primary-secondary sectors	0.26	0.19	0.26	0.25	0.88	0.25	0.26
Agriculture	0.33	0.24	0.33	0.17	0.32	0.18	0.27
Wholesaling and retailing	0.27	0.48	0.27	0.18	0.09	0.18	0.23
Other tertiary sector	0.26	0.20	0.26	0.26	0.07	0.26	0.26

A household is affected by a health shock if any household member is affected by an accident or illness in the last three years. Informal households are those whose household head is either unaffiliated to social health insurance, or does not contribute to the pension system. 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 household head takes part in local groups or organizations of any kind, like political parties, guilds, sports clubs, etc. Labor market variables are calculated always on the household head. "Works with contract" includes households whose head has a verbal contract or a written one. "Other primary and secondary sectors" includes mining, manufacture, 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.

have around a 2 p.p. larger share of expenditure on health relative to their unaffected counterparts. Rural households have a 9 p.p. higher share. Across the board, rural households tend to reduce spending in non-health categories in response to the shock in a larger magnitude than urban households.

3 Empirical Strategy

We estimate the effects of adverse health shocks on spending in different categories by estimating the demand of households for goods in each category and allowing the shocks to shift these demand curves. We estimate the health shock effects by comparing households who experience them to those who do not experience them. We describe the specification, the identification strategy, and the estimation below.

Demand specification. We model household spending in each category of goods as a function of prices, income, and demographics, in line with the literature on demand estimation (Barnett and Serletis, 2008). We guide our estimation from a quadratic demand function with time and household fixed effects:

$$s_{ght} = \beta_0 + P'_{ght}\boldsymbol{\beta}_{\mathbf{P}} + \beta_x \ln x_{ht} + \beta_{x^2} \ln x^2_{ht} + Z'_{ht}\boldsymbol{\gamma} + \delta_h + \delta_t + \varepsilon_{ght}. \quad (1)$$

Here, $s_{ght} \equiv \frac{X_{ght}}{X_{ht}}$ is the budget share for good category g in household h at time t. Demand is linear in the logarithm of prices for good g faced by the household, $P'_{ght} = (P_{1ht}, P_{2ht}, \ldots, P_{Ght})$. It is quadratic on total household expenditure X_{ht}. Additional variables Z_{ht} can shift the level of demand. The variables δ_h and δ_t are household and time fixed-effects, respectively, and ε_{ght} is an error term.

This baseline specification is a reduced-form of demand functions from a quadratic almost ideal demand system (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 δ_i (Lecocq and Robin, 2015).[7]

Estimation issues. We cannot estimate equation (1) 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

[7] In this reduced-form approach, we do not estimate the equations for each good in a system of demand functions, neither do we allow for the error terms ε_{ght} to be correlated across goods. Seemingunrelated-regressions estimation of these equations would yield the same point estimates because the right-hand-side variables are the same.

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

Budget share		Shock	No shock	Diff.	Std. diff.
Food	Urban	0.498	0.511	-0.013	-0.066
	Rural	0.555	0.646	-0.091	-0.402
	Overall	0.498	0.512	-0.014	-0.070
Alcoholic beverages and tobacco	Urban	0.011	0.012	-0.001	-0.026
	Rural	0.010	0.026	-0.016	-0.254
	Overall	0.011	0.012	-0.001	-0.026
Furnishings	Urban	0.002	0.002	0.000	0.000
	Rural	0.001	0.002	-0.001	-0.156
	Overall	0.002	0.002	0.000	0.000
Recreation	Urban	0.028	0.023	0.005	0.078
	Rural	0.004	0.009	-0.005	-0.191
	Overall	0.028	0.023	0.005	0.078
Health	Urban	0.034	0.016	0.018	0.250
	Rural	0.116	0.026	0.090	0.434
	Overall	0.034	0.016	0.018	0.245
Personal services	Urban	0.086	0.091	-0.005	-0.064
	Rural	0.062	0.084	-0.022	-0.362
	Overall	0.086	0.091	-0.005	-0.064
House services	Urban	0.136	0.135	0.001	0.009
	Rural	0.115	0.061	0.054	0.566
	Overall	0.136	0.135	0.001	0.009
Transport and communication	Urban	0.161	0.157	0.004	0.027
	Rural	0.129	0.116	0.013	0.102
	Overall	0.161	0.156	0.005	0.033
Clothing	Urban	0.044	0.053	-0.009	-0.098
	Rural	0.007	0.030	-0.023	-0.405
	Overall	0.044	0.053	-0.009	-0.098

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.

fixed effects absorb any cross-sectional variation in Z_{ht}. To allow for a flexible role of demographics in determining the evolution of expenditure, 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 by municipality.

An additional issue with equation (1) is the presence of division bias because X_{ht} appears both in the left- and right-hand sides. While this is a pervasive problem in cross-sectional demand estimation, we note that it is likely to be much less of an issue in the panel setting. On the cross-section, division bias would imply a mechanical negative correlation between X_{ht} and ε_{ght} because households with larger expenditures would have smaller budget shares. However, this cross-sectional effect is addressed by the fixed effects, δ_h. For an individual household over time, budget shares would be mechanically lower if total expenditure increases. This effect is addressed by the time effects δ_t and the differential trends by demographics. Any remaining division bias would come from the differential evolution of expenditure not addressed by these controls. Nevertheless, in the appendix, we report estimates instrumenting total household expenditure with lagged total household income as is customary in this literature (Barnett and Serletis, 2008; Attanasio et al., 2011). Our results are qualitatively similar, although, as shown in the next section, lagged household income is not a strong instrument in this panel setting (Lecocq and Robin, 2015).

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:

$$\begin{aligned} s_{ght} = \beta_0 + \sum_s \delta_{r(h)} 1(r(h) = s) 1(t = 2016) + \beta_X \ln X_{ht} + \beta_{X^2} \ln X_{ht}^2 \\ + Z'_{h,2013} 1(t = 2016) \boldsymbol{\gamma} + \delta_h + \delta_t + \varepsilon_{ght}. \end{aligned} \tag{2}$$

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. We allow adverse shocks in the previous three years to shift demand as covariates Z in equation (2):

$$
\begin{aligned}
s_{ght} = \beta_0 + \sum_s \delta_{r(h)} 1(r(h) = s) 1(t = 2016) + \beta_X \ln X_{ht} + \beta_{X^2} \ln X_{ht}^2 \\
+ \theta Health\ Shock_{h,t-1} + Shocks'_{h,t-1} \boldsymbol{\gamma}_{\textbf{Shocks}} + Z'_{ht} 1(t = 2016) \boldsymbol{\gamma} + \delta_h + \delta_t + \varepsilon_{ght}.
\end{aligned}
\tag{3}
$$

In this regression, $Health\ Shock_{h,t-1}$ is one if a household experienced an adverse health shock in the previous three years, and zero otherwise. The coefficient of interest θ measures how demand shifts in the presence of health shocks. The vector $Shocks_{h,t-1}$ contains indicator variables for shocks in each one of the other shock categories. The effect of these other shocks is captured in the vector of coefficients $\boldsymbol{\gamma}_{\textbf{Shocks}}$.

Allowing shocks to enter the demand curve linearly amounts to assuming that these shocks shift Engel curves up or down, but do not change the price elasticities nor the income elasticities of demand. Moreover, it assumes that the shocks themselves have an impact on demand beyond the impact they may have on total expenditure. To show evidence supporting this specification we estimate unconditional non-parametric Engel curves for households that experience and do not experience health shocks. We do this through local polynomial regression. The visual evidence on shifts of these demand curves helps to validate our linear specification in equation (3).

While from a demand theory point-of-view equation (3) is a standard demand specification with covariates, conditioning on total expenditure to evaluate the effect of shocks means that we are conditioning on an outcome. This is a source of concern. However, in the appendix, we show that when we instrument total household expenditure with lagged household income, which is unaffected by shocks, our estimates remain similar. We also show that there are no substantial differences in the total expenditure responses to shocks between urban and rural households.

Heterogeneous responses. We examine different responses of spending to health shocks for households with different characteristics by interacting the shock indicators in equation (3) with several household characteristics. We consider different responses of rural and urban households, of households with heads working in the formal or informal sectors, of households with access to safety nets, and with households whose heads work in different economic sectors.

4 Effects of Health Shocks on Spending

In this section, we outline our main results. We show that health shocks have different effects on food and health budget shares across urban and rural households. Conditional on total expenditure, rural households adjust their food and health spending more sharply in response to shocks. Formal households, households with social capital, and employed with contracts are more likely to adjust to the health shock without large spending changes.

Overall effect of health shocks on food and health expenditure. Table 4 shows the coefficients on health shocks from the estimation of equation (3). We find significant changes in food and health spending in response to the health shocks with stark differences across urban and rural households. Our regressions on panel 2 with controls and region-specific trends show that urban households decrease their food budget share by 1.8 p.p. conditional on total spending. They increase their health budget share by 1.2 p.p. Rural households adjust their spending more heavily. Their health spending share goes up by about 5 p.p., and their food spending share decreases by 3 p.p.

Several channels may be at work behind this finding. Rural households may be less insured than urban households, and thus unable to smooth the health shock and incur in additional health spending without reducing their spending in other categories. This reduced insurance may be due to several characteristics such as labor informality. We turn to these mechanisms in section 5.

We show three pieces of additional evidence on the responsiveness of food and health spending to shocks in the appendix. First, we note that we have restricted our attention to food and health spending. In appendix table A.7 we show results for all spending categories. Urban households seem to increase their spending in personal care by a substantial fraction in response to the health shock and seem to steer away from recreation and alcohol purchases. For rural households, there does not seem to be many changes in other budget shares except for transport. An increase would make sense if rural households are far from health service providers. They also seem to decrease their share of spending on clothing. Food and health spending are by far the most reactive for rural households, and we continue to focus on them going forward.

We also show the response of food and health spending to other types of shocks in Appendix table A.3, which includes full estimation results for table 4. Spending seems to be most responsive to health shocks, although some other shocks may also

Table 4: Effect of Health Shocks on Food and Health Spending

	Urban		Rural	
	Food	Health	Food	Health
Panel 1: No controls nor region-specific trends				
Health shock	-0.020***	0.013***	-0.053	0.069
	(0.005)	(0.002)	(0.040)	(0.045)
Observations	2769	2769	2229	2229
R^2	0.049	0.054	0.416	0.330
Mean dep. var.	0.536	0.023	0.622	0.035
Household F. E.	✓	✓	✓	✓
Time effects	✓	✓	✓	✓
Region Trends				
Panel 2: Controls and region-specific trends				
Health shock	-0.018***	0.012***	-0.029*	0.050**
	(0.005)	(0.002)	(0.015)	(0.021)
Observations	2769	2769	2229	2229
R^2	0.062	0.067	0.578	0.485
Mean dep. var.	0.536	0.023	0.622	0.035
Household F. E.	✓	✓	✓	✓
Time effects	✓	✓	✓	✓
Region Trends	✓	✓	✓	✓

The table shows the coefficients on the health shock from estimates of equation (3). Standard errors clustered by municipality 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 spending, and total spending squared in both panels. p<0.1, **; p<0.05, ***: p<0.01.

induce adjustments. Family shocks tend to reduce food spending in rural households and increase it in urban households.

Additionally, we show in appendix table A.5 the unweighted estimation of equation (3). We find that the conclusions derived from table 4 are robust to this change in the estimation procedure, slightly affecting the magnitude of some coefficients. With controls, the unweighted estimates for the effect of a health shock in the share of food spending are larger for urban households and smaller for rural households when compared to the weighted estimates, but the inequality between urban and rural remains.

Last, we show that our results in table 4 are not driven by division bias or by bias from including total household spending on the right-hand side. On appendix table A.4, we show estimates instrumenting total spending and total spending squared with lagged income and lagged income squared. Qualitatively, our results show similar magnitudes to those of table 4. However, income as an instrument does not seem to perform as well in this panel setting (Lecocq and Robin, 2015). As such, our IV estimates are substantially noisy.

Engel curves. To show more evidence on 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.[8]

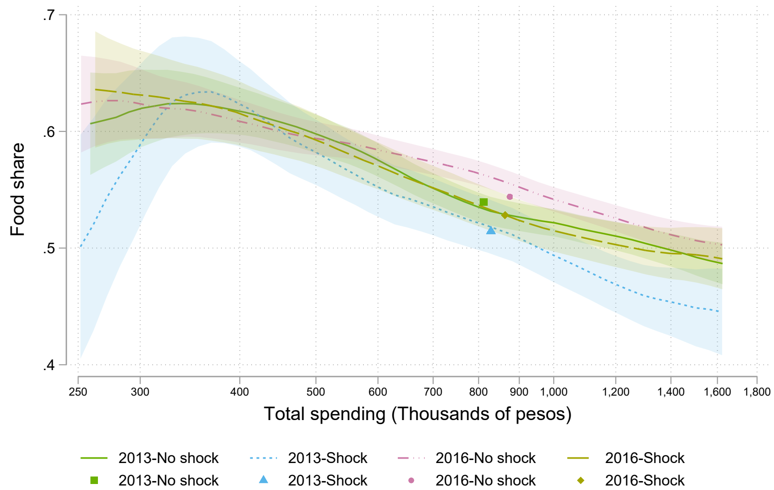
Figures 1 and 2 show Engel curves for food. These are approximately linear for urban households whose total expenditure is over 300.000 pesos a month, and for all rural households. For both waves, and for both urban and rural households, the estimated curves for households affected by the health shock are below those of households unaffected by it. The differences are larger for mid-spending rural households.

Figures 3 and 4 show the equivalent estimates for the health Engel curve. Once again the Engel curves are approximately linear except for low spending urban households. The Engel curves of shock households are above that of unaffected households.

The figure for rural households shows some evidence of a change in slope between the curve for unaffected households and the curve for affected ones. This would invalidate our specification in equation (3), which only allows for level shifts in response to shocks. In Appendix table A.6, we estimate specifications that allow the health shock to change the slope of the Engel curves. Our estimates for the marginal effect of the health shock

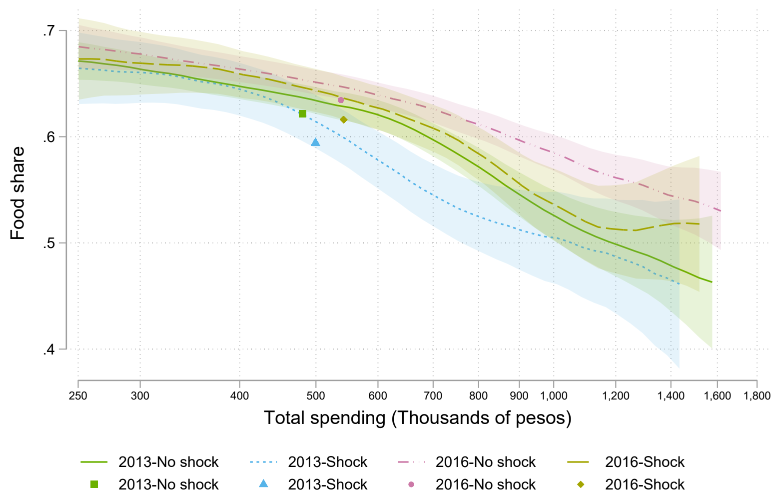
[8] Our estimates are not conditional to other shocks. Given the low impact of other types of shocks on demand shown in Appendix table A.3, the conditional and unconditional Engel curves are similar.

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



Local polynomials estimated using a triangular kernel, where the bandwidths are chosen by the rule of thumb of minimizing the conditional weighted mean integrated squared error. Points represent the average household in each of the four samples.

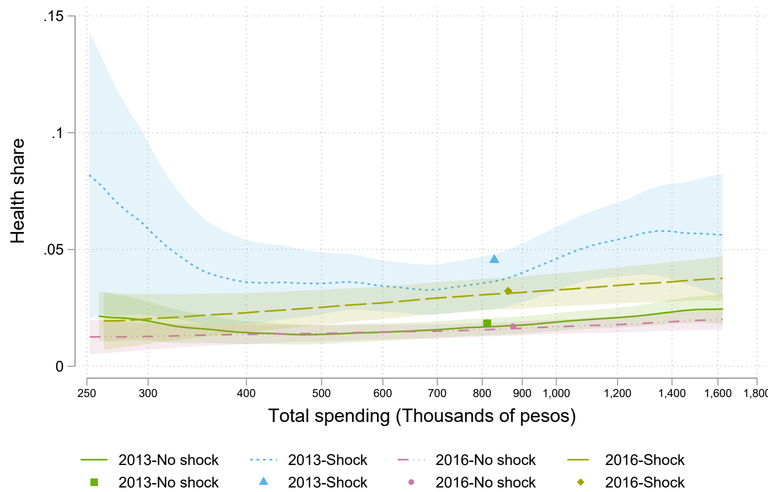
Figure 2: Food Engel Curves, for Rural Households with/without a Health Shock.



Local polynomials estimated using a triangular kernel, where the bandwidths are chosen by the rule of thumb of minimizing the conditional weighted mean integrated squared error. Points represent the average household in each of the four samples.

on the spending shares for the average household are virtually identical to those of table 4.

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



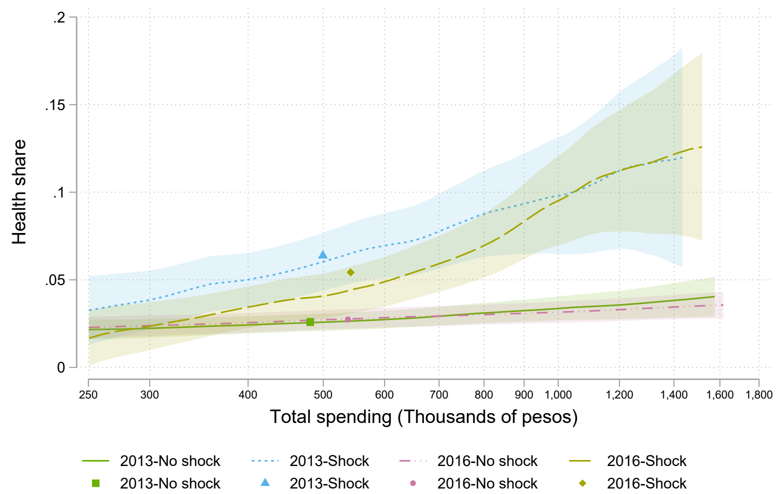
Local polynomials estimated using a triangular kernel, where the bandwidths are chosen by the rule of thumb of minimizing the conditional weighted mean integrated squared error. Points represent the average household in each of the four samples.

5 Heterogeneous Effects

In this section, we examine heterogeneous responses of food and health spending to shocks by types of households. We highlight the role of informality and insurance in shaping the spending response to health shocks. Households whose heads work in the formal sector, and who have access to insurance through social capital, are more able to smooth the shock and reduce their spending adjustments.

Figure 5 shows estimates of the response of food spending to health shocks obtained from interacting the health shock dummy with household characteristics. Overall, as expected from table 4, the adjustments for rural households are larger. This pattern is confirmed in figure 6 which shows that health spending increases more in rural households across groups. We now turn to each one of the categories driving heterogeneity in the spending response.

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

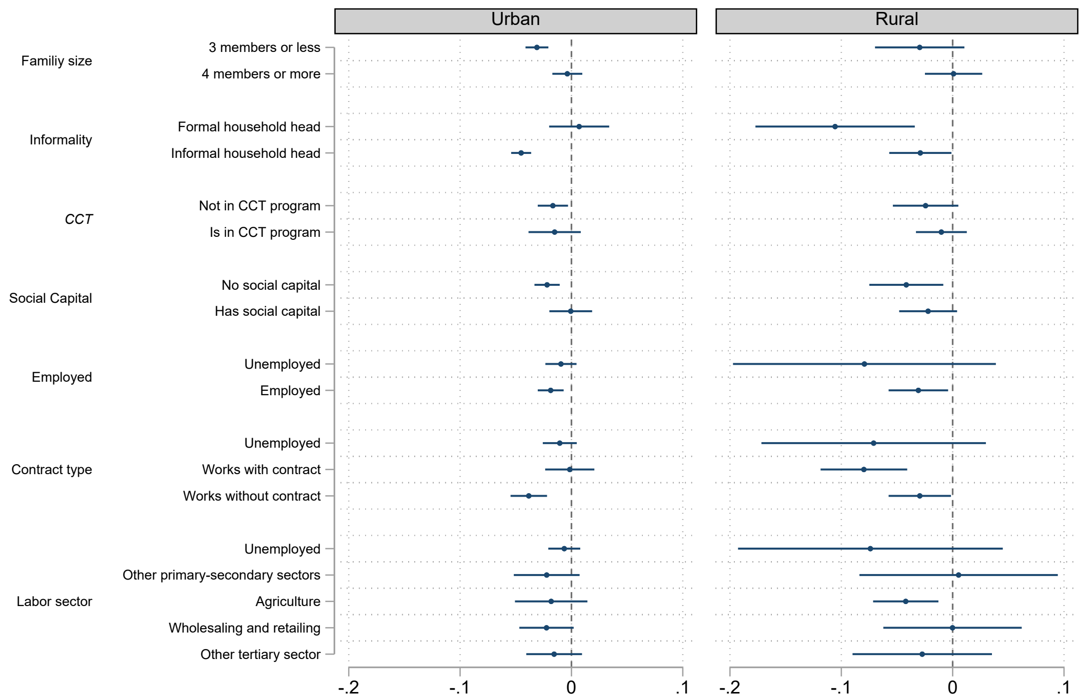


Local polynomials estimated using a triangular kernel, where the bandwidths are chosen by the rule of thumb of minimizing the conditional weighted mean integrated squared error. Points represent the average household in each of the four samples.

Household size. Larger households may have more trouble adjusting food spending because of larger caloric needs at the household level. At the same time, larger households may have the potential of sending more members to the labor force in response to a shock (Wagstaff, 2007). We find that small households reduce their food spending by around 3 p.p. in response to the health shock, whereas large households with 4 or more household members do not adjust food spending. This is independent of whether the household is urban o rural, although the reduction for small rural households is not significant at the 95% level. The increases in health spending are larger for small urban households and large rural households. The labor supply margin may be at play for these large rural households who are able to increase their health spending by a larger fraction without reducing their health spending.

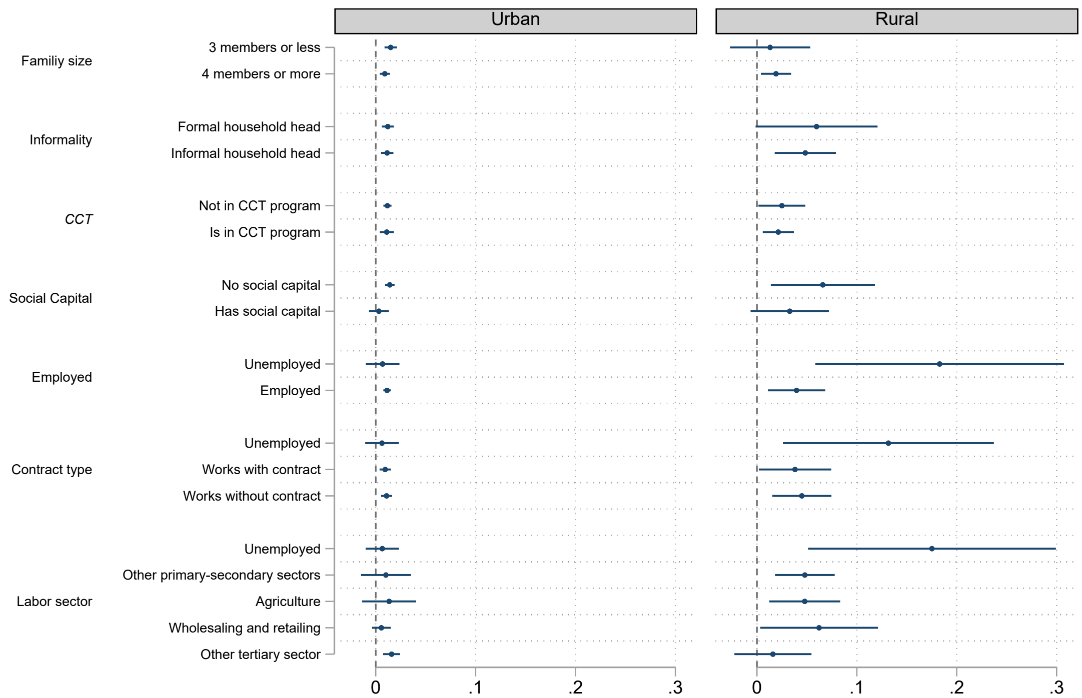
Informality. We classify households as informal if their household head is either unaffiliated to employer-provided health insurance or does not make contributions to the pension system. We find that labor informality plays a large role in shaping the reaction of food spending to health shocks in urban households. The increase in health spending is similar for formal and informal urban households, but only informal households decrease their food spending. This is not necessarily a mechanical effect of access

Figure 5: Heterogeneous Effects of a Health Shock in the Share of Food Spending



The dots are point estimates of the effect of a health shock on food spending for different household characteristics. Estimates are obtained from equation 3, interacting the health shock dummy with household characteristics. Horizontal bars are 95% confidence intervals, from standard errors clustered by municipality. Informal households are those whose household head is either unaffiliated to social health insurance, or does not contribute to the pension system. 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 household head takes part in local groups or organizations of any kind, like political parties, guilds, sports clubs, etc. Labor market variables are calculated always on the household head. "Works with contract" includes households whose head has a verbal contract or a written one. "Other primary and secondary sectors" includes mining, manufacture, 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 6: Heterogeneous Effects of a Health Shock in the Share of Health Spending



The dots are point estimates of the effect of a health shock on health spending for different household characteristics. Estimates are obtained from equation 3, interacting the health shock dummy with household characteristics. Horizontal bars are 95% confidence intervals, from standard errors clustered by municipality. Informal households are those whose household head is either unaffiliated to social health insurance, or does not contribute to the pension system. 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 household head takes part in local groups or organizations of any kind, like political parties, guilds, sports clubs, etc. Labor market variables are calculated always on the household head. "Works with contract" includes households whose head has a verbal contract or a written one. "Other primary and secondary sectors" includes mining, manufacture, 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.

to health insurance since informal households may still be insured through the public health system. The food share falls by about 4 p.p. for informal urban households. Rural households paint a different picture. Formal rural households have large food spending decreases in response to the health shock. However, only a small share of rural households is formal, so this result may be due to small sample size.

CCTs and social capital. We turn to informal sources of insurance and to insurance coming from other sources of income. We do not find large differences in the food spending response of urban households according to whether they receive transfers from *Familias en Acción*, Colombia's flagship conditional cash transfers program. Rural households who receive transfers do not reduce their food spending in response to the health shock in a statistically significant magnitude. However, the estimates are noisy and do not point to a large difference between transfer-receiving and non-transfer receiving rural households. Their health spending increases are also similar and they are also similar for urban households.

Households may also insure themselves by risk-sharing with other households.[9] This risk-sharing may be easier if households belong to informal networks. We create a dummy variable for social capital that is active if the household head takes part in local groups or organizations of any kind, such as political parties, guilds, or sports clubs.

We only find statistically significant decreases in food spending in response to the health shock for households that do not have social capital. In fact, the food spending response of urban households with social capital is close to zero. For rural households, the food spending decrease without social capital is almost twice as large as that of households with social capital.

The results for health spending follow the same pattern. Only households without social capital increase their health budget share in response to the health shock. The estimate for urban households is close to zero and the estimate for social capital rural households is half of the estimate for non-social-capital households.

These results point to a substantial role of social networks and risk-sharing to mitigate health shocks. Other studies have found evidence of smoothing through risk-sharing (Attanasio and Székely, 2004; Genoni, 2012; Gertler and Gruber, 2002; Sparrow

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

et al., 2014). We highlight that access to social capital seems to totally eliminate the need for reducing food spending when illnesses or accidents strike.

Work status, contract, and industry. The last set of variables we explore pertains to the labor market characteristics of the households.

Unsurprisingly, it seems to be harder to smooth consumption in response to the health shock for households whose heads are unemployed. This is particularly the case for rural households. Their food budget share decrease is about three times that of employed rural households and their health spending budget share increase is about four times larger. The urban households' case is surprising, with larger adjustments for employed households.

Households that work without a contract, which are a small share of urban households, reduce their food spending in response to the health shock, while those with a contract do not. This distinction is somewhat meaningless for rural households since most of them work without contracts.

Last, when we turn to the role of the industry where the household head is employed, we do not see substantial differences for urban households. For rural households, workers in the primary sector have the largest health spending increases in response to the shock. The workers may be more prone to be informal or less insured.

6 Concluding Remarks

Health negative shocks cause complex changes in households' spending behavior. We look at how households in Colombia behave when they face such a shock. This case is very interesting because Colombia has an extended health insurance system that covers almost the entire population. In spite of that, we show that such a system does not provide complete insurance. In particular, we show that when facing of 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 play a critical role in the development of more disadvantaged households and in the likelihood of overcoming poverty.

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

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

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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.

Table A.2: Frequency of Shocks

	Wave 2013			Wave 2016		
	Urban	Rural	Overall	Urban	Rural	Overall
Economic shock	0.26	0.12	0.25	0.26	0.41	0.26
Farm Income shock	0.00	0.37	0.00	0.00	0.23	0.00
Family shock	0.19	0.28	0.19	0.04	0.00	0.04
Natural disaster shock	0.06	0.27	0.06	0.08	0.43	0.08
Health shock	0.26	0.24	0.26	0.24	0.35	0.24
Crime shock	0.10	0.03	0.10	0.08	0.01	0.08
Any shock	0.57	0.64	0.57	0.52	0.83	0.52

Source: ELCA.

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

	Urban		Rural	
	Food	Health	Food	Health
Panel 1: No controls nor region fixed effects				
Economic shock	-0.001	0.001	0.052	0.035
	(0.005)	(0.004)	(0.039)	(0.021)
Farm Income shock	0.000	0.000	-0.063*	0.026
	(0.000)	(0.000)	(0.033)	(0.026)
Family shock	0.023**	-0.003	-0.163*	0.139
	(0.009)	(0.005)	(0.096)	(0.098)
Natural disaster shock	0.016	-0.010	-0.014	0.033*
	(0.016)	(0.006)	(0.029)	(0.019)
Health shock	-0.020***	0.013***	-0.053	0.069
	(0.005)	(0.002)	(0.040)	(0.045)
Crime shock	-0.004	0.007*	-0.006	-0.004
	(0.008)	(0.004)	(0.021)	(0.020)
ln(Spending)	0.811***	0.028	2.061***	-0.946***
	(0.159)	(0.076)	(0.537)	(0.335)
ln(Spending)^2	-0.031***	-0.000	-0.082***	0.038***
	(0.006)	(0.003)	(0.021)	(0.013)
Observations	2769	2769	2229	2229
R^2	0.049	0.054	0.416	0.330
Mean dep. var.	0.536	0.023	0.622	0.035
Panel 2: Controls and region fixed effects				
Economic shock	-0.002	0.001	0.024	0.055*
	(0.006)	(0.004)	(0.017)	(0.030)
Farm Income shock	0.000	0.000	-0.021	-0.007
	(0.000)	(0.000)	(0.015)	(0.025)
Family shock	0.023**	-0.003	-0.115***	0.109**
	(0.009)	(0.005)	(0.041)	(0.051)
Natural disaster shock	0.016	-0.008	-0.031*	0.042*
	(0.014)	(0.007)	(0.017)	(0.023)
Health shock	-0.018***	0.012***	-0.029*	0.050**
	(0.005)	(0.002)	(0.015)	(0.021)
Crime shock	-0.005	0.007	-0.031*	0.014
	(0.007)	(0.004)	(0.018)	(0.017)
ln(Spending)	0.736***	0.066	2.238***	-1.074***
	(0.180)	(0.097)	(0.470)	(0.284)
ln(Spending)^2	-0.029***	-0.002	-0.089***	0.043***
	(0.007)	(0.004)	(0.018)	(0.011)
Observations	2769	2769	2229	2229
R^2	0.062	0.067	0.578	0.485
Mean dep. var.	0.536	0.023	0.622	0.035

The table shows estimates of equation (3). Standard errors clustered by municipality 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: Effect of Health Shocks on Food and Health spending. Estimates Instrumenting Total Spending with Lagged Income

	Urban		Rural	
	Food	Health	Food	Health
Panel 1: No controls nor region-specific trends				
Health shock	-0.033*	0.021	-0.082	0.079
	(0.019)	(0.024)	(0.053)	(0.053)
Observations	2733	2733	2087	2087
Kleibergen-Paap rk Wald F Statistic	0.084	0.084	0.383	0.383
Mean dep. var.	0.536	0.023	0.622	0.035
Household F. E.	✓	✓	✓	✓
Time effects	✓	✓	✓	✓
Region Trends				
Panel 2: Controls and region-specific trends				
Health shock	-0.027	0.015	-0.100	0.059
	(0.017)	(0.014)	(0.132)	(0.052)
Observations	2733	2733	2087	2087
Kleibergen-Paap rk Wald F Statistic	0.079	0.079	0.099	0.099
Mean dep. var.	0.536	0.023	0.622	0.035
Household F. E.	✓	✓	✓	✓
Time effects	✓	✓	✓	✓
Region Trends	✓	✓	✓	✓

The table shows the coefficients on the health shock from estimates of equation (3). Standard errors clustered by municipality 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 spending, and total spending squared in both panels. Total spending and total spending squared are instrumented with lagged total income and lagged total income squared. p<0.1, **; p<0.05, ***: p<0.01.

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

	Urban		Rural	
	Food	Health	Food	Health
Panel 1: No controls nor region fixed effects				
Health shock	-0.011**	0.012***	-0.029***	0.021***
	(0.005)	(0.003)	(0.006)	(0.007)
Observations	2769	2769	2229	2229
R^2	0.035	0.046	0.103	0.056
Mean dep. var.	0.536	0.023	0.622	0.035
Household F. E.	✓	✓	✓	✓
Time effects	✓	✓	✓	✓
Region Trends				
Panel 2: Controls and region fixed effects				
Health shock	-0.011**	0.013***	-0.030***	0.022***
	(0.005)	(0.003)	(0.007)	(0.006)
Observations	2769	2769	2229	2229
R^2	0.038	0.053	0.107	0.059
Mean dep. var.	0.536	0.023	0.622	0.035
Household F. E.	✓	✓	✓	✓
Time effects	✓	✓	✓	✓
Region Trends	✓	✓	✓	✓

The table shows the coefficients on the health shock from estimates of equation (3). Standard errors clustered by municipality 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 spending, and total spending squared in both panels. 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 Spending is Interacted with the Health Shock.

	Urban		Rural	
	Food	Health	Food	Health
Panel 1: No controls nor region fixed effects				
Health Shock (Marginal effect)	-0.021***	0.013***	-0.046*	0.060**
	(0.004)	(0.002)	(0.027)	(0.031)
Observations	2769	2769	2229	2229
R^2	0.054	0.054	0.419	0.337
Mean dep. var.	0.536	0.023	0.622	0.035
Household F. E.	✓	✓	✓	✓
Time effects	✓	✓	✓	✓
Region Trends				
Panel 2: Controls and region fixed effects				
Health Shock (Marginal effect)	-0.018***	0.012***	-0.029**	0.046***
	(0.005)	(0.002)	(0.012)	(0.016)
Observations	2769	2769	2229	2229
R^2	0.066	0.067	0.578	0.486
Mean dep. var.	0.536	0.023	0.622	0.035
Household F. E.	✓	✓	✓	✓
Time effects	✓	✓	✓	✓
Region Trends	✓	✓	✓	✓

The table shows marginal effects of the the health shock from estimates of equation (3) allowing the health shock to interact with total spending and total spending squared. The marginal effects are calculated at the means of ln(Spending) and $\ln(\text{Spending})^2$. Standard errors clustered by municipality 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 spending, and total spending squared in both panels. p<0.1, **; p<0.05, ***: p<0.01.

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

	Urban and rural						
	AlcoholT	Furnish.	Recreat.	Personal	House	TransCom	Cloth.
Panel 1: No controls nor region fixed effects							
Health shock Urban	-0.001	0.000	0.010***	-0.002	0.001	0.010**	-0.011***
	(0.001)	(0.001)	(0.002)	(0.003)	(0.006)	(0.004)	(0.004)
Observations	2769	2769	2769	2769	2769	2769	2769
R^2	0.050	0.018	0.035	0.039	0.151	0.027	0.079
Mean dep. var.	0.012	0.002	0.020	0.087	0.130	0.145	0.044
Household F. E.	✓	✓	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓	✓	✓	✓
Region Trends							
Health shock Rural	-0.012	-0.001	0.001	-0.008	0.015	0.022**	-0.032*
	(0.008)	(0.001)	(0.002)	(0.005)	(0.012)	(0.009)	(0.017)
Observations	2229	2229	2229	2229	2229	2229	2229
R^2	0.356	0.110	0.024	0.080	0.058	0.134	0.252
Mean dep. var.	0.020	0.003	0.010	0.082	0.075	0.127	0.025
Household F. E.	✓	✓	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓	✓	✓	✓
Region Trends							
Panel 2: Controls and region fixed effects							
Health shock Urban	-0.018***	0.012***	-0.029*	0.050**	0.001	0.010**	-0.011***
	(0.005)	(0.002)	(0.015)	(0.021)	(0.006)	(0.004)	(0.004)
Observations	2769	2769	2229	2229	2769	2769	2769
R^2	0.062	0.067	0.578	0.485	0.151	0.027	0.079
Mean dep. var.	0.536	0.023	0.622	0.035	0.130	0.145	0.044
Household F. E.	✓	✓	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓	✓	✓	✓
Region Trends	✓	✓	✓	✓	✓	✓	✓
Health shock Rural	-0.012	-0.001	0.001	-0.008	0.015	0.022**	-0.032*
	(0.008)	(0.001)	(0.002)	(0.005)	(0.012)	(0.009)	(0.017)
Observations	2229	2229	2229	2229	2229	2229	2229
R^2	0.356	0.110	0.024	0.080	0.058	0.134	0.252
Mean dep. var.	0.020	0.003	0.010	0.082	0.075	0.127	0.025
Household F. E.	✓	✓	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓	✓	✓	✓
Region Trends	✓	✓	✓	✓	✓	✓	✓

The table shows the coefficients on the health shock from estimates of equation (3). Standard errors clustered by municipality 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 spending, and total spending squared in both panels.