CAUSAL EFFECTS OF HEALTH SHOCKS ON CONSUMPTION AND DEBT: QUASI-EXPERIMENTAL EVIDENCE FROM BUS ACCIDENT INJURIES

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Abstract—Endogeneity between health and wealth presents a challenge for estimating causal effects of health shocks. Using a quasi-experimental design, comprising exogenous shocks sustained as bus accident injuries in India, with controls drawn from travelers on the same bus routes one year later, I present new evidence of causal effects on consumption and debt. Using primary household survey data, I find that households faced with shock-related expenditures are able to smooth consumption on food, housing, and festivals, with small reductions in educational spending. Debt was the principal mitigating mechanism households used, leading to significantly larger levels of indebtedness.

I. Introduction

WHILE there is ample anecdotal evidence of the consequences of adverse health events, there are few empirical estimates of the causal effect of health shocks on economic outcomes. One important reason for this gap is the methodological challenge of endogeneity that continues to handicap the health-wealth research. To address the problem of endogeneity in estimating the effect of health shocks, this paper relies on a quasi-experimental study design comprising a plausibly exogenous health event combined with a matched control design. My identification strategy relies on exogenous variation in exposure to health shocks by focusing on injuries sustained in bus accidents in Karnataka, India, and enrolling matched unexposed individuals drawn from passengers traveling on the same bus route. Conditional on identifying well-matched unexposed individuals, this strategy allows me to treat the exogenous health shock as a random exposure to estimate causal effects of the shock on household consumption and the mechanisms employed to smooth consumption.

Among the various types of shocks households face, especially in developing countries, health shocks are among the most common.[1] The health shock studied in this paper, road traffic accidents, is one of the top ten causes of global disease burden. Road traffic accidents were the eighth most common cause of disease burden in 2002 and, according to WHO estimates, are expected to be the fourth leading cause by 2030 (Mathers & Loncar, 2006).

From an economic point of view, the primary effect of a health shock comes through reduction in labor supply and increased expenditures on health, both of which could contract the lifetime budget constraint and force consumption to decline. A decline in health might also reduce the marginal utility of consumption (Finkelstein et al., 2013). In addition to various effects on labor supply, consumption, savings, and investment, there is some evidence of health shocks having particularly large effects on dissavings, borrowing, and asset sales (Wagstaff & Lindelow, 2010). As Baeza and Packard (2006) argue, the effects of health shocks on nonmedical consumption have been poorly understood in terms of impoverishing impacts, yet these effects could prove to be greater than income losses during acute health shocks.

In contrast to experimental studies on the effects of positive health shocks that improve health status (Miguel & Kremer, 2004; Thomas et al. 2006), there are no comparable experimental studies on the economic effects of negative health shocks for obvious reasons. Another important distinction is that in contrast to previous research that has looked at labor market or educational impacts of health (Bleakley, 2007, 2010), this paper focuses on consumption and debt. Qualitative studies indicate that households falling into poverty traps report health expenditures to be one of the critical reasons for poverty (Sauerborn, Adams, & Hien, 1996; Narayan et al., 2000; Krishna et al. 2003). Much of the quantitative literature on medical impoverishment comprising observational studies and cross-sectional correlations between household expenditures, poverty levels, and health expenditures is unable to provide causal evidence (Gottlieb, 2000; Liu, Rao, & Hsiao, 2003; Xu et al., 2003; Himmelstein et al. 2005; van Doorslaer et al. 2005; Dranove & Millenson, 2006).

A large body of literature shows decreases in wages and participation associated with declines in health status (Pitt & Rosenzweig, 1986; Strauss & Thomas, 1998; Smith 2003). Previous research efforts showing evidence of changes in wealth and asset levels as a result of health shocks have relied on the onset of new chronic illness (Smith, 1999), serious illnesses (Smith, 2003), self-rated health (SRH) (Hurd & Kapteyn, 2003), and a variety of other health conditions (Adams et al., 2003). Similarly, research focusing on consumption effects of health shocks has employed health measures such as self-rated health and disability (Gertler & Gruber, 2002), hospitalization, BMI, and death (Wagstaff, 2007). The main limitation of many of these studies is that the endogeneity of health status remains

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[1] In countries such as India, where this study was conducted, about 3% of households experience hospitalizations annually, and the average outpatient utilization is three episodes per year per person (Karnataka Household Health Expenditures Survey, 2005).

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a challenge with the identification strategies they employ (Cochrane, 1991; Levy, 2002). I seek to contribute to this literature by employing a quasi-experimental study design to estimate causal effects of health shocks on consumption and debt. I rely on the exogeneity of health shocks in the form of injuries sustained by passengers in bus accidents in Karnataka, India. I identify appropriately matched unexposed individuals using a process of matching that allows me to treat the exogenous health shocks as random. Using data from a household survey administered to the exposed and unexposed groups, my analysis presents three key findings. First, households exposed to the shock, which caused total expenditures worth over two months of income, appear to be able to smooth consumption in terms of food, housing, and festivals.[2] However, exposed households have lower educational expenditures, although the difference is not statistically significant. Second, as a result of households borrowing to pay for health shock–related expenses, the main effect of the health shock was increased debt. Exposed households have a 70% higher relative risk of borrowing in past year and a 40% higher risk of having debt one year after the shock. Third, I find no evidence of asset depletion or differences in asset accumulation. I also do not find evidence in support of labor supply responses. One year after the health shock, exposed households have the same monthly labor income as the unexposed group.

While this study is able to exploit exposure to exogenous health shocks and a matched unexposed group to address the endogeneity problem, three main limitations remain. First, there could be unobserved heterogeneity that predisposes certain types of individuals to injuries, which might not have been adequately captured by the matching process. The second limitation is that of external validity: the health shock used here, bus accident injury, is not directly comparable with other illnesses such as heart disease, diabetes, or cancer. Finally, this study was conducted in mostly rural areas of Karnataka in South India, and hence my findings might not be easily generalized globally. The relatively small sample size limits my ability to further refine this analysis, especially in terms of the effects among poorer subgroups.

The rest of this paper proceeds as follows. Section II describes the study design and sample construction. Section III describes the data and presents results from an analysis of the effect of the shock on household consumption, assets, debt, and labor supply. Section IV discusses the findings and concludes.

II. Study Design and Sample Construction

A. *Study Setting*

This study was conducted in Karnataka, a large state in South India (population 56 million in 2006) in the mostly rural districts surrounding the capital city of Bangalore. Karnataka's per capita GDP in 2005 was Rs 21,696 (approximately $542, at Rs 40 per USD). Although Karnataka is probably best known today for Bangalore, globally renowned for its information technology, over two-thirds of the state's population lives in rural areas.

The bus accident data were compiled from the compensation files of the Karnataka State Road Transport Corporation (KSRTC), an autonomous, publicly owned institution. The KSRTC operates 5,100 schedules running 5,400 vehicles over 1.25 million miles, carrying an average of 2.2 million passengers every day. KSRTC maintains detailed data on all accidents that involve its buses and, to the extent possible, data on passengers injured in these accidents.

B. *Identifying the Exposed and Determining Sample Size*

Information on KSRTC bus passengers injured in all accidents between June 2005 and December 2005 was compiled by the Central Office of the KSRTC in Bangalore. This list included time, date and location of accident; bus route; name, age, sex, and address of each passenger; and compensation amount. In order to make the survey implementation more tractable, the list was then restricted to accidents that occurred on local bus routes in the divisions of KSRTC around Bangalore. The heterogeneity in the types of buses on India's roads (public, private, luxury, semiluxury) introduces the possibility of nonrandom exposure to the health shock. For example, it is possible that the richer populations travel in safer private luxury buses as compared to the local state-run buses used by the poor. I address this issue by restricting the sample to KSRTC-run nonluxury buses on local rural routes. The approach is advantageous primarily because I achieve relative homogeneity among the exposed group in terms of socioeconomic status, focusing on the rural poor. The restriction excluding interstate buses also prevents unmanageable scenarios in which passengers are dispersed over large geographic regions. All individuals injured in these accidents, including those who lived outside the areas covered by the KSRTC divisions, were included as exposed in this study.

After eliminating records that had incomplete or missing names or addresses, 108 traceable cases were identified.[3] Assuming that only 75 exposed individuals would be successfully located to be interviewed, power calculations to test a 10% difference in monthly household expenditures indicated it would be necessary to enroll four unexposed for every exposed individual.

[2] Festivals include weddings and major family events in addition to regular festivals.

[3] Some of the nontraceability occurred due to well-intentioned attempts to award compensation as soon as possible after the accidents (at times when the passenger was still in the hospital). As a result, data on contact information of victims were not consistently collected across accidents and divisions. In some instances, compensation sums of Rs 5,000 (large by KSRTC compensation standards) were handed out without collecting complete details. In the large majority of cases, however, the data collected were of exceptionally good quality and included complete information on name, age, and sex of the injured passengers with contact details.

C. Matching and Identifying the Unexposed

Unexposed individuals were identified at the time of the survey, one year after the bus accidents, by matching on observable characteristics of the exposed individuals: age, sex, geographic area of residence, and bus route traveled. The geographic area of residence (matched at the level of the village) was used as a proxy for matching socioeconomic status. In order to account for any unobserved heterogeneity reflected in travel preferences, we required that the unexposed individuals be frequent travelers on the bus route and should have traveled on that bus route at least once in the past month. Mean frequency was six times in the past month. As an example, for a 45-year-old female resident of Atown who was injured in an accident on a bus traveling from Btown to Ctown, we identified four unexposed subjects who are female residents of Atown in the 40 to 50 age group, who traveled frequently on this route. In rural settings, interviewers asked the village secretary or another key respondent to help identify potential subjects in the village who met the age, gender, and travel criteria. In rare instances where it was not possible to find someone who traveled the same bus, matching individuals who traveled on a similar bus route that traversed the accident location were enrolled. In large urban areas, matched unexposed individuals were enrolled at the bus station at the time of departure after confirming that their travel plan would traverse the accident location.

D. Household Survey

The survey was conducted by the Center for Population Dynamics, a Bangalore-based survey agency, during November and December 2006. Interviewers were recruited and trained specifically for enrolling subjects. Of the 108 traceable exposed cases, 85 were successfully located, and 84 agreed to be interviewed. The final sample thus includes 84 exposed households and 336 unexposed. All survey respondents were compensated Rs 100 (approximately \$2.50 in 2006). Data on household composition, assets, income, savings, consumption, health expenditures, health status, labor, and other social variables were collected.

III. Data and Results

A. Data

Since the exposed and unexposed samples were matched on age, gender, and area of residence the exposed and unexposed should be identical across the matching variables (table 1). Table 1 also shows balance across variables used for verifying the match (religion, caste, occupation, literacy, and household size). In addition, I include potentially endogenous variables on income and asset levels in the table to check for any major differences. While monthly income cannot be reliably used to test for balance in this context, there is no evidence of obviously large differences across the two groups. Asset index scores were calculated using data on household assets and durable items, following the methodology employed in the National Family Health Survey.[4] The balance across the variables used for verifying the match indicates that the matching was likely successful in identified unexposed households that were socioeconomically identical to the exposed.

The exposure to the bus accident also led to additional expenditures related to health care for the household: health care costs, travel, and lost income for the household. The average total expenditures related to the shock were Rs 9,142 (approximately \$228, at Rs 40 per USD). The health shock caused injuries of varying severity. Table 2 describes the injuries and health status of the sample in terms of self-rated health (SRH) and disability levels. With the exception of one passenger who had a severe leg injury that required amputation, all other injuries can be treated as relatively minor health shocks.

TABLE 1.—SUMMARY STATISTIC OF MATCHING AND VERIFCATION VARIABLES

Variables	Exposed ($N = 84$)	Unexposed ($N = 336$)	Difference (SE)
Matching variables[a]			
Sex (male)	71.43%	71.43%	
Age	38	39	
Rural	83%	82%	
Verifying the match			
Religion (% Hindu)	99%	99%	0
			(0.01)
Low caste	57%	52%	0.05
			(0.05)
Occupation			
Farmers	23%	24%	0
			(0.05)
Day laborers	42%	38%	0.04
			(0.06)
Illiterate	35%	34%	0.01
			(0.05)
Household size	4.4 [0.18]	4.08 [0.07]	0.34
			(0.18)
Asset score	15.09 [0.65]	15.72 [0.31]	0
			(0.37)
Total monthly income (Rs)	4,482 [167]	4,365 [345]	116
			(319)

Standard errors of difference clustered by accident are in parentheses. Standard errors of means are reported in brackets.
[a]Samples were matched on these variables; hence it is expected that there are no differences.

[4] The NFHS calculates the asset index based on scores assigned to household ownership of assets and durables, as well as access to sanitation and water supply as follows: type of house: Pucca = 4, Semipucca = 2, Kuccha = 0; ownership of house: own = 2, not owned = 0; drinking water facility: own tap/borewell = 2, public tap/borewell = 4, others = 0; toilet facility: flush toilet/own = 4, flush toilet/shared/ pit/own/public toilet = 2 open field = 0; main fuel for cooking: LPG or Gobar gas = 2, kerosene = 1, others = 0; source of lighting: electricity = 2, kerosene = 1, others = 0; owns: agricultural land = 4, motor car = 4, two-wheelers = 3, television = 3, refrigerator = 3, radio/tape recorder = 2, sewing machine = 2, bicycle = 2, fan = 1. Households were categorized into income groups based on their asset scores, which ranged from 5 to 32. Households with a score less than 9 were classified as poor, from 9 to 16 as lower middle, 17 to 23 as upper middle, and over 23 as upper. Pucca houses are meant to be permanent, and Kuccha houses are made of such materials as hay and sticks. Semipucca are a mix of construction materials.

TABLE 2.—SUMMARY STATISTICS OF INJURY AND HEALTH

Injury from shock			
Loss of limb	1.20%		
Fractures	7%		
Health status			
Self-rated health			<0.001
Very good	1%	26%	
Good	14%	60%	
Moderate	60%	13%	
Bad	23%	1%	
Very bad	1%	0%	
Disability (functional difficulty with activities of daily living)			<0.001
No difficulty	8%	46%	
One serious or two minor	5%	10%	
More than one serious difficulty	87%	44%	
Hospitalization in last year	29%	24%	0.37
Minor illness in past 30 days	29%	26%	0.69
Chronic illness over last year	27%	20%	0.12

p-values are from chi-square tests.

Given the nature of the shock and the interview conducted in the context of this health shock, it is not surprising that SRH is worse and reported functional disability levels are higher among the exposed.[5] Functional disability was measured using six items that asked about difficulties in activities of daily living (ADLs). However, as the last three rows of the table show, health care utilization in terms of hospitalization (excluding accident related), minor illnesses, and chronic conditions (all of which were asked earlier in the interview as part of routine health history) is similar between the two groups.

B. *Empirical Strategy and Results*

The empirical analysis in this paper focuses on testing effects of health shocks on consumption and exploring mechanisms that households rely on to mitigate the effects of health shocks. I employ a reduced-form estimation of the effect of the plausibly exogenous health shock on households by comparing household-level outcomes across exposure groups measured one year after the shock. If the matching succeeds in achieving a quasi-experimental design, the differences in means across the exposed and unexposed would yield average causal effects. Adding in further controls in a regression framework would not in this case change the results significantly. Using S as an indicator for the health shock, the estimating equation that I employ in the regressions is of the following form:

$$C_{ht} = \alpha + \delta X_{ht} + \pi S_{h(t-1)} + \varepsilon_{ht}. \tag{1}$$

C represents the outcome of household h at time t, including household spending on housing, food, festivals, health, and education as dependent variables in separate regressions. X is a vector of controls including age of head of household, sex of injured passenger, dummies for education level of head, caste, and size of household (captures household age structure effects). I also include the compensation paid by KSRTC in all models.[6] An important reason that π can be estimated without bias is that S is orthogonal to X, the vector of controls, as well as plausibly omitted variables such as current income. Although estimates of δ are likely to suffer from omitted variable bias (since X is not orthogonal to the omitted income), this is a smaller concern given our focus on the estimation of π.[7]

The health shock enters the regressions as a dummy variable on the right-hand side. The dependent variable in the regression of health expenditures includes spending on all health events in the past year, including expenditures from hospitalization, outpatient visits, and chronic conditions. This variable does not include expenses directly incurred at the time of the shock but could potentially include follow-up costs. All exposed households and 95% of unexposed households had positive total health spending and are included in the analysis of health expenditures.

Table 3 presents differences between the exposed and unexposed in household expenditures, assets, and debt. The average monthly household expenditures on housing and food are similar between the exposed and unexposed groups. Health-related expenditures among the exposed over the past year (not including the Rs 9142 related to the health shock) are significantly higher than among the unexposed, even though the share of households that have no health care expenditures among both the exposed and unexposed is comparable (100% and 95%). Health care utilization in developing countries, and especially in India, is very frequent. Previous studies in Karnataka have reported outpatient care utilization to be as high as three episodes per person per year (Government of Karnataka, 2005). Similarly, although the share of households in both groups that had positive expenditures on education was similar (52.1% among exposed and 54.8% among unexposed), among households with positive expenditures on education, mean educational expenditures among the unexposed (Rs 3,323) was 16% higher than among the unexposed (Rs 2878).

Debt and borrowing over the past year are significantly more common among the exposed households, and the amounts owed by the exposed are also higher than those by the unexposed. The exposed have almost 40% higher rates of current household debt as compared to the unexposed. It is noteworthy that the mean difference of the amount bor-

[5] The questions on self-rated health and disability were administered at the end of the survey after questions on expenditures related to the health shock.

[6] Compensation received provided only a small partial insurance. In 50% of the cases, the compensation was less than 10% of total expenditures, and in 75% of the cases, it covered less than 25% of total expenditures. The average size of compensation was Rs 1,687 (SE, 625).

[7] One possible test for orthogonality is by regressing the shock variable on all the X variables in equation (1): age of head of household, dummies for education level of head, caste, and size of household. As expected, none of variables were statistically different from 1, with the exception of household size. The household size variable is driven by three outliers among exposed with nine family members. When these observations were excluded, it was no longer significant ($p = 0.34$).

TABLE 3.—DIFFERENCES IN KEY OUTCOMES BETWEEN EXPOSED AND UNEXPOSED

Variables	Exposed	Unexposed	Difference (SE)[a]
Expenditures (rupees)[b]			
Housing	848	796	51.99
			(66.86)
Food	1,430	1,351	78.39
			(64.64)
Festivals (annual)	6,904	7,169	−265.03
			(465.17)
Total health (annual)	3,756	2,217	1,539.44***
			(525.16)
% nonzero health expenditures	100	95	4.76
			(2.39)
Education (annual)	2,878	3,323	−445.17
			(380.25)
% nonzero education expenditures	54.8	52.1	2.68
			(7.27)
% bought assets in past year	14.29	16.67	−2.38
			(4.40)
% sold assets in past year	2.38	1.79	.59
			(2.01)
% pledged assets in past year	19.05	8.63	10.42***
			(4.32)
% any household debt	90.48	65.18	25.29*
			(4.89)
Amount of debt (Rs)	44,762	24,975	19,787.2*
			(8,635.89)
Borrowed last year	78.57	47.02	31.55***
			(5.45)
Amount borrowed (Rs)	21,821	14,092	7,729
			(5,076.62)
Interest rate	45.36	42.05	3.31
			(3.19)

Significant at *5%, **1%, and ***0.1% respectively.
[a]Standard errors of differences are clustered at the level of accident bus route.
[b]Education and health expeditures reported among those with nonzero expenses.

rowed in the past year between the two groups (Rs 7,729) is fairly close to the average size of the shock (Rs 9,142).

I also examine these differences using regressions to include additional controls described in the empirical strategy. Table 4 shows results from OLS regressions of household expenditures on food, housing, festivals, health, and education on the health shock in columns 1 to 5.[8] The dependent variables are all log-transformed expenditures. Festivals, health, and education are reported as annual expenditures; food and housing are monthly expenses. The education regressions are restricted to households that have no educational expenditures. The rows at the bottom of the table interpret the coefficients on the shock variable as the percentage change in dependent variable.

As expected, annual health spending (column 4) among the exposed is significantly higher. The coefficient on the shock dummy translates into total health expenses that are 52% higher ($e^{0.42} = 1.52$) among the exposed, with an additional total health spending of Rs 1,364 per year. Note that this increase is over and above the Rs 9142 incurred at the time of the accident.[9]

The regressions confirm that households for the most part are able to smooth consumption. Although expenditures on food, housing, and festivals appear to be unaffected by the health shock, there are some negative effects on educational spending, as seen in column 5. It is useful to note that in the rural areas where this study was conducted, most students are enrolled in free public schools. Previous studies of education in India reveal that only 12% of villages in Karnataka have access to private schools (Muralidharan & Kremer, 2008). It is hence safe to assume that the educational expenditures are primarily for uniforms, books, and supplies. The results in column 5 suggest that, controlling for household demographics, the shock has a significant effect, reducing educational expenditures by 20% ($e^{-.25} = 0.80$). This represents a reduction of Rs 548, which is relatively small compared to the size of shock-related expenses (Rs 9,141). In a separate regression (not shown in tables), where the log of total shock-related expenditures was instrumented with exposure to the shock, the point elasticity of educational expenditures with respect to the size of health shock–related expenses (instrumented with exposure to shock) was −0.03.[10] Not surprisingly, the education level of the head of household, being correlated with socioeconomic status, is significantly associated with higher consumption. However, it is important to bear in mind that the estimates for variables other than the shock could be possibly biased as a result of the omitted current income. Low caste is associated with lower expenditures on housing and education.

C. *Household Responses to Health Shocks*

The ability of households to smooth consumption and the relatively small size of the reduction in educational expenditures compared to that of the shock-related expenditures raises questions about the mechanisms that households rely on to pay for this unexpected expense. Households could respond by adopting a variety of strategies such as a labor supply response, autarkic consumption, or using credit. The labor supply response could introduce a substitution by another member of the household or an increase in labor supply with the existing working members working more (Kochar, 1999). Households might resort to an autarkic

[8] In the literature on income shocks and consumption smoothing, a common empirical strategy is to employ instruments such as rainfall shocks. I do not attempt an IV estimation of the consumption effects of income shocks caused by health shocks because the health shock is poorly correlated with income (corr = 0.015). This poor correlation in fact reflects the success of the matching design employed in this study. Instead, my analysis aims to exploit this matching strategy by directly estimating the effects of health shocks.

[9] Since the accident compensation amounts were decided by inspecting KSRTC officials, in alternate specifications of the models, I also included accident-level fixed effects. The results were identical to those shown in Table 4 (−0.03 for housing, −0.02 for food, −0.11 for festivals, 0.39 (significant at the 0.1% level, for health, and −0.27 for education).

[10] In order to test whether the changes in educational spending were higher for girls, I also ran separate models including the share of school-aged children in the household who were female. The effect of percent female school-aged children was insignificant and very small (coefficient = −0.06, with t-statistic = 0.39) and a Wald test could not reject the null hypothesis of this effect being equal to 0: $F(1, 76) = 0.16$, $p = 0.69$.

TABLE 4.—REGRESSIONS OF HOUSEHOLD EXPENDITURES, BORROWIING, AND DEBT ON HEALTH SHOCK

	OLS Regressions on Household Expenditures				Logit Regressions on Debt (OR)				
	(1) Housing	(2) Food	(3) Festivals	(4) Health	(5) Education	(6a) Have Debt	(6b) Have Debt	(7a) Borrowed	(7b) Borrowed
Shock	−0.03	0.01	−0.07	0.42***	−0.25	5.68***	5.94***	4.53***	4.74***
	(0.08)	(0.05)	(0.08)	(0.11)	(0.14)	(2.16)	(2.38)	(1.33)	(1.49)
Compensation	0.00***	−0.00***	0.00	0.00***	−0.00**	1.00	1.00**	1.00*	1.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age of household head	0.00	0.00	0.00	0.00	−0.01	0.99	1.00	0.99	1.00
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Sex of injured	0.01	−0.17	−0.22	−0.13	0.10	1.59	1.73	0.89	0.89
	(0.08)	(0.11)	(0.15)	(0.30)	(0.16)	(0.62)	(0.68)	(0.30)	(0.34)
Low caste	0.25**	0.05	0.08	−0.13	0.38*	0.77	1.05	0.84	0.90
	(0.08)	(0.06)	(0.09)	(0.23)	(0.17)	(0.27)	(0.38)	(0.28)	(0.32)
Education of head									
Primary school	0.34**	0.15*	0.05	0.31	0.22	0.89	1.16	0.86	0.87
	(0.11)	(0.07)	(0.08)	(0.27)	(0.17)	(0.34)	(0.47)	(0.29)	(0.30)
Middle school	0.59***	0.15	0.11	−0.28	0.76**	0.71	1.60	0.92	1.34
	(0.13)	(0.11)	(0.13)	(0.34)	(0.22)	(0.31)	(0.82)	(0.40)	(0.68)
High school	0.89***	0.27	0.32	−0.55	1.16***	0.27***	0.79	0.30**	0.50
	(0.12)	(0.13)	(0.17)	(0.59)	(0.27)	(0.10)	(0.32)	(0.12)	(0.25)
College	−0.21*	0.00	0.03	−0.15	−0.45**	0.65	0.65	0.46**	0.50**
	(0.10)	(0.09)	(0.12)	(0.24)	(0.14)	(0.20)	(0.20)	(0.12)	(0.13)
Household size	0.04	0.07*	0.01	0.11	0.27***	1.39**	1.39**	1.33**	1.28*
	(0.03)	(0.02)	(0.03)	(0.05)	(0.06)	(0.15)	(0.15)	(0.13)	(0.12)
Asset index level									
Poor							5.11*		3.14*
							(3.51)		(1.75)
Lower middle							3.46**		2.81**
							(1.62)		(1.10)
Upper middle							2.26		2.16
							(1.08)		(0.88)
Occupation									
Laborer							0.63		0.36**
							(0.24)		(0.13)
Salaried							0.27**		0.31*
							(0.13)		(0.17)
Merchant							0.43		0.51
							(0.21)		(0.24)
Other							0.62		0.67
							(0.30)		(0.32)
% change × mean (Rs)	−3.00%	1.00%	−7.00%	52%	−20.0%				
	807	1,368	7,116	2,624	2,740				
% change × mean	−24	14	−498	1,364	−548				
N	420	420	420	404	221	420	420	420	420

Dependent variables for OLS regressions are log-transformed. Housing and food are monthly expenditures; others are annual. Model 5 on education is restricted to households that have school-going children. Robust standard errors in parentheses, clustered at the level of accident bus route. The reference group for education variables is "No School / Illiterate"; unit of compensation is scaled to 100 rupees. *p*-values less than or equal to ***0.001, **0.01, and *0.05.

consumption strategy where current consumption is financed by depleting savings or assets (Rosenzweig & Wolpin, 1993; Besley, 1995). Alternately, households could borrow from formal and/or informal sources (Morduch, 1995). The following sections examine these three mechanisms in relation to the health shock.

I do not find evidence of labor substitution as a mechanism of coping with the shock. Only five unexposed households and two exposed reported that a member started working in the previous year.[11] However, this result on the extensive margin must be qualified by the fact that the survey did not collect data on an intensive response; I am unable to rule out the possibility of increasing the number of hours worked. The two groups differed significantly in terms of the number of days that the respondent was unable to work or had to cut back. Exposed individuals were unable to go to work almost 5 days of the preceding 30, compared to half a day among the unexposed. Furthermore, exposed individuals cut back on work on 3.5 days in the preceding month as compared to less than half a day among the unexposed. The data indicate that increasing labor supply in response to a health shock appears to be an unlikely candidate for households to rely on to smooth consumption.

Households reported relying on a range of sources to pay for the expenditures related to the health shock, including out of pocket or savings, borrowing, selling or pledging assets, and KSRTC compensation. Over 70% of households facing the health shock resorted to borrowing from a variety of sources. The most common source of borrowing was from money lenders (55%), followed by friends or family

[11] Among both groups, only one household reported a member stopping work, It appears plausible that this question was misinterpreted, and the responses might not be reliable.

and employers. Asset depletion was a relatively uncommon method to pay for shock-related expenses (10%).[12] The assets sold or pledged in this sample (mainly pots, pans, and small jewelry items) were not assets included in the asset index score. Interestingly, only 65% reported having received compensation from KSRTC (clearly an inconsistency because the list of exposed households was created from KSRTC compensation data). We revisited some of these households and learned that the likely cause of this apparent inconsistency is that some households reported KSRTC compensation as "other sources."[13]

As noted in table 3, 90% of exposed households had debt compared to 65% of unexposed households ($p < 0.001$). Similarly, 79% of exposed households borrowed money in the past year as compared to 47% of the unexposed ($p < 0.001$).

The regression models in columns 6 and 7 in table 4 estimate debt and borrowing as a function of the health shock. Columns 6a and 7a show regressions that include the health shock dummy, compensation, and variables that are strictly exogenous (demographic covariates and education of head of household). Results from column 6a indicate that controlling for exogenous variables, the odds of having household debt among exposed households are 5.68 times that of the unexposed. This translates to a risk ratio of 1.40 (95% CI: 1.26–1.48).[14] Importantly (from column 7a), the odds of exposed households borrowing in the past year are 4.53 times that of the unexposed, which translates to a risk ratio of 1.70 (95% CI: 1.45–1.88). In terms of magnitude, the size of this effect (70% higher relative risk of borrowing in the past year and 40% higher relative risk of having debt) is far greater than that of being in the poorest asset index group as compared to the richest group.

Models in columns 6b and 7b introduce asset levels and occupation, which could be potentially endogenous in this context. Including these potentially endogenous variables does not alter the estimates of the effect of the shock on debt and borrowing significantly. For both household debt and borrowing in the past year, the estimates of the effect of the shock on having debt or borrowing from the regressions in table 4 are almost identical to the simple differences seen in table 3, another indication of the success of the matching procedure employed in the study design.

Using analogous OLS regression models, I also estimated the effect of the health shock and size of shock-related expenses on the total amount of debt and the amount of money borrowed in the past year (results available on request). The models yield an estimate of elasticity of around 0.3 for both debt and borrowing. A 10% increase in the size of the health shock causes a 3% increase in both the amount of debt owed and the amount borrowed in the past year. When applying this point elasticity estimate to the variable means presented in table 1, a 10% increase in shock-related expenses (Rs 914) among the exposed causes an increase of Rs 1,343 in household debt and an increase of Rs 655 of borrowing in the past year.

D. Robustness Checks

The results in this paper suggest that households met unanticipated expenses related to the health shock mainly by borrowing rather than by reducing consumption, adjusting labor supply, or depleting assets. If such an interpretation is true, a regression of the amount borrowed on total shock-related expenses and on total health spending (shock-related and health expenses in following year) would yield coefficients close to 1. Controlling for age, sex, education, caste, household size, and size of compensation, I find that the coefficient for spending on shock-related expenses is 0.64 ($t = 2.87$) and that for total health spending is 0.71 ($t = 3.19$). F-tests for a more precise test of robustness could not reject the null hypothesis that the coefficients are equal to 1 ($p = 0.12$ and 0.19, respectively). These results lend further support to the conclusion that the principal mechanism that households rely on to meet shock-related expenditures is debt.

I also investigate the differences in the amount of debt owed by households and the amounts borrowed. As mentioned in table 3, the average total amount of debt owed by the exposed was Rs 19,787 higher than by the unexposed. The difference in amount borrowed was Rs 7,729. The gap between these two figures could potentially be explained by lost income over the course of the year. The imputed lost income from number of days of labor lost and reported monthly income was Rs 9,658. Taken together, lost income and amount borrowed account for 87% of reported differences in the amount of outstanding debt.

To verify that there was nothing unusual about this sample, I also investigated the effect of disability on consumption smoothing, following Gertler and Gruber (2002), using an alternate specification of the models in table 4 using disability measures (results available on request). The results are consistent with those of Gertler and Gruber, as well as Meyer and Mok (2008), in that severe disability levels are associated with decreased consumption levels, especially in

[12] The exposed and unexposed groups also accumulated assets at a similar rate: 14.3% of the exposed and 16.7% of the unexposed reported having purchased at least one asset over the past year.

[13] We investigated a few cases where there were large compensation amounts reported in the original data, but households did not report using compensation money for paying for treatment. In some cases, because the compensation was received after the discharge from the hospital, the respondents did not perceive that money to have paid for the treatment. In another instance, the victim's relatives were given the compensation money at the hospital, but they had assumed it was a charitable donation from an anonymous donor. We further verified that in certain instances, KSRTC had sent representatives to provide financial compensation to the victims as soon as possible, and in some instances the compensation was indeed handed over at the hospital with minimal paperwork to assist the injured.

[14] The odds ratios from logit models include clustered standard errors. Relative risk ratios were computed using ODDSRISK function in STATA (Hilbe, 2008). ODDSRISK: Stata module to convert logistic odds ratios to risk ratios. Statistical Software Components S456897, Boston College Department of Economics.

terms of food consumption. Compared to households with no disability, those with severe disability had food consumption that was lower by 17%. Similarly, those with severe disability had 30% lower festival expenditures. Interestingly, disability levels had no significant associations with expenditures on housing or education. It is surprising that although disability independently is associated with lower food consumption, the shock, which caused a large increase in disability levels, did not seem to affect food consumption, which makes the causal interpretation of the disability results questionable.[15] One possible explanation could be that the time frame since injury in my sample was only one year. Unfortunately, since 87% of the exposed reported at least one severe limitation on ADL severe disability, sample size constraints prevent me from pursuing the analysis of disability effects further.

IV. Conclusion

This paper presents causal estimates of the effects of health shocks on household consumption and household responses to mitigate the effects of such shocks. The identification strategy of this quasi-experimental study relies on plausibly exogenous health shocks sustained by passengers in bus accidents, combined with matched unexposed individuals. The consumption responses of households exposed to the shock suggest that households are able to smooth consumption of food and housing, while educational expenses see some reductions. Furthermore, I find strong evidence of households relying on costly borrowing mechanisms to meet shock-related expenditures. Over 70% of exposed households had borrowed to pay for the expenditures incurred as a result of the shock. In addition to having a 70% higher risk of borrowing in past year and a 40% higher risk of having outstanding debt at the time of the survey (compared to the unexposed), exposed households have debt that was approximately equal to ten months income (compared to six months among unexposed).

The focus on consumption smoothing, particularly food consumption, has often been justified by the argument that if a shock limits a household's ability to smooth food consumption, it is the role of society to intervene to protect such households. Indeed, there is credible evidence of consumption effects of income shocks, especially among poorer subpopulations from previous research (Townsend, 1994; Morduch, 1995; 1999; Ravallion & Chaudhuri 1997; Dercon & Krishnan, 2000; Kazianga & Udry, 2006). However, it is equally important to understand the effect on households' economic well-being beyond consumption smoothing, such as that on asset levels, labor responses, savings, debt, and investments in human capital. While this paper is able to demonstrate the effect of the health shock on borrowing and debt, I am unable to test long-term effects on assets, savings, or bankruptcy since the data were collected only a year after the shock. It would be informative to follow up on these households in a few years to learn about the long-term effects of these health shocks. Similarly, it is too early to learn whether the reduced expenditures on education have lasting effects on human capital. Further, it remains to be determined if the reduction in educational expenses is a consumption effect in terms of reduced spending on uniforms, books, and supplies or one that affects investment in human capital through reductions in attendance or educational attainment. Future waves of data from similar studies could help estimate potential effects on education as a result of these reductions.

[15] The health shock doubled the proportion of those with severe disability. The average disability score among the exposed was 1.5 standard deviations higher.

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