Causal Effects of Health Shocks on Consumption and Debt: Quasi-Experimental Evidence from Bus Accident Injuries

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ABSTRACT: Endogeneity in the health-wealth relationship presents a challenge for estimating causal effects of health shocks. Using a quasi-experimental study design, comprising exogenous shocks sustained as bus accident injuries, with "controls" drawn from travelers on the same bus routes, I present new evidence of causal effects of health shocks on household consumption, assets and debt. Using survey data collected one year after the accidents, I find negative effects on festival and education spending. Debt was the principal mechanism used by households to mitigate effects of the shock, leading to significantly larger levels of indebtedness among the exposed.

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SECTION 1: Introduction

While there is ample anecdotal evidence of the consequences of adverse health events, there are few empirical estimates of the causal effect of heath shocks on economic outcomes. An important reason for this gap is the methodological challenge of endogeneity that continues to handicap the health-wealth research: wealth levels affect health status, while health can also impact wealth. Wealthier households also protect themselves better from adverse health events, making it further difficult to establish a causal relationship between health and consumption levels, assets or other measures of economic wellbeing of households.

To address this 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 drawn from passengers traveling on the same bus route. Conditional upon identifying well matched unexposed individuals, this strategy allows me to treat the exogenous health shock as a random exposure. I estimate causal effects of the shock on consumption smoothing and household responses in terms of borrowing, asset depletion and labor supply.

Among the various types of income shocks faced by households, especially in developing countries, health shocks are among the most common.[1] However, health shocks differ from other income shocks, such as changes in rainfall, in that health shocks affect the individual's human capital directly. Partly due to human capital effects, economic theory predicts an ambiguous effect of a health shock on labor supply. Assuming efficiency wages and no downward rigidity in wages, a decline in health status would depress wages. At the same time, decline in health might cause a decrease in the marginal utility of consumption. Taken together, these two changes yield an ambiguous effect of health shocks on labor supply. Further, the health shock could actually lead to reductions in labor supply due to transient or permanent disability as a result of the shock. Changes in health status might affect the way households value productive assets and discount future consumption, leading to patterns of autarkic consumption or debt that might be different from other income shocks. As Baeza and Packard (2006) argue, the effects of health shocks on non-medical consumption have been poorly understood in terms of its 'impoverishing impacts' and these effects could be as large or larger than income losses during acute health shocks. Thus the study of economic consequences of health shocks needs to go beyond testing models of consumption smoothing and also understand the specific mechanisms that households resort to in order to smooth consumption.

Much of the effect of health on economic outcomes has been studied in the context of labor productivity or the impact on education. Experimental studies on iron supplementation in Indonesia demonstrated improved labor participation and higher

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

hourly earnings among those who received 120mg of iron every week for a year (Duncan Thomas et al., 2006). Similarly, the de-worming experiment in Kenya found higher school attendance among those who received treatment, although performance in terms of school scores remained unaffected (Edward Miguel and Michael Kremer, 2004).

For obvious reasons, there are no comparable ‘experimental’ studies on the economic effects of health shocks. Qualitative studies of poverty and health indicate that households falling into poverty traps report illness and health expenditures to be one of the critical reasons for poverty (Anirudh Krishna et al., 2003, Deepa Narayan et al., 2000, R. Sauerborn et al., 1996). Much of the quantitative literature on ‘medical impoverishment’ comprises observational studies and cross sectional correlations between household expenditures, poverty levels and health expenditures (David Dranove and Michael L. Millenson, 2006, S. Gottlieb, 2000, David U. Himmelstein et al., 2005, Yuanli Liu et al., 2003, Eddy van Doorslaer et al., 2005, Ke Xu et al., 2003). While these studies help document the potential extent of medical impoverishment, they do not provide causal estimates or shed light on specific mechanisms through which the economic consequences of health shocks might cause poverty.

Previous efforts to estimate the effects of health shocks on wealth and assets have relied on the onset of new chronic illness (James P. Smith, 1999), serious illnesses (James P. Smith, 2003), Self Rated Health (SRH) (Michael Hurd and Arie Kapteyn, 2003) and a variety of other health conditions (Peter Adams et al., 2003). While many of these papers show evidence of changes in asset levels associated with new diagnoses or changes in

SRH, it is not clear if this effect on household wealth is a causal one. Indeed, Smith (1999) notes that the $17,000 effect of onset of chronic illness in his study appears to be far too high to be explained by the health shock alone. On the labor supply effects, there is a very large body of literature both from high income as well as developing countries that shows decreases in wages and participation associated with declines in health status (Mark M. Pitt and Mark R Rosenzweig, 1986, James P. Smith, 2003, John Strauss and Duncan Thomas, 1998). For an excellent review of health and labor market outcomes, see Currie and Madrian (1999). While estimates vary widely depending on measures of health and labor supply used, most studies find a negative effect. The main limitation of all of these studies is that the identification strategies employed fail to fully address endogeneity.

Research focusing on consumption effects of health shocks encounters similar problems of endogeneity resulting in estimates that vary widely depending upon the data and methods employed(John H. Cochrane, 1991, Helen Levy, 2002). Gertler and Gruber (2002) studied consumption insurance against major illnesses by identifying changes in SRH and disability using panel data from Indonesia (IRMS). They find no effect of changes in SRH on consumption, but find large negative effects with disability. They argue in support of using measures such as disability that capture large health effects since SRH, being endogenous to the labor supply decision, likely yields opposite results as the disability measures. Wagstaff (2007) reports negative effects of health shocks on food consumption. However, his analysis relies on two measures of health -

hospitalization and BMI - that are particularly prone to endogeneity when estimating income or consumption effects of health.[2]

I seek to address the endogeneity problem in this literature by presenting estimates of the causal effect of health shocks on economics outcomes, by employing a quasi-experimental study design. I rely on the exogeneity of health shocks in the form of injuries sustained in bus accidents in Karnataka, India. I identify appropriately matched 'unexposed' individuals using a process of matching on age, sex, area of residence and bus routes traveled, which allows me to treat the exogenous health shocks as random, conditional on matching. Using data from a household survey administered to the exposed and unexposed groups, my analysis presents three key findings: (1) Households exposed to the shock, which caused total expenditures worth over two months of income, reduce educational expenditures by 20% and festival spending by 9%. On the other hand, households appear to be able to smooth consumption in terms of food and housing. (2) I find no evidence of asset depletion or differences in asset accumulation. I also do not find evidence in support of labor supply responses. (3) The principal mechanism that households rely on to pay for health shock related expenses is debt. Exposed households have six times the odds of having household debt, and the size of the debt is almost twice that among the unexposed.

The rest of this paper proceeds as follows: Section 2 describes the study design and analytical methodology. Section 3 describes the data and presents results from analysis of

[2] For example, Wagstaff and Pradhan's (2005) research on the introduction of health insurance in Vietnam, using the same panel data, finds that introduction of the insurance program had significant impacts on BMI.

the effect of the shock on household consumption, assets, debt and labor supply. Section 4 discusses the findings and concludes.

SECTION 2: Study Design and Methods

2.1 Study Setting

This study was conducted in Karnataka, a large state in Southern India (estimated 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. 21696 (approx. $542 @ Rs. 40 per USD). Although Karnataka is probably best known today for the globally renowned IT city of Bangalore, over 2/3rd of the state's population lives in rural areas.

The bus accident data was compiled from the compensation files of the Karnataka State Road Transport Corporation of Karnataka (KSRTC), which is an autonomous publicly owned institution. The KSRTC operates 5100 schedules running 5400 vehicles over 1.25 million miles, carrying an average of 2.2 million passengers everyday. It owns several different types of buses (ranging from local buses that ply on rural local routes to interstate luxury buses that connect Bangalore to major metropolitan hubs across the country such as Mumbai and Hyderabad).A highly enterprising and innovative organization, it has also been the recipient of national and international awards for road safety, innovation and environmental responsibility. KSRTC maintains detailed data on all accidents that involve its buses and, to the extent possible, data on passengers injured in these accidents, without which this research would not have been possible.

[FIGURE I: MAP OF KARNATAKA AND KSRTC DIVISIONS ABOUT HERE]

2.2 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 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 divisions of KSRTC in and around Bangalore City (Bangalore – Central, Bangalore – Rural, Hassan, Dhavangere, Chikkamagalur, Tumkur, Mysore and Kolar). All individuals injured in these accidents, including those who lived outside the divisional areas, were included as ‘exposed’ in this study.

The heterogeneity in the types of buses on India’s roads (public, private, luxury, semi-luxury etc.) introduces a possibility of non random exposure to the health shock if one were to include all bus accidents. For example, since the poor are more vulnerable to shocks as compared to the better off (Jonathan Morduch, 1994), it is possible that the richer populations would travel in luxury buses as compared to the local state run buses used by the poor. The latter types of buses are also older and might have lower safety levels as compared to the luxury buses. I address this issue by restricting the sample to KSRTC-run non-luxury buses that run on local rural routes. There are three advantages to such an approach. First, by restricting the study to KSRTC buses, I achieve relative homogeneity among the exposed group, specifically in terms of socio economic status. Second, since the population traveling on the local routes is mostly the rural poor, the findings from such an empirical investigation are relevant from a public policy perspective. Third, this restriction also prevents large geographic dispersion of passengers introduced by inclusion of interstate buses. For example, a Bangalore-Mumbai bus would include passengers dispersed over 1000 miles, making this research project unmanageable.

In order to verify the information on exposed cases, I visited each of the divisional offices and compared the information in each of the accident case files personally in the presence of the case officers. All data entry errors were rectified and missing details on age or addresses were filled in to match the records on file. After eliminating records that had incomplete or missing names or addresses, 108 "traceable" cases were identified.[3] To calculate sample size for the survey, I assumed that only 75 exposed would be successfully located and 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.

2.3 Matching and Identifying the Unexposed

Unexposed individuals were identified 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 level of village (or neighborhood if town), was used as a proxy for matching socioeconomic status. In order to account for any

[3] Some of the non-traceability occurred due to well-intentioned attempts to award compensation as soon as possible after the accidents (at times when the passenger is still in the hospital). As a result, data on contact information of victims was not consistently collected across accidents and divisions. In some instances, compensation sums of Rs 5000 (large, by KSRTC compensation standards) were handed out without collecting complete details of the individuals. 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 passenger(s) with contact details.

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 6 times in 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*, I identified four unexposed subjects who are female residents of *Atown,* in the 40-50 age-group, who traveled frequently on this route. In rare instances where it was not possible to find someone who traveled the exact same bus, matching individuals who traveled on a similar bus route that traversed the accident location were enrolled. In small villages, matched unexposed individuals were identified with the help of village secretaries or health workers. 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. At the time of enrollment, contact information was collected and a date and time for the household interview was scheduled.

2.4 Household Survey

The survey was conducted by Center for Population Dynamics, a Bangalore-based survey agency during November -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.

2.5 Analytical Methods

The first step of the analysis is to verify that the matching strategy for identifying unexposed was successful. Since the matching was conducted using age-group, sex, geographic area of residence and bus route in order to proxy for socio economic status, I test for differences in household income, asset levels, household size and education level between the two groups. I then focus attention on the transitory health shock and present two sets of analyses, first to test for consumption effects and the second to explore mechanisms that households rely on to mitigate the effects of health shocks.

I employ an analysis that relies on the exogenous health shock to directly test its effect on households one year after the health shock. This is in contrast to identification strategies commonly employed in the consumption smoothing literature that employ instruments such as rainfall shocks to identify the causal effect of income shocks on household consumption (John Giles and Kyeongwon Yoo, 2007, Harounan Kazianga and Christopher Udry, 2006, Christina H. Paxson, 1992). Identification of exogenous exposure to health shocks, combined with the matching procedure, enables me to test for effects on consumption by directly comparing household expenditures across exposure groups. Current consumption C^*, can be expressed as a function of current income Y^* and X, a vector of household level variables. Using the Permanent Income Hypothesis framework (Milton Friedman, 1957), Y^* is the sum of permanent income Y^P and transitory income Y^T.

$$\begin{aligned} C^* &= f(Y^*, X) \\ C^*_{ht} &= \alpha + \beta Y^P_{ht} + \gamma Y^T_{ht} + \delta X^*_{ht} + \varepsilon_{ht} \end{aligned} \tag{1}$$

Substituting $Y^P = Y^* - Y^T$, we have

$$C^*_{ht} = \alpha + \beta Y^*_{ht} + \delta X^*_{ht} + (\gamma - \beta) Y^T_{ht} + \varepsilon_{ht} \quad (2)$$

Thus the empirical test for effects on consumption would be to test if the coefficient for the transitory shock variable Y^T is different from 0 (Angus Deaton, 1997). My estimating equation now can be written as:

$$C^*_{ht} = \alpha + \delta X^*_{ht} + \pi Y^T_{ht} + \varepsilon_{ht} \quad (3)$$

where $\pi = \gamma - \beta$ in equation 2. An important reason why π can be estimated without bias from equation 3 is that Y^T is orthogonal to the omitted Y^* and to X a s well. Although estimates of δ are likely to suffer from omitted variable bias (since X is not orthogonal to the current income Y^*), this is a smaller concern given our focus on the estimation of π.[4] The health shock variable enters the regressions either as a dummy or a continuous measure of the size of the shock. This continuous variable is the log of total expenditures incurred as a result of the health shock, including all medical expenditures, additional expenses such as transport as well as lost wages. The household level variables included in the model are age of head of household, dummies for education level of head, caste and size of household (captures household age structure effects). I also test the effect of including the compensation amount (approximately 25% of the total size of the shock) in the models. I employ household spending on housing, food, festivals, health and education as dependent variables in separate regressions. The dependent variable in the health regression includes spending on *all* health events in the year, including

[4] One possible test for orthogonality is by regressing the shock variable on all the X variables in equation 3 (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 3 outliers among exposed with 9 family members. When these observations were excluded, it was no longer significant (p=0.34).

expenditures resulting from the health shock as well as other hospitalizations, out patient visits and chronic conditions. Total health spending was non-zero for all exposed households and for 95% of unexposed households. The zeros were changed to 1 to facilitate log transformation of the health expenses variable.   The education regression is restricted to households with non-zero expenditures; the share of such households in both groups was almost identical (52.1% among exposed and 54.8% among unexposed; p = 0.66). I also include the percentage of school aged children in the household that are female in the education regressions.

The second set of analyses explores mechanisms employed by households for smoothing consumption, examining data on assets, labor supply and debt. I investigate differences in accumulation and depletion of assets as well as changes in labor supply over the preceding year. I then focus on household debt, using information on amounts borrowed in past year, as well as total amount of household debt. The final analysis employs logit models to test for differences among exposed and unexposed groups in the odds of having debt and borrowing in past year. I also present results from OLS regressions that estimate the effect of size of health shock on the amount of household debt and borrowing.

SECTION 3: Data and Results

3.1 Data

Table I describes the data including verification of the match as well as summary statistics of consumption / expenditure variables and household debt. In order to verify the success of the matching based on age, sex, area of residence and bus route traveled, I compare the exposed and unexposed groups in terms of religion, caste, occupation, literacy, household size, income and asset scores. The two groups are identical across all verifying variables, providing strong evidence that the matching successfully identified unexposed households that were socio-economically identical to the exposed. Being a predominantly rural sample, most households had farming-related occupations. Total monthly income includes both primary and secondary sources of income.

[TABLE I ABOUT HERE]

Asset index scores were calculated using data on household assets and durable items, following the methodology employed in National Family Health Survey.[5] As described in the footnote, the scoring system gives more weight to the type of housing and access to drinking water, electricity and sanitation as opposed to ownership of consumer durables. The survey also collected detailed information on other assets such as livestock, farm equipment, tractors, phone, jewelry and brass / copper pots which were also included in the analysis of asset depletion/accumulation. The total household monthly income among the two groups had similar means (Rs. 4482 among exposed and 4365 among unexposed) and distribution (See Figure 2). The average size of the health shock, including all healthcare and related expenditures and lost income, was Rs.9141 (Approx $228, at Rs. 40 per USD). The mean ratio of shock to household income was 2.3 (SD 3.7).

[5] 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'*.

[FIGURE II: DISTRIBUTION OF INCOME ABOUT HERE]

Table I also presents the summary statistics of household expenditures among the exposed and unexposed. The survey collected data on self reported monthly income as well as disaggregated data on expenditures on food, housing (rent and utilities), as well as annual expenses on items such as festivals (including weddings), health and education. The average monthly household expenditures on housing and food are similar between the exposed and unexposed groups. Among households with non-zero spending on education, the exposed had 13% lower educational expenditures than the unexposed. The share of households that had positive expenditures on education was similar among the two groups (52.1% among exposed and 54.8% among unexposed; p = 0.66).

The survey collected data on household debt in terms of total debts owed by households as well as money borrowed in the past year. Exposed households have significantly higher levels of debt and borrowing in past year, and the amounts owed by such households are also much higher than among the unexposed. It is noteworthy that the mean difference of the amount borrowed in past year between the two groups (Rs. 7729) is fairly close to the average size of the shock (Rs. 9141).

The physical injury caused by the health shock included injuries of varying severity. Table II describes injuries and health status of the sample in terms of self rated health (SRH) and disability levels. All the bus accidents in this study occurred in low speed traffic on local rural routes. As such, most injuries were minor; only 7% of those injured suffered from a fracture. One passenger had severe leg injury that needed amputation and an artificial limb. With the exception of this one case, all other injuries can be treated as transitory health shocks since they are not expected to have permanent physical effects.

[TABLE II ABOUT HERE]

Functional disability was measured using 6 items that asked about activities of daily living limitations (ADLs). Individuals reporting limitations on two or more ADLs were classified as "severely" disabled. Given the nature of the shock, it is not surprising that self rated health is worse and reported disability levels are higher among the exposed. Interestingly however, health care utilization in terms of hospitalizations, minor illnesses and chronic conditions is similar between the two groups.

3.2: Results:

Table III shows results from OLS regressions of household expenditures on food, housing, festivals, health and education on the health shock.[6] Festivals, health and education are reported as annual expenditures, while food and housing are monthly expenses. The dependent variables are all log transformed expenditures. All models use a dummy variable for the health shock with the exception of the last model (6), which is an OLS regression of educational expenditures on the size of the shock, measured as the log of total shock-related expenditures. The rows at the bottom of the table interpret the coefficients on the shock variable as the percent change in dependent variable.

[TABLE III ABOUT HERE]

[6] 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 a success of the matching design employed in this study. My analysis aims to exploit this successful matching by directly estimating the effects of health shocks.

The regressions suggest that evidence of consumption smoothing is mixed. While food and housing consumption appear to be unaffected by the health shock, there are negative effects on educational spending and festivals. Not surprisingly, education level of the head of household, being correlated with socio economic status, is significantly associated with higher consumption. However, as described earlier, 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. As expected, health spending among the exposed is significantly higher (column 4), since it includes expenditures incurred due to the health shock. The coefficient on the shock dummy translates into health expenses that are almost seven times higher ($e^{2.074} = 7.96$) than among the unexposed, which translates into an additional total health spending of Rs 17567 among the exposed.

The education regressions in columns (5) and (6) show a significant effect of the health shock on household educational spending. 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.(Karthik Muralidharan and Michael Kremer, Forthcoming) It is hence safe to assume that the educational expenditures are primarily for uniforms, books and stationary. The education expenditure models also control for share of school aged children in the household that were female. In a modified specification that interacted the health shock with the percent female children variable, the interaction term is negative and significant (t=1.9), implying that the reduction in educational spending might be greater in households with more female children. The results in column (5) suggest that, controlling for household demographics, the shock has a significant effect, reducing educational expenditures by 20% ($e^{-.277} = 0.80$). The log-log regression in column (6) that yields a coefficient that is the elasticity of educational expenditures with respect to the size of health shock. The estimated point elasticity of -0.03 indicates that educational expenditures are relatively inelastic to the size of the shock. Overall, the evidence from Table III indicates that households, faced with a health shock that causes expenditures worth over two months of income are able to smooth consumption only imperfectly. Food and housing expenditures appear to not be affected by the shock, while educational and festival expenditures are negatively impacted by the shock. These results remain unchanged even after controlling for the amount of compensation received.[7]

I also investigate the effect of disability on consumption smoothing, following Gertler and Gruber (2002), using an alternate specification of the model using disability measures (Table IV). This specification aims to compare the consumption effects that would be estimated by disability measures with the estimates shown in Table III. The results of the estimation using disability measures are generally consistent with those of Gertler and Gruber, in that severe disability levels are associated with decreased consumption levels, especially in terms of food consumption. Compared to households where the respondent has no disability, those with severe disability had food consumption that was lower by 18% ($e^{-0.198} = 0.82$). Similarly, those with severe disability had 30% lower festival expenditures. Interestingly, disability levels had no significant associations

[7] The average amount of compensation was 25% of the size of the health shock. Including the compensation variable in the regression did not change coefficients significantly. For example, the coefficient for festivals changed from -0.093 to -0.075; total health changed from 2.07 to 1.99 and education changed from -0.28 to -.36.

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[8]. One possible explanation could be that the time frame since injury in my sample was only one year. The presence of a long term disability could induce households to revise expectations over the long term horizon and adjust consumption downward. But if a 1 year timeframe is not sufficiently long enough for households to make this transition, one would not see such consumption effects in this current sample. Unfortunately, since 87% of the exposed reported severe disability, sample size constraints prevent me from pursuing the analysis of disability effects further.

[TABLE IV ABOUT HERE]

3.3 Household Responses to Health Shocks:

Estimates of consumption responses show that, faced with an unexpected health shock that causes expenditures worth over two months of income, households do not reduce food or housing consumption but reduce spending on festivals and education by 9% and 20% respectively. The relatively small size of these reductions compared to that of the shock raises questions about the mechanisms that households rely on to pay for this unexpected shock. Households could respond by adopting a variety of strategies to insure consumption 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 it could trigger an increase in intensity, where the existing working member(s) increase the amount of labor supplied (hours worked) (Anjini Kochar, 1999). Households might

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

resort to an autarkic consumption strategy where current consumption is financed by depleting savings or assets (Timothy Besley, 1995, Mark R. Rosenzweig and Kenneth I. Wolpin, 1993). Alternately, households could borrow from formal and/or informal sources (Jonathan 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 (1.5%) and two exposed (2.3%) reported that a member (who was not employed earlier) started working in the last year.[9] However, this result must be qualified by the fact that the survey only collected data on labor substitution responses at the extensive margin. To the extent that there could be an intensive response with members increasing number of hours at the same job, the response is possibly underestimated. Unfortunately, due to data limitations, I am unable to rule out the possibility of labor substitution in terms of increasing number of hours worked. However, the two groups differed significantly in terms of number of days that the respondent was unable to work or had to cut back. Table V shows exposed individuals were unable to work almost five days of the preceding 30 compared to half a day among the unexposed. Whether this difference in number of days worked translates into reduced earnings was not assessed in the survey.

[TABLE V ABOUT HERE]

Further, exposed individuals cut back work on 3.5 days in the preceding month as compared to less than half a day among the unexposed. The data indicates that increasing

[9] 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.

labor supply (by the exposed individual) in response to health shock appears to be an unlikely candidate for households to rely on to smooth consumption.

[TABLE VI ABOUT HERE]

Table VI presents an overview of how households paid for treatment for the health shock. The rows-column matrix shows both the percentage of exposed households that used various methods of payment, as well as the degree of overlap between various methods. Each cell shows percentage of exposed households that used *another* source for payment in addition to the one listed in the column heading.[10] For example, the 37% of households who paid out of their own pocket included 1% who sold assets and 13% who borrowed. Since households used multiple sources to meet expenses due to the health shock, the percentages in Table VI add up to more than 100%. Another fact that is noteworthy is that only 65% (55 out of 84 exposed households) report having received compensation from KSRTC. This is an inconsistency because the list of exposed households was created from compensation data of KSRTC. The likely cause of this apparent inconsistency is that the money that some households reported getting from "other sources" was KSRTC compensation.[11]

[10] The survey collected data on a wide range of sources which were collapsed into the column headings shown in Table VI for ease of presentation. For example, households who borrowed money to pay for the health shock included those who borrowed from money lenders (most common), employers, as well as from friends and family, all of whom were collapsed into the "borrowed" category shown in the table. Similarly, the "Sold Assets" category includes those who sold jewelry (most common), livestock and other property. (Table A.1 showing the detailed breakdown into these subcategories is included in the Appendix.)

[11] 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 is indeed handed over at the hospital with minimal paperwork to assist the injured.

The key finding from the matrices in Table VI and Table A.1 is that most households faced with the health shock (70%) resorted to borrowing from a variety of sources: money lenders, friends, family and employers. Asset depletion was a relatively uncommon method used by households to pay for treatment (10%). The exposed and unexposed groups also accumulated assets at a similar rate: 21.45% of the exposed and 22.7% of the unexposed reported having purchased at least one asset over the past year. None of the households sold any assets scored in the asset index. (Table A.2 in appendix shows frequency of households that bought / pledged / sold *any* assets).

The survey also collected detailed data on total outstanding household debt, amounts borrowed in past year, as well as interest rates. The 'debt' and 'borrow' questions enable me to capture different types of debt. 'Debt' could potentially be the amount owed over a long period of time including debt that existed before the shock. Other questions on 'borrowing in the last year' pertain specifically to the debt accrued in the period after the health shock.

[FIGURE III: SHARE OF HOUSEHOLDS WITH DEBT ABOUT HERE]

Compared to 90% of exposed households that had debt, 65% of unexposed households had debt ($p < 0.001$). Similarly, 79% of exposed households borrowed money in the past year as compared to 47% of the unexposed ($p < 0.001$). The average debt owed by the exposed was 79% higher than that among the unexposed ($p<0.01$) and the average amount borrowed was 55% higher ($p = 0.07$)(see Table I). Both groups borrowed at similar interest rates (45.36% among exposed and 42.05% among unexposed).

I now proceed to explore these differences in debt and borrowing between the two groups using OLS and logit regressions. The models estimate debt and borrowing as a function of the exogenous shock and a vector of household demographic variables that include age of head of household, sex of bus passenger, caste, education of head of household, household size, asset index and occupation of head of household. Table VII reports odds ratios of debt and borrowing on the health shock. Columns (1) and (5) show the parsimonious models with univariate regressions, while columns (2) and (6) include additional variables that are strictly exogenous. Models (3), (4), (7) and (8) introduce asset levels and occupation. While these could be potentially endogenous, very few households sold or bought assets that could alter the asset index scores (see Table A.2 in Appendix). Further, as mentioned earlier, there were no changes in labor participation status.

[TABLE VII ABOUT HERE]

For both household debt as well as borrowing in past year, Table VII shows that the estimates of the effect of the shock on the log odds of having debt or borrowing are almost identical across the multivariate models. These estimates are also highly comparable to the parsimonious univariate models (1) and (5): another testament to the success of the matching procedure employed in the study design. These results imply that controlling for demographic covariates, education, occupation and asset levels, odds of having household debt among exposed households is six times that of the unexposed, and their odds of borrowing in the past year is five times. In terms of magnitude, this effect is far greater than that of being in the poorest asset index group as compared to the richest group.

I now direct attention to the amount of debt owed and the amount of money borrowed in past year using OLS regressions. The models in odd numbered columns in Table VIII use a binary health shock, while all even numbered regressions use the log of the size of the health shock. The dependant variables are log of amount of debt and amount of money borrowed in the past year.

[TABLE VIII ABOUT HERE]

The models are extremely robust to various specifications and inclusion of covariates. The log-log models in even numbered columns yield a consistent estimate of elasticity of 0.32 for debt and 0.35 for borrowing. A 10% increase in the size of the health shock causes a 3.2% increase in the amount of debt owed and 3.5% increase in the amount borrowed in past year. Applying this point elasticity estimate to the variable means presented in Table I, this effect can be restated as: A 10% (Rs 914) increase in the size of the shock causes an increase of Rs 925 in household debt and an increase of Rs 547 of borrowing in past year.

3.4: Robustness Check

The analysis above strongly suggests that households finance the health shock related expenses mainly from borrowing. If indeed such an interpretation is true, a regression of the amount borrowed on the total household spending on the shock and total annual health spending would yield coefficients close to 1. Controlling for age, sex, education, caste, household size and size of compensation, I find that the coefficient for the spending on the shock 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 hypothesis that the coefficients are equal to 1 (p= 0.12 and 0.19 respectively). These results lend further confidence to the finding that the principal mechanism that households rely on to meet the shock related expenditures is debt.

3.5: Limitations of this study

While this study is able to exploit random exposure to exogenous health shocks to address the endogeneity problem, it has three main limitations. First, there could be unobserved heterogeneity that predisposes certain types of individuals to get injured in accidents, which might have not been adequately captured by the matching process. Matching on bus routes and ensuring frequency of travel helped control for travel preferences, but there could be residual differences between individuals who were on the bus at the time of the accident and the unexposed who were available to be interviewed. During the survey, we tried to address this concern by making repeated visits to the homes of the matched unexposed if they were unavailable at the first visit. The second limitation is that the health shock used here, bus accident injury, is not directly comparable with other illnesses such as heart diseases, diabetes or cancer. While that is incontrovertibly true, injuries are a leading cause of global burden of disease, accounting for over 12% of the total DALYs lost due to illness (WHO, 2002). Road traffic accidents were the 8th most common cause of DALYs lost in 2002 and, according to WHO estimates, are expected to be the 4th leading cause by 2030 (Colin D. Mathers and Dejan Loncar, 2006). The health shock studied in this paper applies thus directly to one of the top ten causes of global disease burden and hence its findings, although limited in their generalizability, are highly relevant from a public policy perspective. Finally, this study was conducted in mostly rural areas of Karnataka in South India and hence might not be globally generalizable. The relatively small sample size limits my ability to further refine this analysis especially in terms of the effects among poorer subgroups.

SECTION 4: Conclusions and Discussion

This paper presents, to my knowledge, the first causal estimates of the effects of health shocks on household consumption and the responses that households rely on to mitigate the effects of such shocks. The consumption responses of households exposed to the shock suggest that smoothing is imperfect: the health shock reduces educational expenses by about 20% and festival expenses by 9%. Households with higher share of female school aged children are more likely to make these reductions on educational spending. I find no evidence of food consumption being affected by this specific shock. 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. The magnitude of the increase in the size and frequency of household debt is cause for concern. In addition to having 6 times odds of having debt (compared to the unexposed), exposed households have debt that was approximately equal to 10 months' income, while that among the unexposed was less than half their annual income.

The focus on consumption smoothing, particularly food consumption, has often been justified by the argument that if a shock limits the 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 sub-populations from previous research (Stefan Dercon and Pramila Krishnan, 2000, Harounan Kazianga and Christopher Udry, 2006, Jonathan Morduch, 1999, 1995, Martin Ravallion and Shubham Chaudhuri, 1997, Robert Townsend, 1994). However, it is equally, if not more, important to understand the effect on households' economic wellbeing beyond consumption smoothing – such as that on asset levels, labor responses, savings, debt and investments in human capital. Chetty and Looney (2006) argue against using consumption smoothing alone as an indicator of welfare in determining the value of insurance against risks. Particularly, the consumption smoothing observed in the instance where a family near subsistence reduces investments in human capital or resorts to other costly smoothing mechanisms can be severely detrimental to net welfare. An observed small consumption response can be a result of either ability to smooth consumption inexpensively through easy access to credit markets or due to underlying high risk aversion leading to expensive risk mitigation strategies employed by households. Evidence in this paper suggests that the costly mechanisms adopted by households to partially smooth consumption are indicative of high risk aversion. These findings imply that developing risk protection mechanisms can post major welfare gains and highlight the need to develop health insurance systems in developing countries. Another potential insight is in terms of consumption commitments, as suggested by Chetty and Szeidl (2007). Given large transaction costs for altering expenses such as housing, households faced with small to moderate sized shocks might alter consumption on other discretionary expenses such as festivals, food or, in this case, educational spending.

The idea that households in developing countries use credit to smooth consumption is not new (Mukesh Eswaran and Ashok Kotwal, 1989). Such borrowing is, however, a costly strategy and can perpetuate poverty traps. First, exposed households borrow at fairly high rates of interest (mean over 45% per year). Second, the health shock leads to functional disability levels that are almost twice that in the unexposed. Because increased disability limits the potential to provide additional labor supply, it might take longer to repay the debt - making it even costlier. Even without any additional borrowing, decreased ability to repay existing loans can increase the size of total debt as compared to the unexposed. This possibly explains why the difference in total household debt between the exposed and unexposed groups is greater than the new borrowing. With limited options to increase labor supply, the new borrowing and deepening debt can cause loan default or eventual asset depletion. Since this study was conducted only a year after the shock, it is too early to see long term effects on bankruptcy or asset depletion. It would be very informative to follow up these households in a few years to learn about long term effects of these exogenous shocks.

Another potential interpretation of the results in this paper could be in terms of savings and investment. Bloom, Canning et al (2003) show that increases in longevity of life increases savings rates, which in turn spurs a propensity to invest more in physical and human capital. The evidence in this paper suggest that the converse of such a relationship might also exist: Decreases in health status (as experienced by a health shock) causes higher rates of dissaving and lower level of human capital investments in terms of educational expenditures. Since the survey was conducted a year after the accident, it is too early to learn whether the reduced expenditures on education have lasting effects on human capital. Further, it is not yet clear if the reduction in education 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 will help estimate potential effects on educational attainment as a result of these reductions. Finally, the large effects of health shocks on household debt, along with the effects on consumption, make a strong case for investing in improving road safety especially in developing countries.

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TABLE I

SUMMARY STATISTICS OF MATCHING, VERIFICATION, HOUSEHOLD EXPENDITURES, ASSETS AND DEBT

Variables	Exposed	Unexposed	p-value*
	N = 84	N = 336	
Panel A: Matching Variables			
Male^	71.43%	71.43%	1
Age	38	39	0.5
Rural	83%	82%	0.89
Panel B: Verifying the Match			
Religion (% Hindu)	99%	99%	0.88
Low caste	57%	52%	0.38
Occupation			
Farmers	23%	24%	0.86
Day Laborers	42%	38%	0.48
Illiterate	35%	34%	0.88
Household Size	4.4 [0.18]	4.08 [0.07]	0.08
Total Income (Rs.)	4482 [167]	4365 [345]	0.76
Asset Score	15.09 [0.65]	15.72 [0.31]	0.39
Panel C: Summary Statistics			
Size of Shock (Rs.)**	9142 [1940]	0	
Average KSRTC compensation	1687 [625]	0	
Expenditures (Rupees)			
Housing	848 [75]	796 [30]	0.47
Food	1430 [88]	1351 [36]	0.42
Festivals (Annual)***	6904 [523]	7169 [260]	0.65
Health (Annual)***	3755 [410]	2327 [146]	0.00
% Non-Zero Health Exp	100%	95%	0.05
Education (Annual)***	2276 [339]	2423 [269]	0.76
% Non-Zero Educ Exp	54.80%	52.10%	0.66
Bought assets in past year	14.29%	16.67%	0.59
Sold assets in past year	2.38%	1.79%	0.72
Pledged assets in past year	19.05%	8.63%	<0.01
Any Household Debt	90.48%	65.18%	<0.001
Amount of Debt	44762 [6405]	24975 [2461]	<0.01
Borrowed last year	78.57%	47%	<0.001
Amount Borrowed	21821 [3731]	14092 [1982]	0.07
Interest Rate	45.36 [2.85]	42.05 [1.66]	0.29

* p-values are from t-tests and Chi-2 tests; Std Errors reported in brackets

^ The exposed and unexposed were matched on sex, hence it is trivial that p-value is equal to 1

**Size of Shock is sum of health expenditures, other out of pocket expenses and lost income

*** Education and health spending recorded as annual expense; Mean reported among those with non-zero expenses only

TABLE II

SUMMARY STATISTICS OF INJURY AND HEALTH

Variables	Exposed	Unexposed	p-value*
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			**<0.001**
No Disability	8%	46%	
Mild Disability (One Serious / Two Minor)	5%	10%	
Serious Disability (> One Serious)	87%	44%	
Hospitalization in last year	68%	73%	0.45
Minor Illness in past 30 days	71%	74%	0.69
Chronic Illness over last year	73%	80%	0.12

* p-values are from Chi-2 tests

TABLE III

REGRESSION OF LOG HOUSEHOLD EXPENDITURES ON HEALTH SHOCK

	(1) Housing		(2) Food		(3) Festival		(4) Total Health		(5) Education		(6) Education	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Shock	0.006	0.10	-0.025	-0.59	**-0.093**	**-1.75**	**2.074**	**10.01**	**-0.277**	**-2.00**		
Shock (Log Expenditure)											**-0.029**	**-1.80**
Age of Household Head	0.001	0.28	0.002	0.52	-0.002	-0.51	0.001	0.11	-0.005	-0.81	-0.005	-0.80
Sex of injured	0.018	0.17	-0.179	-1.94	-0.225	-1.77	-0.116	-0.4	0.140	0.85	0.140	0.84
Education of Head												
Primary School	**0.253**	**2.92**	0.049	0.76	0.082	0.84	-0.127	-0.54	**0.337**	**2.06**	**0.337**	**2.06**
Middle School	**0.343**	**3.39**	0.143	2.02	0.051	0.5	0.334	1.43	0.179	0.99	0.177	0.97
High School	**0.593**	**5.50**	0.154	1.74	0.110	0.82	-0.277	-0.93	**0.804**	**3.63**	**0.812**	**3.68**
College and above	**0.896**	**7.95**	**0.259**	**2.33**	**0.311**	**2.01**	-0.526	-1.15	**1.115**	**4.91**	**1.110**	**4.83**
Caste	-0.215	-2.83	0.010	0.14	0.033	0.4	-0.177	-0.77	**-0.468**	**-3.46**	**-0.467**	**-3.44**
Household Size	0.035	1.27	**0.069**	**3.11**	0.014	0.5	**0.102**	**2.02**	**0.288**	**5.78**	**0.286**	**5.72**
% Female school age kids									-0.159	-1.00	-0.158	-1.00
% Change in Dep Var	1.00%		-2.00%		-9.00%		696%		-20.0%			
Mean (Rs)	807		1368		7116		2524		2740		2740	
% Change * Mean	8.07		-27.36		-640.44		17567.04		-548.00			
N (Clusters)	420 (84)		420 (84)		420 (84)		420 (84)		201 (77)		201 (77)	

Note: All Dependent variables are log transformed. Housing and Food are monthly expenditures, others are annual

All regressions used robust standard errors, clustered at the level of matching household. Number of clusters in each regression are indicated in parentheses next to N

The reference group for Education variables is "No School / Illiterate"

TABLE IV

EFFECTS OF DISABILITY ON CONSUMPTION

	(1) Housing		(2) Food		(3) Festival		(4) Total Health		(5) Education	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Disability										
Mild Disability	0.086	0.86	-0.103	-1.18	**-0.224**	**-2.15**	-0.144	-0.39	0.002	0.01
Severe Disability	0.103	1.44	**-0.198**	**-3.06**	**-0.356**	**-4.67**	**0.541**	**2.51**	-0.022	-0.14
Age of Household Head	0.000	0.08	0.003	1.01	0.000	0.08	-0.001	-0.05	-0.005	-0.7
Sex	0.010	0.1	-0.165	-1.87	-0.200	-1.73	-0.130	-0.44	0.158	0.96
Education										
Primary School	**0.254**	**2.89**	0.048	0.76	0.080	0.9	-0.144	-0.6	0.332	1.95
Middle School	**0.352**	**3.51**	0.126	1.83	0.020	0.22	0.366	1.43	0.167	0.91
High School	**0.597**	**5.41**	0.148	1.69	0.098	0.75	-0.311	-0.83	**0.794**	**3.47**
College and above	**0.896**	**8.03**	**0.262**	**2.55**	0.309	**2.19**	-0.366	-0.7	**1.068**	**4.52**
Caste	**-0.206**	**-2.7**	-0.004	-0.06	0.004	0.06	-0.097	-0.37	**-0.453**	**-3.38**
Household Size	0.030	1.08	**0.079**	**3.54**	0.030	1.12	**0.139**	**2.24**	**0.268**	**5.44**
% Female school age kids									-0.164	-1.04
Mean (Rs)	807		1368		7116		2524		2740	
N	420 (84)		420 (84)		420 (84)		420 (84)		201 (77)	

Note: All Dependent variables are log transformed. Housing and Food are monthly expenditures, others are annual

All regressions used robust standard errors. Number of clusters in each regression are indicated in parentheses next to N

The reference group for Education variables is "No School / Illiterate"

NOTE: Including the exogenous shock variable did not alter the estimates of the effect of disability significantly. For example, the coefficient on severe disability in the food regression changed from -0.198 (t=3.06) to -0.214 (t=3.04).

TABLE V
EFFECTS ON LABOR SUPPLY

Variables	Exposed Mean [SE]	Unexposed Mean [SE]	p-value*
Any household member starting new work	1.50%	2.30%	0.75
Days unable to work due to disability in last 30 days	4.81 [0.6]	0.51 [0.1]	<0.001
Days cut back due to disability in last 30 days	3.51 [0.5]	0.40 [0.1]	<0.001

* p-values are from Chi2 and t-tests comparing exposed and unexposed

TABLE VI

VARIOUS SOURCES USED BY HOUSEHOLDS TO PAY FOR HEALTH SHOCK EXPENDITURES

	Paid own	Sold Asset	Borrowed	Other	KSRTC
Paid own	37%				
Sold Asset	1%	10%			
Borrowed	13%	8%	70%		
Other	24%	6%	1%	36%	
KSRTC	26%	8%	54%	20%	65%

TABLE VII

EFFECT OF HEALTH SHOCK ON ODDS OF HAVING HOUSEHOLD DEBT AND BORROWING

	Odds Ratio of Having Debt				Odds Ratio of Having Borrowed in Past Year			
Model No.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Health Shock	**5.08 (<0.001)**	**6.04 (<0.001)**	**6.26 (<0.001)**	**6.81 (<0.001)**	**4.13 (<0.001)**	**4.97 (<0.001)**	**5.03 (<0.001)**	**5.46 (<0.001)**
Age		0.99 (0.68)	1.00 (0.85)	1.00 (0.85)		0.99 (0.56)	0.99 (0.92)	0.99 (0.82)
Sex		1.59 (0.23)	1.59 (0.24)	1.75 (0.16)		0.90 (0.75)	0.90 (0.75)	0.92 (0.83)
Caste		0.64 (0.14)	0.63 (0.12)	0.64 (0.13)		**0.45 (<0.01)**	**0.44 (<0.01)**	**0.48 (<0.01)**
Education								
Primary School		0.76 (0.46)	1.00 (0.98)	1.04 (0.91)		0.84 (0.60)	0.97 (0.95)	0.89 (0.75)
Middle School		0.88 (0.76)	1.11 (0.78)	1.16 (0.70)		0.86 (0.67)	0.97 (0.94)	0.90 (0.76)
High School		0.70 (0.43)	1.23 (0.64)	1.56 (0.39)		0.92 (0.85)	1.29 (0.57)	1.31 (0.60)
College and above		**0.26 (<0.001)**	0.55 (0.15)	0.79 (0.55)		**0.30 (<0.01)**	0.47 (0.10)	0.50 (0.17)
Household Size		**1.38 (<0.01)**	**1.41 (<0.01)**	**1.38 (<0.01)**		**1.32 (<0.01)**	**1.34 (<0.01)**	**1.26 (0.02)**
Asset Index level								
Poor			**5.27 (0.01)**	**4.83 (0.02)**			2.67 (0.07)	2.80 (0.07)
Lower Middle			**4.04 (<0.01)**	**3.29 (0.01)**			**2.83 (0.01)**	**2.52 (0.02)**
Upper Middle			2.42 (0.07)	2.12 (0.12)			**2.13 (0.07)**	1.92 (0.12)
Occupation								
Laborer				0.62 (0.21)				**0.36 (<0.01)**
Salaried				**0.27 (0.01)**				**0.32 (0.04)**
Merchant				0.42 (0.08)				0.49 (1.13)
Other				0.60 (0.30)				0.65 (0.37)

p-values are in parentheses; All regressions use robust standard errors, clustered at level of matching household. The reference group for schooling is "No school / illiterate".
The reference group for Asset Index groups is "Upper" and that for Occupation is "Farmer/Poultry"; "other" includes retired, housewife and student

TABLE VIII
Effect of Health Shock on Amount of Household Debt and Borrowing

	Dependent Variable: Log Amount of Debt				Dependent Variable: Log Amount Borrowed Last Year			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Health Shock	**2.68 (6.07)**		**2.64 (5.97)**		**3.03 (6.25)**		**3.08 (6.26)**	
Expenditure on Health Shock (Ln)		**0.32 (6.45)**		**0.32 (6.37)**		**0.35 (6.23)**		**0.36 (6.22)**
Age	0.00 (0.14)	0.00 (0.14)	0.00 (0.37)	0.00 (0.38)	-0.01 (0.30)	-0.01 (0.30)	-0.00 (0.02)	-0.00 (0.00)
Sex	0.72 (1.13)	0.72 (1.13)	0.90(1.38)	0.88 (1.36)	-0.27 (0.39)	-0.27 (0.38)	-0.04 (0.06)	-0.06 (0.08)
Caste	**-1.17 (2.21)**	**-1.17 (2.21)**	**-1.06 (2.05)**	**-1.06 (2.04)**	**-1.82 (3.52)**	**-1.82 (3.47)**	**1.57 (3.10)**	**1.57 (3.06)**
Education								
Primary School	-0.32 (0.51)	-0.32 (0.51)	0.00 (0.00)	0.00 (0.00)	-0.19 (0.28)	-0.19 (0.28)	-0.16 (0.23)	-0.16 (0.23)
Middle School	0.02 (0.03)	0.01 (0.02)	0.30 (0.45)	0.29 (0.43)	-0.04 (0.06)	-0.06 (0.08)	-0.04 (0.06)	-0.05 (0.08)
High School	-0.17 (0.19)	-0.23 (0.26)	0.81 (0.90)	0.76 (0.84)	0.15 (0.16)	0.09 (0.09)	-0.59 (0.60)	-0.53 (0.54)
College and above	**-2.26 (2.87)**	**-2.28 (2.90)**	-0.49 (0.63)	-0.50 (0.64)	**-2.09 (2.60)**	**-2.09 (2.59)**	-1.18 (1.26)	-1.18 (1.24)
Household Size	**0.56 (3.19)**	**0.56 (3.21)**	**0.51 (3.00)**	**0.51 (3.01)**	**0.58 (3.17)**	**0.58 (3.18)**	**0.47 (2.57)**	**0.48 (2.59)**
Asset Index level								
Poor			2.07 (1.93)	2.17 (2.03)			1.56 (1.45)	1.69 (1.57)
Lower Middle			**1.88 (2.02)**	**1.93 (2.08)**			1.42 (1.76)	1.48 (1.85)
Upper Middle			1.62 (1.63)	1.69 (1.71)			1.30 (1.42)	1.38 (1.51)
Occupation								
Laborer			-1.02 (1.72)	-1.01 (1.68)			**-2.19 (3.17)**	**-2.18 (3.12)**
Salaried			**-2.56 (2.61)**	**-2.52 (2.60)**			**-2.23 (2.09)**	**-2.18 (2.05)**
Merchant			-1.69 (1.69)	-1.63 (1.65)			-1.45 (1.47)	-1.42 (1.44)
Other			-0.95 (1.15)	-0.89 (1.08)			-1.18 (1.27)	-1.13 (1.21)

t-statistics are in parentheses; All regressions use robust standard errors, clustered at level of matching household. The reference group for schooling is "No school / illiterate".
The reference group for Asset Index groups is "Upper" and that for Occupation is "Farmer/Poultry"; "other" includes retired, housewife and student

TABLE A.1

METHODS USED BY HOUSEHOLDS TO PAY FOR HEALTH SHOCKS

Panel A: Number of Households

	own	b_emp	b_ml	b_ff	supp_ff	sld_jwl	sld_prop	sld_lfstk	insur	ksrtc
Paid own	**31**									
Borr from employer	3	**7**								
Borr from money lender	5	1	**46**							
Borr from friends family	3	0	7	**14**						
Support from friends family	18	3	7	2	**27**					
Sold jewelry	1	1	4	0	1	**6**				
Sold Property	0	1	0	0	0	0	**1**			
Sold Lifestock	0	0	1	1	0	0	0	**1**		
Insurance	2	0	1	0	0	0	0	0	**3**	
KSRTC	22	5	32	8	14	5	1	1	3	**55**

Panel B: Percentage of households

	own	b_emp	b_ml	b_ff	supp_ff	sld_jwl	sld_prop	sld_lfstk	insur	ksrtc
Paid own	37%									
Borr from employer	4%	8%								
Borr from money lender	6%	1%	55%							
Borr from friends family	4%	0%	8%	17%						
Support from friends family	22%	4%	8%	2%	33%					
Sold jewelry	1%	1%	5%	0%	1%	7%				
Sold Property	0%	1%	0%	0%	0%	0%	1%			
Sold Lifestock	0%	0%	1%	1%	0%	0%	0%	1%		
Insurance	2%	0%	1%	0%	0%	0%	0%	0%	4%	
KSRTC	27%	6%	39%	10%	17%	6%	1%	1%	4%	66%

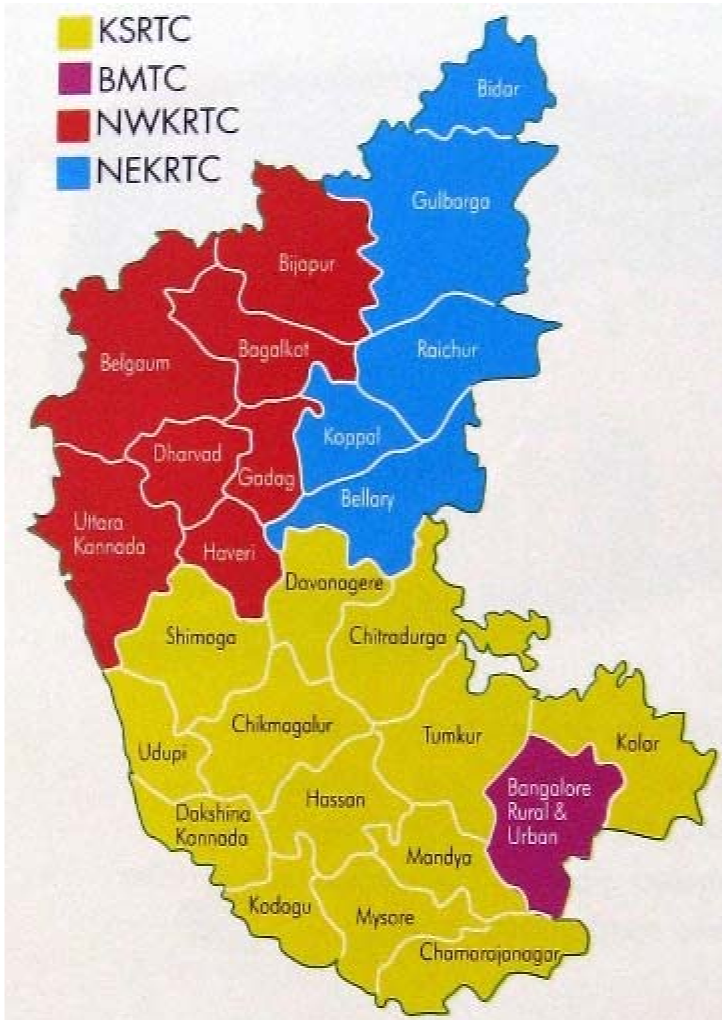
TABLE A.2

HOUSEHOLD ASSET ACCUMULATION AND DEPLETION, BY EXPOSURE TO SHOCK

	Own		Purchased		Pledged		Sold	
	Unexp	Exposed	Unexp	Exposed	Unexp	Exposed	Unexp	Exposed
Assets scored for Asset Index								
House	87.8%	86.9%	0.0%	0.0%	0.6%	0.0%	0.0%	0.0%
Land	64.3%	67.9%	0.0%	0.0%	1.5%	3.6%	0.0%	0.0%
Sewing Machine	6.3%	2.4%	0.6%	0.0%	0.0%	0.0%	0.0%	0.0%
Fan	29.5%	37.4%	0.3%	0.0%	0.0%	0.0%	0.0%	0.0%
Radio	29.9%	30.5%	0.9%	0.0%	0.0%	0.0%	0.0%	0.0%
TV	47.4%	40.4%	6.1%	1.2%	0.0%	0.0%	0.0%	0.0%
Refrigerator	4.8%	6.0%	1.5%	1.2%	0.0%	0.0%	0.0%	0.0%
Bicycle	27.0%	19.3%	1.8%	0.0%	0.3%	0.0%	0.3%	0.0%
Scooter / Motorcyle	15.1%	11.1%	1.8%	2.4%	0.0%	0.0%	0.3%	0.0%
Car	0.3%	1.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Other Assets								
Phone	23.3%	34.2%	2.4%	7.2%	0.3%	1.2%	0.0%	0.0%
Bullock Cart	5.8%	4.8%	0.0%	1.2%	0.0%	0.0%	0.0%	0.0%
Livestock	35.6%	28.9%	0.6%	1.2%	0.0%	0.0%	0.6%	1.2%
Tractor	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Water pump	1.8%	3.6%	0.0%	2.4%	0.0%	0.0%	0.0%	0.0%
Farm Equipment	21.5%	27.6%	0.6%	2.4%	2.4%	3.6%	0.0%	0.0%
Jewelry	94.3%	92.9%	3.0%	1.2%	3.6%	8.3%	0.9%	1.2%
Silver	86.4%	86.9%	0.0%	0.0%	0.0%	2.8%	0.0%	0.0%
Brass/Copper Pots	90.2%	89.2%	1.5%	2.4%	0.3%	1.2%	0.0%	0.0%
Other	1.5%	0.0%	0.3%	0.0%	0.3%	0.0%	0.3%	0.0%

FIGURE I

MAP OF KARNATAKA
DIVISIONS OF KARNATAKA STATE ROAD TRANSPORT CORPORATION (KSRTC)



Source: KSRTC

Legend:
BMTC: Bangalore Municipal Transport Corporation;
NWKRTC: North West Karnataka Road Transport Corporation
NEKRTC: North East Karnataka Road Transport Corporation

FIGURE II

TOTAL MONTHLY HOUSEHOLD INCOME, BY EXPOSURE

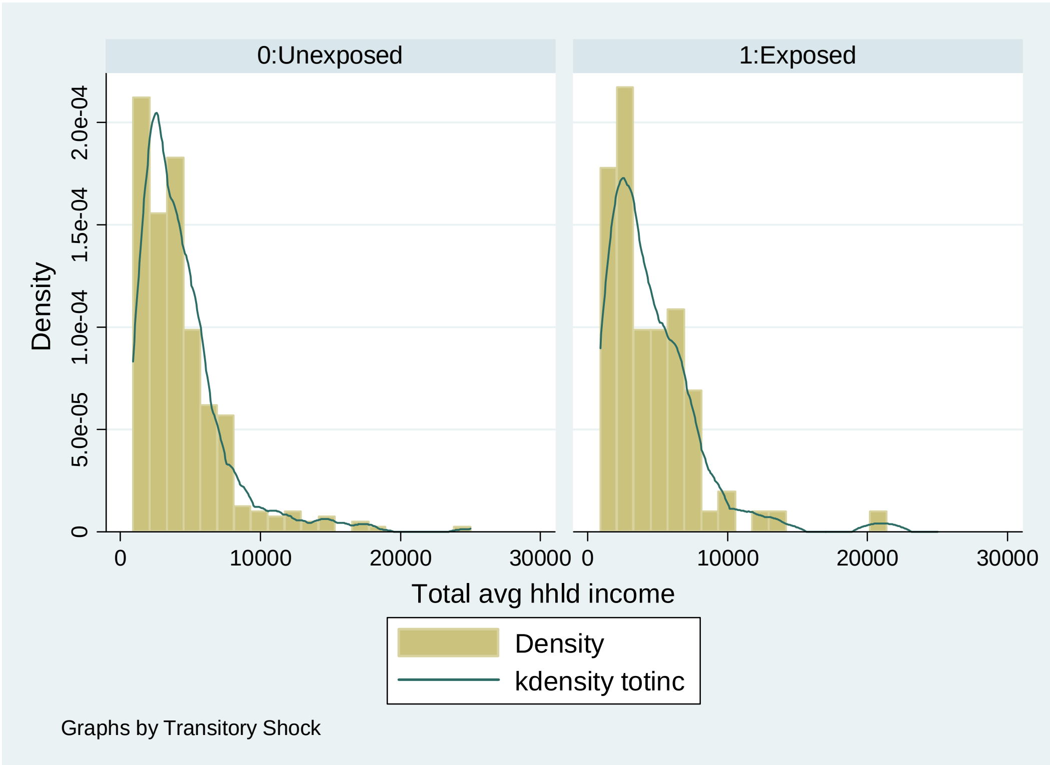


FIGURE III

SHARE OF HOUSEHOLDS WITH DEBT AND BORROWING IN PAST YEAR