CONSUMPTION SMOOTHING AND HOUSEHOLD RESPONSES: EVIDENCE FROM RANDOM EXOGENOUS HEALTH SHOCKS*

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Abstract

This paper presents new evidence of causal effects of health shocks on consumption smoothing, household assets and debt using a novel study design. The identification strategy relies on random exogenous health shocks suffered as passengers injured in a bus accident, with appropriately matched controls. Using household survey data, I find evidence of imperfect smoothing, with reductions in educational and festival expenditures. The principal mechanism employed by households to pay for health shock-related expenses is debt. In addition to having 6 times odds of having debt compared to the unexposed, exposed households have debt that was almost twice the size.

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SECTION 1: Introduction

While there is plenty of anecdotal evidence that describes the consequences of adverse health events, there is little empirical literature that has estimated the causal effect of heath shocks on economic outcomes. An important reason for this gap is the methodological challenge of endogeneity as a result of reverse causality that continues to plague the research on health and wealth: income levels affect health status, while health can impact earnings. Households with higher incomes can 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.

This paper relies on a uniquely innovate study design to get around the problem of endogeneity, comprising a random exogenous health event combined with a matched control design to estimate the effect of a health event on economic wellbeing. The identification strategy exploits the fact that exposure to a health shock in the form of being a passenger injured in a bus that met with an accident is completely random and exogenous. The second critical aspect of this study design is the enrollment of unexposed households by matching on age group, gender, geographic area of residence and bus routes traveled. Based on identifying well matched unexposed households, the study exploits the random exogenous nature of the health shock to estimate causal effects of the shock on consumption smoothing and household responses in terms of labor response, asset depletion and borrowing.

Health shocks are among the most common type of income shocks faced by households, especially in developing countries.[†] Health shocks are different from other income shocks, such as changes in rainfall, in that health shocks affect the individual's human capital directly. Partly due to the 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 argue in their recent book, 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.(Baeza and Packard 2006) 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. There are a few convincing studies that

[†] 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.

demonstrate causal effects of improvements in health status on labor and educational outcomes. Experimental studies on iron supplementation in Indonesia demonstrated improved labor participation and higher hourly earnings among those who received 120mg of iron every week for a year.(Thomas, Frankenberg 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.(Miguel and 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.(Sauerborn, Adams et al. 1996; Narayan, Patel et al. 2000; Krishna, Kapila et al. 2003) Much of the quantitative literature on ‘medical impoverishment’ comprises observational studies and cross sectional correlations between household expenditures, poverty levels and health expenditures. (Gottlieb 2000; Liu, Rao et al. 2003; Xu, Evans et al. 2003; Himmelstein, Warren et al. 2005; van Doorslaer, O’Donnell et al. 2005; Dranove and Millenson 2006) While these studies help document the potential extent of medical impoverishment, they do not provide causal estimates of any of the mechanisms through which the economic consequences of health shocks might cause poverty.

The bulk of economic research focuses on the associations between health shocks and household wealth / assets, consumption smoothing and labor supply. Previous efforts to estimate the effects of health shocks on wealth and assets have relied on the onset of new chronic illness (Smith 1999), serious illnesses (Smith 2003), Self Rated Health (SRH) (Hurd and Kapteyn 2003) and a variety of other health conditions (Adams, Hurd et al. 2003). While many of these papers show evidence 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 (Pitt and Rosenzweig 1986; Strauss and Thomas 1998; Smith 2003). 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.(Cochrane 1991; 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 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.(Gertler and Gruber 2002) Adam Wagstaff's recent paper also relies on two measures of health, hospitalization and BMI, that are particularly prone to endogeneity when estimating income or consumption effects of health.(Wagstaff 2007)[‡]

In this paper, I address one of the biggest gaps in this literature by presenting one of the first causal estimates of the economic effects of health shocks by employing a unique study design. I rely on the randomness of health shocks in the form of injuries sustained in bus accidents. Using a process of matching on age, gender, area of residence and bus routes traveled, I identify appropriately matched 'unexposed' individuals. Using data from the survey administered to the exposed and unexposed households, my analysis of the effect of this shock, which amounts to roughly two months' worth of household income, presents three key findings: (1) Households exposed to the shock 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 as a result of the shock. I also do not find evidence in support of labor supply responses to the health shock. (3) The principal mechanism that households rely on to pay for the 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.

[‡] For example, Wagstaff and Pradhan's 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. Wagstaff, A. and M. Pradhan (2005). Health Insurance Impacts on Health and Nonmedical Consumption in a Developing Country. World Bank Policy Research Working Paper Series. Washington DC.

The rest of this paper proceeds as follows: Section 2 introduces the theoretical model that I rely on to test for consumption smoothing effects of health shocks. Section 3 describes the study design and analytical methodology. Section 4 describes the data and presents the results from the empirical analysis of tests for consumption smoothing. I estimate the effect of the shock on household assets, labor supply and debt. Section 5 discusses the findings of this empirical research and concludes.

SECTION 2: Consumption Smoothing and the Permanent Income Hypothesis

One of the major challenges in empirically testing the Permanent Income Hypothesis[§] is that of separating the consumption effects of transitory income from the permanent income.(Friedman 1957). The following model, adapted from (Deaton 1997) and (Musgrove 1979), illustrates the method that has been traditionally employed in the literature and its limitation. Consumption of the household is expressed as a function of permanent income, transitory income and a vector of other explanatory variables such as household size and occupation. Total measured income (*Y*)* is the sum of permanent and transitory income, denoted by P and T as follows:

$$Y^{*} = Y^{P} + Y^{T} \tag{1}$$

Current consumption, denoted as C^*, can be expressed as a function of current income Y^* and X, a vector of household level variables:

[§] The 'permanent income hypothesis' (PIH) predicts that consumers, being forward looking and rational, form expectations of their long run income over a time horizon and can optimize the time path of consumption. A time horizon equal to a lifetime yields Modigliani's life cycle hypothesis, where individuals save during their working years and dissave in retirement Modigliani, F. and R. Brumberg (1954). Utility Analysis and the Consumption Function: An Interpretation of Cross-Section Data. Post-Keynesian Economics. K. K. Kurihara. New Brunswick, NJ, Rutgers University Press..

$$\begin{aligned} C^* &= f(Y^*, X) \\ C^*_{ht} &= \alpha + \beta Y^P_{ht} + \gamma Y^T_{ht} + \delta X^*_{ht} + \varepsilon_{ht} \end{aligned} \tag{2}$$

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

$$C^*_{ht} = \alpha + \beta(Y^*_{ht} - Y^T_{ht}) + \gamma Y^T_{ht} + \delta X^*_{ht} + \varepsilon_{ht} \tag{3}$$

$$C^*_{ht} = \alpha + \beta Y^*_{ht} + \delta X^*_{ht} + (\gamma - \beta) Y^T_{ht} + \varepsilon_{ht} \tag{4}$$

Since Friedman's permanent income hypothesis considers transitory income effects to be analogous to measurement error, the transitory income term in equation 4 gets absorbed into the error term. The estimation strategy in this case now depends on the identification of instruments that are correlated with permanent income, but not with transitory income. Clearly, the biggest challenge then is the identification of good instruments for permanent income that do not directly affect the propensity to consume in relation to transitory income. Some of the seminal empirical studies on consumption smoothing effects of income shocks employed instruments such as assets, education, lagged income, and long-run average rainfall. (Hall 1978; Musgrove 1978; Bhalla 1979; Musgrove 1979; Bhalla 1980; Wolpin 1982) While earlier work focused on identifying reliable instruments for permanent income, more recently researchers studying consumption and assets have focused on using instruments for transitory income shocks such as rainfall to test hypotheses of consumption and saving. (Paxson 1992; Kazianga and Udry 2006; Giles and Yoo 2007) The estimation of the consumption smoothing effects of health shocks in this paper employs an analogous strategy by identifying transitory health shocks in the form of injuries sustained in a bus accident.

SECTION 3: Study Design and Methods

3.1 Study Setting

The setting for this study is Karnataka, a large state in Southern India (estimated population 56 million in 2006), with Bangalore as its capital. 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 still 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 1: MAP OF KARNATAKA AND KSRTC DIVISIONS ABOUT HERE]

3.2 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 location of accident, bus route number, name, age, sex, address of passenger and compensation amount. In order to make the survey implementation more tractable, the list was then restricted to accidents that occurred 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 the road (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, given that the poor are more vulnerable to shocks as compared to the better off.(Morduch 1994) It is likely that the richer populations would travel in private or public luxury buses as compared to the local state run buses that the poor(er) sections of the population travel in. The latter types of buses are also older and might have lower safety levels as compared to the private luxury buses. I address this issue by focusing on KSRTC-run non-luxury buses that run on local rural routes. There are three advantages to such an approach. First, by restricting our 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 perused 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.[**] Using a conservative estimate of about 20% non-traceability I conducted power calculations and sample size estimations for 75 exposed cases, which indicated it would be necessary to enroll 300 unexposed cases. Based on this estimate, it was decided to enroll four unexposed for every exposed individual.

3.3 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 on. The geographic area of residence was used as a proxy for socioeconomic status and the bus route helped to account for any unobserved heterogeneity reflected in travel

[**] 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.

preferences. 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.

3.4 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. With a response rate of 78%, the final sample includes 84 exposed households and 336 unexposed (4 unexposed for each exposed case). All survey respondents were compensated Rs. 100 (approximately $ 2.50 in 2006) for their time. Data on household composition, assets, income, savings, consumption, health expenditures, health status, labor and other social variables were collected during the household survey.

3.5 Analytical Methods

The first step of the analysis is to verify that the matching strategy for identification of the unexposed group was successful. Since the matching was conducted using age-group, gender, 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 to verify the match. I then focus attention on the transitory health shock and present two sets of analyses, first to test for consumption smoothing and the second to explore mechanisms that households rely on to mitigate the effects of health shocks.

Using household expenditures on food, housing and human capital investments in terms of educational expenditures as dependent variables, I test for consumption smoothing in response to health shocks. I employ an analysis that relies on the exogenous health shock and other time-invariant covariates that are relevant in the model to directly test the effect of the transitory shock on consumption one year after the shock. Thus the empirical test of consumption smoothing would be to test that the coefficient for the transitory shock variable is different from 0. The estimating equation now can be written as:

$$C_{ht}^{*} = \alpha + \delta X_{ht}^{*} + \pi Y_{ht}^{T} + \varepsilon_{ht} \qquad (5)$$

where $\pi = \gamma - \beta$ in equation 4. An important reason why π can be estimated without bias from equation 5 is that Y^T is orthogonal to the omitted Y^* and to X as 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.

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 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 expenditures resulting from the health shock as well as other hospitalizations, out patient visits as well as chronic conditions. The educational spending regressions are restricted to households with any educational expenditure. 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 4: Data and Results

4.1 Data

Table 1 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 process, which was 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 the verifying variables, providing strong evidence that the matching was successful in identifying unexposed households that were socio-economically identical to the exposed group. Being a predominantly rural sample, most households had farming-related occupations. Total monthly income includes both primary and secondary sources of income.

[TABLE 1 ABOUT HERE]

Asset index scores were calculated using data on household assets and durable items, following the methodology employed in National Family Health Survey.[††] 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 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'*.

The survey also collected detailed information on other assets such as livestock, farm equipment, tractors, phone, jewelry and brass / copper pots. 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. 7358 (Approx $184, at Rs. 40 per USD). The mean ratio of shock to household income was 1.96 (SD 1.95).

[FIGURE 2: DISTRIBUTION OF INCOME ABOUT HERE]

Table 1 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 non-zero expenditures on education was similar among the two groups (52.5% among the exposed and 54.8% among unexposed).

The survey collected data on household debt in terms of total debts owed by households as well as money borrowed in the year after the accident. 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 remarkably close to the average size of the shock (Rs. 7358).

The physical injury caused by the health shock included injuries of varying severity. Table 2 describes injuries and health status of the sample in terms of self rated health (SRH) and disability levels. Most injuries were minor; only 7% of all 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 2 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.

4.2: Results:

Table 3 shows results from OLS regressions of household expenditures on food, housing, festivals, health and education on the health shock. [‡‡] Festivals, health and education are reported as annual expenditures as compared to food and housing, which 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 (VI), 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.

The regressions suggest imperfect consumption smoothing, particularly for educational spending and festivals. Food and housing consumption is unaffected by the health shocks. Not surprisingly, education level of the head of household, being correlated with socio economic status, is significantly associated with higher consumption. Controlling for household demographics, the exposed had festival expenditures that were lower by 9% as compared to unexposed households (given by $e^{-0.093}$ = 0.91 in the log linear regression). As a reference for the size of this effect, households with college or higher levels of education have festival spending that is 36% higher ($e^{0.311}$ = 1.36). 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

[‡‡] It is also possible estimate the consumption function in equation 4 using current income or instruments for current income following the methodology typically employed in the consumption smoothing literature. The key results from this estimation are similar to those presented in Table 3. For details see Appendix and Tables A1 and A2

spending among the exposed is significantly higher, since it includes expenditures incurred due to the health shock. The coefficient on the shock dummy translates into health expenses that are over 450% higher ($e^{1.710}$ = 5.53) than among the unexposed. This difference translates into an additional total health spending of Rs 11433 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.(Muralidharan and Kremer 2006) It is hence safe to assume that the educational expenditures are primarily for uniforms, books and stationary. The education expenditure models in columns 5 and 6 also include the share of school aged children in the household that were female to examine potential differential effects of the shock on female children. I do not find any evidence of education expenditures for female children being disproportionately affected. The results in column 5 suggest that, controlling for household demographics the shock has a significant effect, reducing educational expenditures among the exposed by 20% ($e^{-.277}$ = 0.80). The analogous model of educational spending presented the last column is a log-log regression that yields a coefficient that is readily interpretable as 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. The evidence from Table 3 indicates that households, faced with a health shock that causes expenditures worth two months of household 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 and statistically significantly impacted by the shock.

I also investigate the effect of disability on consumption smoothing using an alternate specification of the model, following Gertler and Gruber's use of disability measures. This specification aims to compare the consumption effects that would be estimated by disability measures with the estimates shown in Table 3. The results of the estimation using disability measures, shown in Table 4, are generally consistent with those of Gertler & 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%. 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 the shock, which caused a large increase in disability (doubled the proportion of those with severe disability, and 1.5 SD increase in average disability score) did not seem to affect food consumption. This raises the possibility that the effect of disability reported by Gertler and Gruber could be biased upwards due to reporting biases, endogeneity or even due to the possibility of lower marginal utility of consumption in disabled states.

[TABLE 4: EFFECTS OF DISABILITY ABOUT HERE]

4.3 Household Responses to Health Shocks:

Estimates of consumption responses in the previous section show that faced with an unexpected health shock that causes expenditures worth two months of income, households do not reduce food or housing consumption, and 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 use 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) (Kochar 1999). Households might resort to an autarkic consumption strategy where current consumption is financed by depleting savings or assets.(Rosenzweig and Wolpin 1993; Besley 1995) Alternately, households could borrow from formal or/and informal sources to smooth consumption.(Morduch 1995) The following sections examine these three mechanisms in relation to the health shock.

I find little evidence to support the labor substitution as a mechanism of coping with the shock. Only five unexposed households (1.5%) and two exposed (2.3%) reported a member (who was not employed earlier) started working in the last year.[§§] 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

[§§] 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.

intensive response with other members increasing number of hours at the same job, it is possibly underestimated. 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 5 shows that exposed individuals unable to work almost five days of the preceding 30 compared to half a day among the unexposed.

[TABLE 5 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 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 6 ABOUT HERE]

Table 6 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. The survey collected data on a wide range of sources which were collapsed into the column headings shown in Table 6 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 A3 showing the detailed breakdown into these subcategories is included in the Appendix.) Since households used multiple sources to meet expenses due to the health shock, the percentages in Table 6 add up to more than 100%. Another fact that is noteworthy from the above table 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.[***]

The key finding from the matrices in Table 6 and Table A3 is that most households faced with the health shock (over 70%) resorted to borrowing from a variety of sources: money lenders, friends, family members and employers. Asset depletion was a relatively uncommon method used by households to pay for treatment (less than 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. (Table A4 in appendix shows frequency of households that bought / pledged / sold *any* assets).

[***] 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.

Since the use of household debt to smooth consumption was one of the key hypotheses that this study aimed to examine, my survey collected detailed data on this topic. The survey included questions 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 3: 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% among 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 1). 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 7 reports findings from logit regressions of debt and borrowing on the health shock.. Columns I and V show the parsimonious models with univariate regressions, while Models II and VI include additional variables that are strictly exogenous. Models III, IV, VII and VIII introduce asset levels and occupation. While these could be potentially endogenous, the data from the survey show that none of the households sold, bought or mortgaged assets that could alter the asset index scores (see Table A4 in Appendix). Further, as mentioned earlier, there were no changes in labor participation status.

[TABLE 7: LOGIT REGRESSIONS OF DEBT ON HEALTH SHOCK ABOUT HERE]

For both household debt as well as borrowing in past year, 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 8 use a binary health shock, while all even numbered regressions use the log of the sum of all expenditures caused due to the health shock (including lost income). The dependant variables are log of amount of debt and amount of money borrowed in the past year.

[TABLE 8: OLS REGRESSIONS OF DEBT ON HEALTH SHOCK ABOUT HERE]

As evident in Table 8, 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 1, this effect can be restated as: A 10% (Rs 735) 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.

4.4: 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 health spending would yield coefficient close to 1. Controlling for age, sex, education, caste and household size, I find that the coefficient for the spending on the shock is 0.69 (t=3.17) and that for total health spending is 0.73 (t=3.56). These results lend further confidence to the finding that the principal mechanism that households rely on to meet the shock related expenditures is debt.

4.5: Limitations of this study

While this study is fortunate to not have to claim the usual disclaimer about not being able to make causal arguments as a result of endogeneity, it has three main limitations. The main limitation is that the health shock used here, injuries sustained in bus accidents, are not comparable with other illnesses such as heart diseases, diabetes or cancer. While that is incontrovertibly true, injuries are a leading cause of the global burden of disease. According to the 2002 estimates of the Global Burden of Disease study, injuries account for over 12% of the total DALYs lost due to illness.(WHO 2002) Road traffic accidents were the 8th most common cause of DALYs in 2002 and, according to WHO estimates, are expected to be the 4th highest cause by 2030. (Mathers and Loncar 2006) The health shock studied in this paper applies 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 the perspective of public policy. The second limitation is that the study was conducted in mostly rural areas of Karnataka in South India. Finally, the relatively small sample size limits my ability to further refine this analysis especially in terms of the effects among poorer subgroups.

SECTION 5: Conclusions and Discussion

This paper presents the first causal estimates of the effects of random exogenous 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: exposure to the health shock reduces educational expenditures by about 20% and festival expenses by 9%. 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 an income 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. (Townsend 1994; Morduch 1995; Ravallion and Chaudhuri 1997; Morduch 1999; Dercon and Krishnan 2000; Kazianga and Udry 2006) 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 as a result of high risk aversion can be severely detrimental to net welfare. Evidence in this paper supports

Chetty and Looney's argument that focusing attention on smoothing food consumption would detract from more important negative consequences of costly responses adopted by households in terms of reducing human capital investments and accruing large expensive debts.

The idea that households in developing countries use credit to smooth consumption is not new. (Eswaran and Kotwal 1989) What makes this response a costly strategy is that households borrow from informal sources at fairly high rates of interest (average rate was over 45% per year) and that this health shock leads to disability levels that are twice as high as among the unexposed population. Because increased disability can severely limit the potential to provide additional labor supply (the exposed lose 6 to 8 times as many days of work as the unexposed), it might take longer to repay the debt - making it an even costlier option. With limited options to increase labor supply, it is possible that increased borrowing might result in either 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 investments. Specifically, 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.

The findings presented in this paper can also inform the development and implementation of health insurance programs, especially in developing countries. One of the major challenges in the monitoring and evaluation of investments in health insurance programs is to identify the appropriate outcomes to measure the success of the insurance. Rates of utilization of services such as admissions, health outcomes and out of pocket expenditures are measures that are often used, but do not adequately capture the true effect of financial risk protection provided by insurance. The evidence in this paper suggests that household debt can be used as a sensitive indicator of financial risk protection to test the impact of health insurance. Finally, the large effects on household debt, along with the effects on consumption, make a strong case for investing in improving road safety.

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APPENDIX

Using instrumented current income for estimating consumption smoothing:

Given that current income is often endogenous and is measured with error especially in developing country (rural) settings, this errors-in-variables problem can be addressed by using predicted income as an instrument for current income. Before proceeding to develop the predicted income variable, I empirically test whether current income is indeed endogenous in this setting. This test is conducted as follows:

Current income Y^* is first regressed on variables included in the X vector of household demographic variables (health shock, age, sex of bus passenger, education, caste, and household size) in as well as other exogenous variables (Z) that are not normally included in equation A.1, but are correlated with current income. The exclusion restriction criteria are defined by the fact that exogenous variable in Z (URBAN/RURAL) does not appear in X in the estimating equations for consumption (4), and the assumption that they are uncorrelated with the error term μ in equation A.1.

$$Y_{ht}^{*} = \phi + \lambda_1 Z_{ht}^{*} + \lambda_2 X_{ht}^{*} + \lambda_3 Y_{ht}^{T} + \mu_{ht} \tag{A.1}$$

The residuals from estimating this equation are then included as an additional regressor in the OLS estimation of the consumption function to yield:

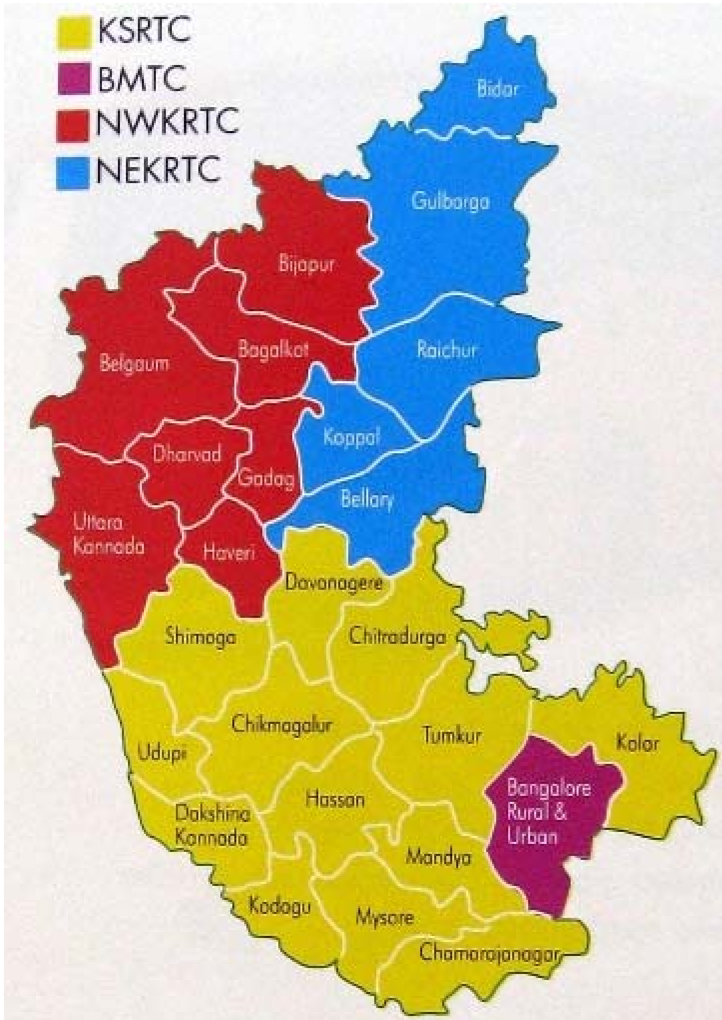
$$C_{ht}^{*} = \alpha + \beta Y_{ht}^{*} + \delta X_{ht}^{*} + \pi Y_{ht}^{T} + \theta \hat{\mu}_{ht} + \varepsilon_{ht} \tag{A.2}$$

The test for endogeneity of Y^* is then simply a test of the hypothesis that $\theta = 0$ using a t-statistic. The results in Table A.1 from estimating equations above show the t-test confirming that current income is endogenous in this equation and rejects the hypothesis that $\theta = 0$ (t-statistic = 2.31). Similar regressions were run for other consumption variables used in the paper and the t-test rejected all of them (Housing: 4.95; Festival: 4.25; Health: 1.90; Education: 2.97). Since there is only one additional exogenous variable in *Z,* we have no overidentifying restrictions that need to be tested.

Having confirmed that current income is endogenous, I use an instrumental variable regression, where the current income is instrumented with predicted income, using all the exogenous variables except household size in the *X* vector in the first stage regression (age, education, caste and sex). The second stage estimation is thus a regression of household consumption on predicted income, household size and the shock. The results of this IV estimation are shown in Table A.2. The coefficients on the shock variable do not change appreciably, although the t-statistics for the shock variable in the education regressions are now smaller.

FIGURE 1

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 2

TOTAL MONTHLY HOUSEHOLD INCOME, BY EXPOSURE

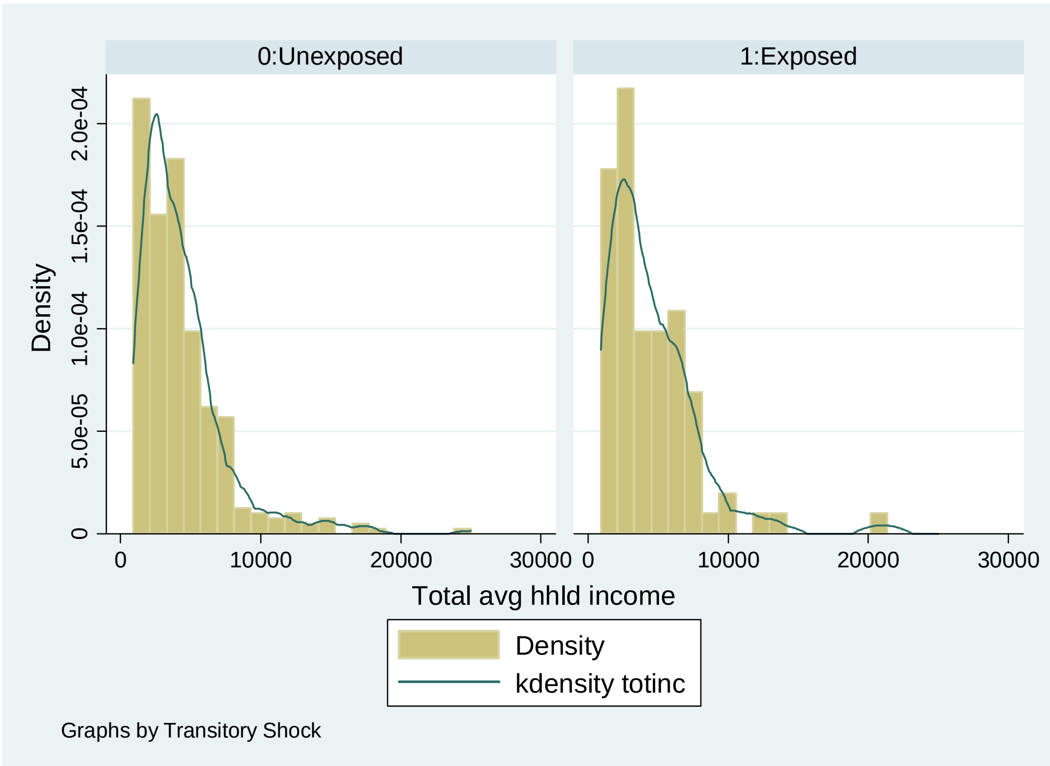


FIGURE 3

SHARE OF HOUSEHOLDS WITH DEBT AND BORROWING IN PAST YEAR

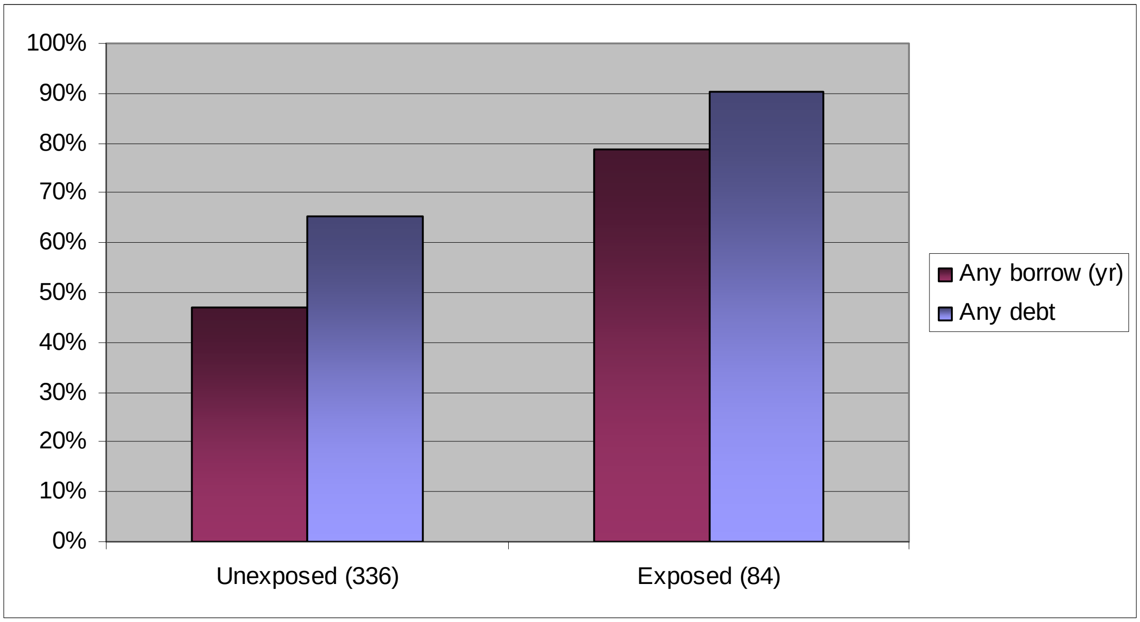


TABLE 1

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]	0.84
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.)**	7358 [774]	0	
Average KSRTC compensation	812 [59]	0	
Expenditures (Rupees)			
Housing	848 [75]	796 [30]	0.468
Food	1430 [88]	1351 [36]	0.415
Festivals (Annual)***	6904 [523]	7169 [260]	0.65
Health (Annual)***	3755 [410]	2327 [146]	0.001
Education (Annual)***	2276 [339]	2423 [269]	0.761
Bought assets in past year	22.78%	21.45%	
Sold Assets in past year	2.39%	2.40%	
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 2
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%	
One Serious / Two Minor	5%	10%	
Severe Disability	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 3

REGRESSION OF LOG HOUSEHOLD EXPENDITURES ON HEALTH SHOCK

	(I) Housing		(II) Food		(III) Festival		(IV) Total Health		(V) Education		(VI) 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**	**1.710**	**4.63**	**-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	-0.003	-0.78	-0.005	-0.81	-0.005	-0.80
Sex of injured	0.018	0.17	-0.179	-1.94	-0.225	-1.77	0.108	0.97	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	0.126	0.98	**0.337**	**2.06**	**0.337**	**2.06**
Middle School	**0.343**	**3.39**	0.143	2.02	0.051	0.5	0.207	1.67	0.179	0.99	0.177	0.97
High School	**0.593**	**5.50**	0.154	1.74	0.110	0.82	-0.123	-0.72	**0.804**	**3.63**	**0.812**	**3.68**
College and above	**0.896**	**7.95**	**0.259**	**2.33**	**0.311**	**2.01**	0.122	0.82	**1.115**	**4.91**	**1.110**	**4.83**
Caste	-0.215	-2.83	0.010	0.14	0.033	0.4	**-0.211**	**-2.31**	**-0.468**	**-3.46**	**-0.467**	**-3.44**
Household Size	0.035	1.27	**0.069**	**3.11**	0.014	0.5	**0.082**	**2.85**	**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%		453%		-20.0%			
Mean (Rs)	807		1368		7116		2524		2740		2740	
% Change * Mean	8.07		-27.36		-640.44		11433.72		-548.00			
N (Clusters)	420 (84)		420 (84)		420 (84)		404 (84)		201 (77)		201 (77)	

TABLE 4
EFFECTS OF DISABILITY ON CONSUMPTION

	(I) Housing		(II) Food		(III) Festival		(IV) Health		(V) 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**	**0.331**	**2.39**	0.002	0.01
Severe Disability	0.103	1.44	**-0.198**	**-3.06**	**-0.356**	**-4.67**	**0.571**	**6.3**	-0.022	-0.14
Age of Household Head	0.000	0.08	0.003	1.01	0.000	0.08	-0.007	-1.64	-0.005	-0.7
Sex	0.010	0.1	-0.165	-1.87	-0.200	-1.73	0.080	0.83	0.158	0.96
Education										
Primary School	**0.254**	**2.89**	0.048	0.76	0.080	0.9	0.132	1.1	0.332	1.95
Middle School	**0.352**	**3.51**	0.126	1.83	0.020	0.22	**0.249**	**2.04**	0.167	0.91
High School	**0.597**	**5.41**	0.148	1.69	0.098	0.75	-0.093	-0.52	**0.794**	**3.47**
College and above	**0.896**	**8.03**	**0.262**	**2.55**	0.309	**2.19**	0.185	1.31	**1.068**	**4.52**
Caste	**-0.206**	**-2.7**	-0.004	-0.06	0.004	0.06	-0.150	-1.82	**-0.453**	**-3.38**
Household Size	0.030	1.08	**0.079**	**3.54**	0.030	1.12	**0.065**	**2.27**	**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)		404 (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"

Including the exogenous shock variable did not change the estimates of the effect of disability. 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 5

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 6

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 7
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.	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
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 8
EFFECT OF HEALTH SHOCK ON AMOUNT OF HOUSEHOLD DEBT AND BORROWING

	Dependent Variable: Log Amount of Debt				Dependent Variable: Log Amount Borrowed Last Year			
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
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 A1
TESTING ENDOGENEITY OF CURRENT INCOME

Testing for Endogeneity of Income

	Equation A.1 DV: Log Income		Equation A.2 DV: Log Food Exp.	
	Coefficient	t-stat	Coefficient	t-stat
Residuals from A.1			**1.072**	**2.31**
Shock	-0.017	-0.34	-0.034	-0.99
Log Income			-0.405	-0.87
Age	0.000	0.05	0.002	1.16
Education				
Primary School	0.096	1.16	0.089	1.46
Middle School	0.118	1.41	0.196	2.41
High School	0.303	2.77	0.294	1.7
College and above	0.578	4.27	0.524	1.87
Caste	-0.104	-1.38	-0.038	-0.66
Sex	-0.171	-1.71	-0.242	-2.86
Household Size	0.035	1.28	0.085	4.05
Urban / Rural	0.177	1.79		

TABLE A2

REGRESSION OF CONSUMPTION ON SHOCK USING INSTRUMENTED CURRENT INCOME

	Housing		Food		Festival		Health		Education		Education	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Predicted Log Income	1.193	9.16	0.457	4.62	0.526	3.42	0.107	0.59	1.338	6.46	1.341	6.35
Household Size	-0.012	0.7	0.057	4.12	-0.003	0.13	0.069	2.31	0.168	3.52	0.169	3.51
Shock (0/1)	0.024	0.54	-0.017	0.53	-0.081	1.74	1.697	16.59	-0.225	-1.58		
Shock (Size)											-0.026	-1.56
Shock (**from Table 3**)	0.006	0.1	-0.025	-0.59	-0.093	-1.75	1.710	4.63	-0.277	-2	-0.029	-1.80

TABLE A3

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 A4

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%
TOTAL			21.45%	22.78%	9.26%	20.69%	2.40%	2.39%