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Natural Disaster and Sickness Shocks: Evidence of Informal Social Insurance from Bangladesh

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Abstract

Bangladesh is prone to large scale natural disasters with consequent impacts on human health and survival. In 1998, Bangladesh experienced the "flood of the century". Households exposed to flooding had major crop failure, suffered from various water-borne diseases, lost shelter, assets and ability to meet their basic needs. Based on multiple rounds of household survey data from rural Bangladesh collected after the 1998 flooding, this article investigate the factors that contribute to reduce sickness shocks after a massive natural disaster. Results indicate that social cohesion built on group-based microfinance programs may provide an informal social insurance mechanism to reduce sickness shocks. Simply put, households with stronger social bonds built on microfinance programs spend less for medical expenses in recovering from post-flood sickness shocks. Policy implications are explored in a developing country context, where sickness significantly impacts household welfare and no formal health insurance exists.

Keywords: Natural Disasters, Sickness Shock, Informal Social Insurance, Social Capital**.**

JEL Classification: Q540, Z130, G220, I380

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Bangladesh, one of the world's poorest countries, is prone to large-scale natural disasters with consequent impact on human health and survival because of its geographical location and topographical features (WHO 2004).1 By one estimate, Bangladesh is at risk of being inundated over at least 10% of its land mass within the first half of this century, due to predicted rises in sea level as a result of global climate change (UNDP 2001). Poverty, demographic pressure and rapid urbanization are forcing a vast majority of people to migrate to high risk areas (e.g. flood plains and islands), which are very vulnerable to human settlement. Bangladesh, like many other developing countries, does not have any major public health insurance program. While the government's allocation of resources to the public health care system is generally considered to be grossly inadequate, it is also argued that the allocated money is not spent effectively (Chaudhury and Hammer 2003). The combined effect leads to the dismal performance and quality of the health sector in Bangladesh. The frequency of disaster events combines with increasing human vulnerability resulting from demographic pressure, poverty, inequality and underdevelopment to worsen the situation. The degree of post-disaster recovery is significantly affected by the incidence of sickness (Hossain 1990).

In 1998, Bangladesh experienced the "flood of the century." Households exposed to flooding had major crop failure, suffered various water-borne diseases, lost shelter, assets and the ability to meet basic needs. Based on multiple rounds of identical household survey data from rural Bangladesh, collected after the 1998 flooding, this article investigates the factors that contribute to reduce sickness shocks after a massive natural disaster. Results show that the burden of medical expenditures due to flood-related sicknesses is significantly higher for poorer households, and for households more exposed to flooding. More positively, econometric results indicate that social cohesion built on group-based microfinance programs provide an informal social insurance that reduces sickness shocks. Households with stronger social bonds spend less for medical expenses in recovering from post flood sickness shocks. The policy implication of this finding is explored in a developing country context where sickness significantly impacts household welfare and no formal health insurance exists.

Ill-Health: The Economic and Social Dimensions

The economic costs attributable to illness shocks are significant and cause large welfare losses to households, especially in developing countries.[2] For example, from analysis based on Tanzanian household survey data, Dercon and Weerdt (2002) show that an illness shock event reduces a household's overall consumption. Specifically, households reduce their non-food consumption by 30% and the risk against such shocks is not fully shared even within smaller closely-knit village networks. Jiang, Asfaw, and Braun (2004) report that the share of economic costs of illness as a proportion of household income is quite high in rural China (29%). They find that illnesses in the household adversely affect basic food consumption and induce poverty in some instances.

Asfaw and Braun (2004) argue that the direct and indirect impacts of illness and its unpredictability, coupled with the absence of formal health insurance schemes and rampant poverty, can greatly affect the stability of household consumption. Asfaw and Braun (2004) study the impact of illness on consumption of the Ethiopian households and their risk sharing ability against health shocks. Asfaw and Braun (2004) show that illness has negative impacts on the stability of consumption, and that a household's risk sharing ability varies across different consumption items. They show that change in the household head's health status from a healthy to unhealthy state reduces weekly purchased food consumption by 24% and non-food consumption by 28%. Pandey (2001) finds that illness reduces the labor supply of households and imposes the additional burden of medical expenditure. Pandey (2001) also shows that households experiencing illness face more constraints in making production choices.

All these factors put the poor in a greatly disadvantaged position for coping with sickness shocks. Poor health is exacerbated by poverty, and is aggravated by the lack of access to health services. In many cases, diseases are the result of their poor living conditions. Illnesses that afflict the poor include infectious and parasitic diseases that result primarily from physical environment due to exposure to vulnerable ecology, environmental contaminants, low quality foods, contaminated water, and lack of access to preventive health care. Stillwaggon (1998) argues that health is primarily an economic problem (rather than a medical problem) as the market rations medical care to the rich. In contrast to investigating economic factors, the social and community dimensions of health status are relatively under-investigated (Kawachi et al. 1997; Kawachi, Kennedy, and Glass 1999). However, academic researchers are increasingly turning their attention to this issue.

Berkman and Syme (1979) analyze the relationships between social and community links and mortality in Alameda County, California. They find that persons with weak or nonexistent social links had a greater probability of dying than those who had strong links. Kawachi et al. (1997) investigate the relationships between income distribution, mortality and social capital by using General Social Surveys and the US census data. They establish a relationship between civic participation and the mortality rate and state that communities with the highest rate of civic participation had the lowest rate of mortality from heart disease and malignant tumors.

While few studies have succeeded in showing, that there are direct relationships between social status (measured by trust, civic participation and networks) and health, the mechanisms underlying these links are not well-understood. However, increasing levels of consensus argue that a better social and economic situation goes hand in hand with better health and the relationship between socio-economic status and health exists (van Kemenade 2002). Social cohesion is built on shared values and norms, shared challenges and opportunities based on a sense of trust, hope, and reciprocity. Exploring the links between health status and social cohesion are one of the emerging concerns in the field of social epidemiology and medical sociology (Kawachi et al. 1997; Kawachi, Kennedy, and Glass 1999; Wilkinson 1999). Since a large number of literatures argue that group based microfinance fosters social capital, (Anderson and Locker 2002; Larance 2001), it is pertinent to explore how microfinance programs affect health outcome. In this direction, Gertler, Levine, and Morreti (2001) study the role of microfinance programs in helping families to insure consumption against illness. In Indonesian context, they find that access to micro-financial savings and lending institutions support families to ensure consumption against illness shocks.

Microcredit Programs in Bangladesh

The microcredit program initiated by the Grameen Bank is a major innovation in the credit delivery system for the poor people (Hung 2003).[3] In offering credit to the poor, it has largely replaced the traditional system of physical collateral requirement with group responsibility (the group members are mutual granters of each other). The successful model of group-based credit delivery system encouraged many NGOs to introduce similar programs. A large number of microcredit programs are operating in Bangladesh to help fight against poverty; there are now over 7,000 NGOs, widely known as Microfinance Institutions (MFIs), serving sixteen million poor people with an annual turnover of around US $2.5 billion (GDRC 2000).[4] Microcredit plays an important role in alleviating rural poverty in developing countries (Morduch 1999).

Microcredit programs are designed to offer small amount of loan (usually ranges from 20-200 US$) to poor people for generating income through self-employment projects (e.g. for buying sewing machine, livestock and cattle rearing, poultry, small business etc.). Women members are given a priority in offering the credit. To obtain credit, a borrower must form a group with other borrowers and repay the loan in weekly or biweekly installments. The borrowers create a group fund from the savings of the group members. Some MFIs also have provision of individual savings in addition to group savings. The group savings are used to make up installments in case any member defaults to repay. The loans are mainly disbursed by non-profit organizations with a mandate to serve the poorest (Microcredit Summit 1997). A number of MFIs emphasize on clients' human capital accumulation through providing health and education related services. They also emphasize building social capital through the creation of leadership skills and the formation of groups (Elahi and Danopoulos 2004).

Microcredit Programs and Social Capital

Anderson, Locker, and Nugent (2003) note that the Microcredit scheme fosters social capital, which could be effectively utilized in managing various common-pool resources (e.g. irrigation systems, fishing pools, grazing lands and forests).[5] The innovative design of group lending in microcredit scheme reduces information asymmetry through self selection process. It reduces the possibility of moral hazard and adverse selection and promotes group homogeneity which in turn develops a strong network of trust and reciprocity through sharing knowledge and information and through cooperation in repaying the loans. In this way the joint liability scheme in microcredit program reduces the cost of cooperation and collective action. It also changes the discount rate between present and future in addition to changing borrowers' financial and human capital (Anderson, Locker, and Nugent 2003). Sharma and Zeller (1998) explore how group characteristics significantly affect risk pooling benefits of groups and their loan repayment performance. In the microcredit program the group dynamics get reinforced through regular mandatory group meetings (Rahman 1999). A number of studies (van Koopen and Mahmud 1994; Mahmud and Huda 1998) report that credit- based group formation and its operation influence a variety of economic and social outcomes (e.g. income rise, school enrollment, family planning, mutual support, self esteem etc.).

Anderson, Locker, and Nugent (2003) argue that group lending technique used in microcredit program affects the stock of social capital in a number of ways: by drawing upon existing social capital, creating new social capital and bridging the disaggregated stock of social capital.[6] A number of theoretical studies have analyzed how microcredit scheme use existing social networks to reduce the transaction costs (Besley and Coate 1995; Varian 1990; Stiglitz and Weiss 1981). Ostrom (1992) argues that microcredit framework can lower the costs of crafting new rules and add to the stock of social capital. It not only gears up the effectiveness of existing stock of social capital but also enhances the stock of social capital through joint liability and through following up the practice of shared norms and values through mandatory regular group meetings. Schrieder and Sharma (1999) view that microcredit has the potential to enable collective action and to promote sustainable-community based organizations. Ostrom (1994) also notes that it takes effort and energy to generate social capital. The microcredit program which requires regular meetings, repeated interactions and sets common credit goals can facilitate sharing of information, knowledge and incentives for cooperation and collective action. Van Bastelaer (1999) holds the view that social capital is generated when an NGO requires all members to engage in similar norms and behavior (e.g. repeating decisions in group meetings conducted by Grameen Bank branches). Mondal (2000) describes how NGOs in Bangladesh play an instrumental role in building social capital through group formation.

Ostrom's (1990) view is that there is a basic difference between those who have broken the shackles of a commons' dilemma and those who have not. She also notes that "participants may simply have no capacity to communicate with one another, no ways to develop trust, and no sense that they must share a common future" (Ostrom 1990, p. 21). Anderson, Locker, and Nugent (2003) add that a stronger community network among microcredit borrowers may lead to agreements about sharing arrangement to manage natural resources. Along the same line, the stronger network among microcredit borrowers can be used to foster cooperation in times of distress or shocks created by natural disasters. Here, I argue that enhanced social capital generated through group lending and group meeting can be effectively used in reducing sickness shocks caused by natural disaster.

Social Capital and Health

More than a century ago, Durkheim (1895, 1982) concluded that the lowest rate of suicide occurred in societies with the highest degrees of social integration, and excess suicides occurred in societies undergoing various forms of dislocation and loosening of social bonds. Durkheim (1897, 1951, p. 210) held the view that in a cohesive society "mutual moral support which instead of throwing the individual on his own resources, leads him to share in the collective energy and supports his own when exhausted". A cohesive society is characterized by a higher stock of social capital. Commonly, social capital is generated as a by-product of various social interactions in stead of a result of conscious investment by the members of a society. A number of studies attempt to link social isolation and poor heath outcomes. Kawachi and Berkman (2000) investigate the pathways through which social capital affects the health outcomes. They outline three channels through which social capital could affect individual health. These are: (1) by influencing the health related behavior, (2) by influencing access to services and amenities and (3) by affecting psychological processes.

Health outcomes achieved through these channels are termed as non-market behavior in the healthcare policy literature. Non-market health outcome are obtained through reciprocal exchange of information, medicine, loans to cover medical expenses, networks of personalized contracts with health workers and doctors, nursing and sharing the workload for those who fall ill (Sauerborn, Adams, and Hien 1996; Moser 1998). Mackintosh and Gilson (2000) state that this types of non-market behavior that provides mutual insurance against illness plays an important role especially in low and middle income countries. They illustrate the notion of mutual insurance into three categories: (1)

individualized exchange, (2) contribution to building a common pool resource (of mutual help) in return for access to it, and (3) contribution to looser networks of reciprocity. Gregory (1982) argues that the exchange of mutual insurance is built on social relations of dependence and obligation and sustain when embedded in other non-market relationships. The joint liability framework in the group lending technique can effectively provide the glue to sustain the mutual insurance scheme. The voluntary mutual insurance is hard to sustain just on the basis of ethical commitment especially in the presence of social and income inequality (Giridhar 1993). In contrast, the group lending framework divides the heterogeneous community into homogeneous groups to establish the social bond non-market reciprocity.

A Theoretical Framework of Mutual Insurance under Joint Liability

Especially in developing countries, group lending by NGOs has been attributed to the institution's ability to mitigate asymmetric information problems in credit markets. Previous research has investigated a number of hypotheses to explain the success of group lending in recovering loans. Social ties between borrowing group members, internal group pressure to repay loans, and peer monitoring are highlighted. For instance, Stiglitz (1990) has explored the role of joint liability among individual borrowers of microcredit and has shown that since the liability is joint, borrowers have an incentive to monitor one another's behavior. In addition to monitoring, under a group lending program, a group of persons can benefit from a mutually advantageous course of actions. Such actions include providing mutual insurance through reciprocal exchange of information, medicine, loans for medical expenses, networks of personalized contacts with health workers and doctors, nursing and sharing the workload for those who fall ill.

To model mutual insurance under a group-based joint liability framework, consider a strategic default model introduced by Rai and Sjostrom (2004). The borrowers observe each other's situation, performance and output realizations. To induce repayment, the NGO punishes the borrowers who default on repaying. Following Rai and Sjostrom (2004), first assume that punishment (e.g. denying loans in future) is a deadweight loss. Second, assume that borrowers honestly put their effort in producing output and repaying the loan if they succeed (free from moral hazard).[7] However, failure in producing output may occur due to sickness, if the borrowers cannot work in their self-employment-based project. Third, assume that sick borrower can recover from sickness if the non-sick borrower timely reacts and provides mutual insurance to the sick borrower.[8] Fourth, assume that there is a cost involved in providing mutual insurance, which can be denoted as m.

When a borrower gets sick and fails to produce enough output and repay the installment on her loan, she receives a very low pay-off unless a non-sick borrower steps in to help her to recover from sickness. All agents are better-off ex ante if non-sick agents can be induced to help the sick agents to recover. In this sense, mutual insurance is efficiency enhancing. Since, punishment is assumed to be a deadweight loss, the NGO is also better-off by inducing borrowers to help each other in times of sickness. Under a joint liability framework, the borrowers in a group are made liable for each other's repayment. The NGO punishes the whole group if any member fails to repay. The collective punishment must be sufficiently harsh, so that a non-sick group member will have an incentive to help recovering the sick member.

To illustrate, we can first introduce a simple 2X2 prisoners dilemma type game among two borrower *i* and *j*. The borrowers face two states of world *Sick* and *Not Sick* with equal probability. To keep the game simple, assume that a borrower (*i, j*) earns a net benefit pay-off, *b* if she is not sick and –*b* if she is sick. As shown in figure 1a, under individual liability there is no incentive for a non-sick individual to cooperate and provide mutual insurance to the sick borrower. However, under joint liability (figure 1b) the ultimate pay-off of both borrowers is a weighted average of individual pay-offs. Assume the simplest case of equal weight to obtain the weighted average pay-offs as shown in figure 1b. As reported in figure 1b, when one agent is sick (the weighted average pay-off is 0 for both players), the other agent will cooperate (if she is not sick too) to overcome sickness (leading to a weighted average pay-off of *b* for both players) as long as the cost of providing mutual insurance, $m < b$.

Note that under the joint liability framework of a group-based lending contract, when both of the borrowers get sick they cannot help each other to recover and both may fail to repay and the punishment is imposed. Since punishment is a deadweight loss, in that case a simple joint liability framework is not efficient. However, Rai and Sjostrom (2004) propose adding a cross-reporting component to overcome this shortcoming.[9] In the cross-reporting framework, if any member defaults, borrower *j* gets punished only if borrower $i \neq j$ complains about borrower *j*. This framework allows the sick borrower *i* to threaten the non-sick partner borrower *j*: "help me to recover from sickness, otherwise I will fail to repay my loan and I will complain that you refused to help me out and they will impose a harsh punishment on you (but not on me)." The threat induces the non-sick borrower to help the sick borrower to recover from sickness. In the case where borrower *i* and j both get sick, borrower i cannot gain anything by using the threat of complaint. Thus, in equilibrium no threat is made and no punishment is imposed. There is a possibility that borrowers may collude against the NGO to defer the repayment. However, this is not an attractive option to the borrowers since deferring increases future repayment burdens. There might be a case where borrowers i and j submit false complaints each other. In practice, since most group-lending schemes comprise slightly more than two borrowers (usually around 5), the NGO can feasibly cross-check.

The model provided by Besley and Coate (1995) can be used to show mutual insurance under the joint liability with cross reporting framework. Consider a group that has two identical borrowers 1 and 2. The group is granted 2 equal units of a loan, one for each borrower. The borrowers are under a joint liability contract and guarantee each other's loan. Both borrowers invest the loan in their projects and the returns are independent. The returns of the projects are θ_1 and θ_2, respectively for borrower 1 and borrower 2. The amounts to be repaid (including interest) at the end of the period are r_1 and r_2, respectively for borrower 1 and 2. The NGO imposes punishment only if a borrower complains of non-cooperation against the other. The penalties imposed on the borrower 1and 2 are P_1 and P_2 both of which are at least as high as the joint repayment ($r_1 + r_2$). The extensive form of the game is provided in figure 2.

When both borrowers fall sick, they cannot gain anything by complaining. So no complaint is made and no penalty imposed and both get 0 pay-off. When both are non sick, they make the repayment and the pay-offs are $\theta_1 - r_1$ and $\theta_2 - r_2$, respectively. Now, say, borrower 1 is on the verge of failure due to sickness. Borrower 2 can cooperate and provide the mutual insurance, which costs her m, or she can defect. If she decides to cooperate her pay-off will be $\theta_2 - r_2 - m$, and if she defects her pay-off will be $\theta_2 - P_2$. Since $P_2 \geq r_1 + r_2$, borrower 2 will cooperate as long as $r_1 > m$. In that case, providing mutual insurance is the best strategy for both players (since for borrower 1, $\theta_1 - r_1 > 0$).

It is critical to note that in offering microcredit NGOs use the dynamic incentive framework. That is they start from a small amount of loans and issue higher amount of loans subsequently. So the higher the number of loans a borrower receives, the larger the amount of loan and associated repayment to be paid at each installment. Thus the higher the repayment of borrower 1 (r_1), the more likely she receives the mutual insurance (also at a larger amount) from borrower 2 (otherwise borrower 2 is penalized by a higher amount). If that is the case, then the implication is that the higher the number of loans any borrower receives under such an incentive framework, the lesser the amount of medical expenditure she will have to cover.[10] The issue is whether there is empirical evidence to support this theoretical proposition. In the empirical section that follows, we attempt to explicitly test for the absence or presence of such evidence.

Data and Empirical Specification of Incidence of Sickness Shock

The empirical analysis presented here is based on the International Food Policy Research Institute's Food Management and Research Support Project (IFPRI-FMRSP) Household Survey of 1998. The data was collected from 757 households in rural areas in Bangladesh at three points in time over a period of a year between November 1998 and December 1999 following the flood. The survey was conducted to understand the coping strategies adopted by the households to recover from the shock caused by massive flooding. The first round of data collection took place between the 3rd week of November to 3rd week of December 1998, two months after the receding of floodwater. The second round for the data collection was carried out between April and May 1999 and the third round of data collection was taken place in November 1999, exactly a year after the first round. To get a fair representation of the parts of the country affected by the flooding, 757 households in total were selected from seven flood-affected *thanas*.[11] Then a panel data set was constructed based on survey responses that included households' incomes, consumption expenditures, medical expenditures, assets, inter-household transfers, credit availability, and other household level characteristics including household level flood exposure. Household level flood exposure was measured by an index based on (1) the maximum depth of water in the homestead, (2) the maximum depth of water in the house, and (3) the numbers of days the water stayed in the house.

We estimate the following equation of incidence of sickness shock

$$HHMEDIEXP_{ht} = \alpha + \beta\, HHFLEXP_{ht} + \chi\, X_{ht} + \gamma\, SC_{ht} + \delta(D_t) + \varepsilon_{ht} \qquad (1)$$

where, the subscript *h* denotes the household and *t* denotes the time period. Thus $HHMEDIEXP_{ht}$ represents medical expenditures (includes cost of medicine, counseling, hospital charges and cost of conveyance) of household *h* at time *t*. The variable $HHFLEXP_h$ represents an index of household flood exposure and X_h is a vector of household or household head's characteristics (e.g. household size, age, sex, dependency ratio, years of schooling, body mass index, asset, current earnings, gift received by the household etc.). SC_h represents the level of stock of social capital a household holds. Here we measure the stock of social capital (i.e., the strength of its social network) by number of loans received from NGOs. D_t represents a time-specific dummy and ε_{ht} is a time-corresponding household-specific stochastic error term capturing the unobservable components affecting household medical expenses.

While estimating household medical expenditure, we test a number of specific hypotheses. First, we investigate whether household level flood exposure affects their medical expenditure. Against the null ($H_0; \beta = 0$), we test alternative hypothesis $\beta \neq 0$. Second, we test whether any household characteristics affect medical expenditure (whether $\chi \neq 0$ against the null, $H_0; \chi = 0$). Third, we test whether social capital impacts medical expenditure. Thus, against the null ($H_0; \gamma = 0$), we test the alternative hypothesis ($H_0; \gamma \neq 0$). In this case, $\gamma < 0$ implies that social capital reduces medical expenditure.

Results

Full definitions of the variables and associated descriptive statistics are provided in table 1. In table 2 we present the regression results for the estimated household medical expenditure equation. From random-effects panel generalized least square (GLS) regression estimates, we see that medical expenditure across household is determined by a host of factors.[12] In table 2, the estimated coefficient of *HHFLEXP* is positive and significant (at 1% level) in models 1 to 7. This indicates that households more exposed to flood had higher medical expenditures than households less exposed to flood. Thus the finding supports the first alternative hypothesis ($\beta > 0$).

However, results may be due to unobserved heterogeneity at the household level. We control for such possibilities by including variables that represent variations at the household level. Household medical expenditure is highly sensitive to household size (*HHSIZE* is significant at 1% level in models 1 to 7 in table 2). The positive sign of the coefficient of *HHSIZE* implies that bigger households had to spend more to recover from flood related sickness shocks, which is very usual. The education level of the household also influences household medical expenditure. The coefficient of *EDUC* is significant (at 5% level) and positive in models 1 to 7 in table 2. This implies that the more educated the household head, the larger the medical expenditure. In addition to health consciousness argument (Strauss and Thomas 1995), the finding can be linked to human capital argument that education raises the opportunity costs of sickness (Schultz 1984). Thus educated households spend more to protect them against sickness shocks.

A number of statistical control variables are included in the analysis. The variables *AGE* and AGE^2 are included in the regressions to rule out the possibility that the observed result is simply due to the age structure of the household members. We also include a household dependency ratio (*DEPEND* is defined as the number of dependents as a ration of the number of working age members) variable to control for the number of dependents in the household who may be more vulnerable to flood-related sickness. Sex of the household head (*SEX*) is included to see if there is any gender bias in dealing with household sickness shock. Additionally, households with good nutritional status may be less prone to flood related sickness; thus, average body mass index of household members (*BMI*) is included.[13] However, as shown in table 2, none of these control variables significantly affect household medical expenditures.

One of the variables of prime interest in this study is NGO_{LOAN}, which represents the number of loans received from NGOs. The variable, NGO_{LOAN} is considered as a measure of the stock of social capital. The estimated coefficient of NGO_{LOAN} is significant (at 5 to 10% level) and negative in models 1 to 7 in table 2. That is, the higher the stock of social capital a household has the less money it spends on medical expenses to recover from post flood sickness shocks. The finding provides some evidence of mutual informal insurance among the group members who borrow money from NGOs.

Since the NGOs lend money to the groups under a joint liability framework, the group members have an incentive to help each other to recover from sickness. Also, since the NGOs use a dynamic incentive mechanism for issuing subsequent loans, higher number of loans implies higher amounts of repayment to be made as installments. As outlined in the theoretical section, higher amounts of repayment of the sick borrower put a larger burden of punishment on the non-sick borrower if she does not cooperate. This provides incentives to provide higher amounts of mutual insurance by the non-sick borrower to the sick borrower to avoid the punishment. This in turn reduces the burden of medical expenditure on the sick household. Thus the negative coefficient of NGO_{LOAN} (γ in equation 1) supports the third alternative hypothesis. Specifically, social cohesion built on group-lending provided by the NGOs tends to reduce the household medical expenditure.

It is important to note that this study deals with a special situation of major flooding that caused huge economic shocks due to crop failure, income and asset losses. Post flood sickness shocks further aggravated income shocks to the affected households. These factors, in addition to the covariate nature of massive flooding, would be expected to limit the scope of cooperation and mutual insurance (Pitt 2004). However, we find that even in the case of a large scale natural disaster a microcredit program is effective in reducing the burden of sickness shocks. By inference, the strength of this instrument may be higher if the disaster is not largely covariate and damages not so severe.

We also control for some other household-level variables (*INCOME*, *ASSET*, *GIFTR*) to see if they significantly affect household medical expenditures. Results indicate that the estimated coefficient of *INCOME* is negative and significant (Models 4, 5, 6, 7 in table 2). This finding implies that the burden of medical and health expenditures is significantly higher for poorer households. In other words, richer households can substantially avoid sickness shocks caused by flooding. The estimated coefficient of the ASSET variable is not significant. The variable *GIFTR* (measuring inter-household private transfer) was included as it is sometimes argued that sickness is likely to drive gifts and private transfers in the household (Petrova 2004). However, there is no evidence to support this argument in this case.

A question in any empirical investigation is how stable are the key conclusions to a variety of econometric modeling issues? To check the robustness of the results, we examine the full set of models presented in table 2 under a number of alternative econometric modeling approaches to handle censoring, potential autoregressive errors, and potential selectivity and endogeneity bias. Results are reported in tables 3, 4 and 5.

First, we run all the models reported in table 2 with a TOBIT specification. Since the dependent variable (*HHMEDIEXP*) has numerous zero observations we set the lower censoring limit at zero. Results are reported in table 3 and are largely similar to those in table 2.[14] Second, we re-estimate the models of table 2 allowing an autoregressive error process and report the results in table 4.[15] Since there are multiple rounds of household survey data, the current level of household medical expenditures can be influenced by that of previous round. If this is the case, then assuming that the errors of household medical expenditure equation (ε_{ht}) are iid may lead to biased estimates. Assuming an AR(1) error process can control for this potential bias. As shown in table 4, similar results are found after controlling for potential bias through the AR(1) error structure and using the same econometric specification (random-effects panel GLS). The implication is that results are robust across different specification of the error process. Third, the number of loans received from NGOs (NGO_{LOAN}) may be subject to selectivity and endogeneity bias. Note that in table 2 there are a number of variables (*AGE*, AGE^2, *DEPEND*) that do not significantly affect household medical expenditures but may explain the variability of NGO_{LOAN}, given the nature of microcredit programs. So using these variables we instrument the NGO_{LOAN} variable and run a random-effects two stage panel GLS (G2SLS) model. Both first and second stage results are reported in table 5.

The first stage regression results in table 5 show that *AGE*, AGE^2, *DEPEND* significantly affect NGO_{LOAN}. A family with proportionately more dependents (household members below or above the working age of 15-64) is less attractive to other households to form a group. A large household (*HHSIZE*) is also seen to be less attractive to be selected to collectively form a group. Average age composition of households (*AGE*, AGE^2) also significantly affects the number of loans received from NGOs. The coefficient of *AGE* is positive and significant. Higher average age, an observable characteristic that signals a household's potential of supplying adequate labor into credit-based projects, makes the household more attractive to be selected by other group members. However, as age gets too high, it acts as a negative signal of household labor productivity (revealed by the negative and significant coefficient of AGE^2). The *INCOME* variable is found to be significantly explaining the variability of NGO_{LOAN}. Socially well-connected households that receive more gifts and private transfers (*GIFTR*) are less likely to demand NGO loans. Household flood exposure (*HHFLEXP*) also shows some evidence of increased demand of NGO loans. In first stage regression, we also control for heterogeneity of nutritional status across households (*BMI* is included in model 2, table 5) since households more prone to illness may spend a lot in health expenditure and may not be selected by other households to form groups to receive loans. The economic and demographic characteristics as a determinant of number of loans received from NGOs are consistent with the self-selection process discussed in the microcredit literature (Morduch 1999).

In table 5, the second stage regressions, even after controlling for these potential factors that contribute to the variability of NGO loans across households, the NGO_{LOAN} variable is still negative and significant (at 5 to 10% level) implying its role on household medical expenditure. The coefficients of *HHFLEX*, *HHSIZE*, *EDUC* are significant and positive (in models 1 to 5 in table 5), confirming the basic results reported in tables 2, 3 and 4.[16] Lastly, a few alternative hypotheses may be considered from the finding reported here. First, if there is a pressure for repayment, members will not be able to spend much on medical and other household expenditure. We create another dependent variable (*PROPORTION*) dividing household medical expenditure by monthly household expenditure and run similar TOBIT regressions in order to control for the potential effect of the budget constraint on household medical expenditure. As reported in table 6, results confirm the previous findings. Another alternative hypothesis is that households that receive more loans may become efficient in spending money in medical expenditures. However as a counter argument, it can be said that social capital built through NGO loans may also contribute to enhanced health awareness and efficient use of medical expenditures. While many other potential underlying factors like this is difficult to tackle with the available data, future research can address these issues through careful design of survey questions.

Discussion and Conclusions

The strength of group-based microcredit in coping with natural disasters is yet to be fully explored. Recently, Pitt (2004) provides a basic template for exploring the pathways through which microcredit programs can be an effective tool for dealing with natural disasters. However, consideration of such a template still lacks a body of empirical investigations. This study is an attempt to begin to fill that gap. Empirical results indicate that social capital as developed or reflected through group lending has a significant impact in reducing the burden of medical expenditures caused by flood-related sickness shocks. Pitt (2004) notes that the informal arrangements facilitated by microcredit may not be effective in the case of a large-scale natural disaster that creates a covariate shock. However, even in the case of a large-scale natural disaster (e.g. 1998 flooding), social capital developed through microcredit programs is shown to play a positive role in reducing the burden of sickness shocks. By inference, the strength of this impact may be higher if the disaster is not largely covariate.

Thus, group-based credit programs operated by NGOs tend to help poor households to cope with natural disaster by reducing the burden of sickness shocks. Borrowers under a group-based credit program have incentive to provide mutual insurance by exchanging health-related information (e.g., use of oral re-hydration therapy, avoiding contaminated water, taking vaccination immediately), preventive medicine (e.g. water purification pills), loans to cover instant medical expenses, networks of personalized contacts with health workers and doctors, as well as by providing nursing and sharing the workload for those who fall ill.

In the context of the least-developed countries, the inadequate public health care system interacts with the vulnerability of the poor to exacerbate problems with health care provision. The policy relevant question (e.g., for aid and planning programs) is where to purchase a foothold in attempting to reverse the downward spiral. The empirical results suggest that microcredit may be a potentially effective instrument for providing access to health care, especially to those who get excluded from both market-based and public health care provision systems. Because of the joint liability framework, group-based credit has the ability to provide peer monitoring and mutual insurance in times of sickness for the borrowers. Thus, as one possible proposal, it may be useful to bundle systematic health insurance programs with microcredit programs at a reduced cost. In closing, the ability of microcredit programs to circumvent moral hazard and adverse selection problems in credit markets can be utilized effectively in providing access to health care to the poor in underdeveloped countries, where such asymmetric information problems are prevalent.

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Figure 1: A Simple* 2X2 *Prisoners' Dilemma (PD) type Game under Individual and Joint Liability

a. Individual Liability

		B_i	
		Sick	***Not Sick***
B_j	***Sick***	*-b, -b*	*b, -b*
	Not Sick	*-b, b*	*b, b*

b. Joint Liability

		B_i	
		Sick	***Not Sick***
B_j	***Sick***	*-b*	*0*
	Not Sick	*0*	*b*

Note: The first pay-off corresponds to column player, the second to the row player.

Figure2: The Extensive Form of Joint Liability Game under Cross Reporting

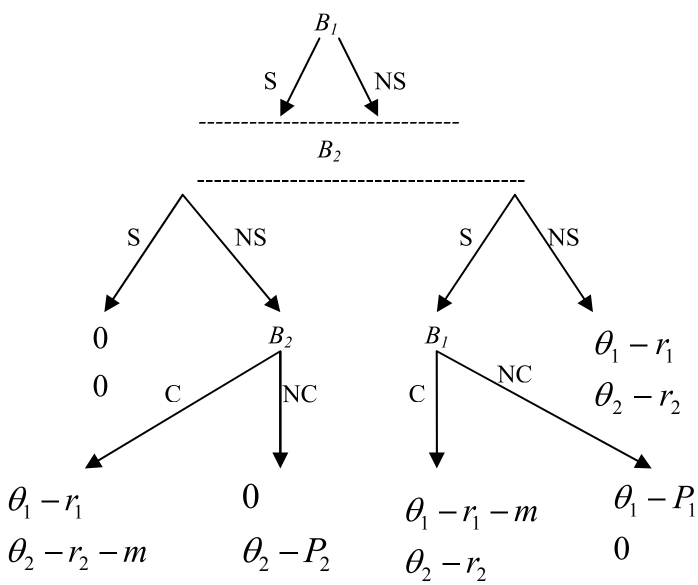

Table 1. Definitions and Descriptive Statistics of Variables Used

Variable	Definition	N	Mean	S.D.	Min	Max
HHFLEXP	Household flood exposure index	2272	3.962	4.799	0	16
HHMEDIEXP	Log of household medical expenses (includes cost of medicine, counseling, hospital charges and conveyance)	2272	2.863	2.406	0	9.691
HHSIZE	Log of household size	2244	1.798	0.319	0.693	2.773
EDUCATION	Years of schooling of the household head	2187	2.584	3.736	0	14
SEX	Sex of the household head, male=1, female=2	2193	1.041	0.198	1	2
AGE	Log of average age of household members	2202	3.208	0.310	2.397	4.343
AGE^2	Squared *AGE*	2202	10.389	2.043	5.744	18.859
DEPEND	Household dependency ratio	2184	1.045	0.749	0	5
BMI	Log of average body mass index of household members	2045	2.863	0.118	2.487	3.375
ASSET	Log of present estimated value of assets	2272	5.725	4.187	0	13.133
INCOME	Log of household current earnings	2272	5.684	3.150	0	11.361
GIFTR	Log of gifts received by the household	2272	0.948	1.883	0	8.699
NGO_{LOAN}	Number of loans received from NGOs	2272	0.161	0.468	0	4
HHEXP	Monthly household expenditure	2237	3726.149	2686.946	134.141	31319.990
PROPRTION	Household medical expenses/Monthly household expenditure	2237	0.040	0.126	0	4.051

Note: Household flood exposure index is calculated based on 3 variables: (1) depth of water in the homestead; (2) depth of water in the house (feet); and (3) number of days of water in the home (del Ninno et al. 2001). Household dependency ratio is the number of household members less than 15 or above 64 years old, divided by the number of household members aged 15 to 64. Present estimated value of assets, gift received, household medical expenses and current earnings are measured in Taka, the local currency of Bangladesh. At present 1 U.S. Dollar is worth of around 58 Taka. Monthly household expenditure includes both food and non-food expenditure but do not include other major expenditures (e.g. house repairs, medical expenditures etc.). Household current earnings include wage earnings and earnings from business and agriculture.

Table 2. Random-effects Panel GLS Estimation of Household Medical Expenditure Equation

Variable	Dependent Variable: *HHMEDIEXP*						
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
HHFLEXP	0.033 (0.001)***	0.032 (0.003)***	0.036 (0.001)***	0.035 (0.001)***	0.038 (0.001)***	0.033 (0.002)***	0.032 (0.002)***
HHSIZE	1.111 (0.000)***	1.153 (0.000)***	1.153 (0.000)***	1.149 (0.000)***	1.183 (0.000)***	1.176 (0.000)***	1.178 (0.000)***
NGO_{LOAN}	-0.233 (0.041)**	-0.214 (0.064)*	-0.199 (0.092)*	-0.217 (0.058)*	-0.193 (0.100)*	-0.202 (0.081)*	-0.196 (0.091)*
EDUC	0.041 (0.012)**	0.043 (0.009)***	0.039 (0.023)**	0.037 (0.022)**	0.034 (0.047)**	.0385 (0.019)**	0.038 (0.020)**
SEX	-0.027 (0.932)	0.076 (0.820)	0.069 (0.848)	-0.106 (0.739)	-0.005 (0.990)	0.0003 (0.999)	-0.006 (0.986)
AGE	0.164 (0.412)	-4.422 (0.216)	-2.569 (0.576)	0.181 (0.366)	0.083 (0.719)	-4.071 (0.253)	-4.015 (0.260)
AGE^2		0.728 (0.184)	0.425 (0.554)			0.675 (0.216)	0.667 (0.222)
DEPEND		0.073 (0.465)	0.060 (0.564)			0.068 (0.491)	0.070 (0.481)
BMI			0.573 (0.265)		0.564 (0.264)		
INCOME				-0.034 (0.045)**	-.036 (0.049)**	-0.033 (0.056)*	-0.033 (0.056)*
ASSET						0.005 (0.651)	0.006 (0.607)
GIFTR							0.018 (0.503)
Constant	0.199 (0.823)	7.107 (0.212)	2.679 (0.723)	0.363 (0.684)	-1.104 (0.534)	6.737 (0.235)	6.624 (0.243)
N	2186 (729 HHs)	2168 (723 HHs)	1997 (702 HHs)	2186 (729 HHs)	1997 (702 HHs)	2168 (723 HHs)	2168 (723 HHs)
R^2	0.039	0.038	0.041	0.042	0.044	0.041	0.041
Wald (χ^2)	63.65 (0.000)***	61.32 (0.000)***	58.05 (0.000)***	68.19 (0.000)***	61.55 (0.000)***	65.47 (0.000)***	65.99 (0.000)***

Note: Random-effect specification is preferred over fixed-effect based on Hausman specification test; ***, **, * implies significance at 1%, 5% and 10% levels respectively; numbers in parentheses are the corresponding *p* values.

Table 3. Random-effects Panel TOBIT Estimation of Household Medical Expenditure Equation

Variable	Dependent Variable: *HHMEDIEXP*						
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
HHFLEXP	0.048 (0.002)***	0.0455 (0.004)***	0.052 (0.001)***	0.051 (0.001)***	0.055 (0.001)***	0.047 (0.003)***	0.047 (0.003)***
HHSIZE	1.584 (0.000)***	1.665 (0.000)***	1.649 (0.000)***	1.646 (0.000)***	1.696 (0.000)***	1.699 (0.000)***	1.701 (0.000)***
NGO_{LOAN}	-0.322 (0.065)*	-0.291 (0.097)*	-0.270 (0.128)†	-0.292 (0.094)*	-0.255 (0.149)†	-0.270 (0.124)†	-0.266 (0.131)†
EDUC	0.054 (0.026)**	0.058 (0.018)**	0.051 (0.044)**	0.048 (0.048)**	0.044 (0.088)*	0.050 (0.042)**	0.050 (0.043)**
SEX	-0.055 (0.911)	0.127 (0.802)	0.083 (0.879)	-0.191 (0.695)	-0.042 (0.938)	0.0004 (0.999)	-0.003 (0.995)
AGE	0.145 (0.632)	-7.425 (0.166)	-3.453 (0.616)	0.172 (0.569)	0.027 (0.937)	-6.839 (0.201)	-6.804 (0.203)
AGE^2		1.197 (0.145)	0.556 (0.605)			1.109 (0.175)	1.104 (0.178)
DEPEND		0.107 (0.475)	0.079 (0.608)			0.100 (0.501)	0.101 (0.497)
BMI			0.691 (0.368)		0.684 (0.365)		
INCOME				-0.059 (0.023)**	-0.059 (0.029)**	-0.057 (0.030)**	-0.057 (0.031)**
ASSET						0.011 (0.522)	0.011 (0.507)
GIFTR							0.011 (0.784)
Constant	-1.369 (0.312)	10.045 (0.239)	2.088 (0.853)	-1.083 (0.423)	-2.815 (0.287)	9.431 (0.267)	9.358 (0.271)
N	2186 (729 HHs)	2168 (723 HHs)	1997 (702 HHs)	2186 (729 HHs)	1997 (702)	2168 (723 HHs)	2168 (723 HHs)
Log-likelihood	-4436.189	-4405.715	-4064.794	-4433.624	-4062.740	-4403.297	-4403.260
Wald (χ^2)	55.57 (0.000)***	54.29 (0.000)***	51.36 (0.000)***	61.09 (0.000)***	55.76 (0.000)***	59.47 (0.000)***	59.52 (0.000)***

Note: The lower censoring limit is set at 0 for TOBIT specifications; ***, **, *, † implies significance at 1%, 5%, 10% and 15% levels respectively; numbers in parentheses are the corresponding *p* values.

Table 4. Random-Effects Panel GLS Estimation of Household Medical Expenditure Equation with AR (1) Error Process

Variable	**Dependent Variable: *HHMEDIEXP***						
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
HHFLEXP	0.033 (0.001)***	0.032 (0.003)***	0.037 (0.001)***	0.035 (0.001)***	0.038 (0.000)***	0.033 (0.002)***	0.032 (0.002)***
HHSIZE	1.111 (0.000)***	1.153157 (0.000)***	1.156 (0.000)***	1.149 (0.000)***	1.185 (0.000)***	1.176 (0.000)***	1.178 (0.000)***
NGO_{LOAN}	-0.234 (0.041)**	-0.215 (0.063)*	-0.200 (0.090)*	-0.217 (0.058)*	-0.194 (0.098)*	-0.203 (0.080)*	-0.196 (0.090)*
EDUC	0.041 (0.011)**	0.043 (0.008)***	0.039 (0.022)**	0.037 (0.021)**	0.034 (0.045)**	0.039 (0.018)**	0.038 (0.019)**
SEX	-0.027 (0.933)	0.076 (0.819)	0.072 (0.841)	-0.107 (0.737)	-0.004 (0.992)	-0.0003 (0.999)	-0.006 (0.985)
AGE	0.165 (0.408)	-4.416 (0.215)	-2.593 (0.570)	0.182 (0.362)	0.086 (0.707)	-4.062 (0.252)	-4.009 (0.259)
AGE^2		0.727 (0.183)	0.429 (0.547)			.673 (0.215)	0.666 (0.221)
DEPEND		0.072 (0.468)	0.059 (0.564)			0.068 (0.493)	0.069 (0.483)
BMI			0.598 (0.242)		0.593 (0.238)		
INCOME				-0.035 (0.045)**	-0.036 (0.045)**	-0.034 (0.053)*	-0.034 (0.054)*
ASSET						0.006 (0.620)	0.006 (0.579)
GIFTR							0.0174 (0.512)
Constant	0.196 (0.826)	7.097 (0.211)	2.635 (0.725)	0.361 (0.685)	-1.199 (0.497)	6.722 (0.234)	6.615 (0.242)
N	2186 (729 HHs)	2168 (723 HHs)	1997 (702 HHs)	2186 (729 HHs)	1997 (702)	2168 (723 HHs)	2168 (723 HHs)
R^2	0.040	0.038	0.041	0.042	0.044	0.041	0.041
Wald (χ^2)	63.92 (0.000)***	61.71 (0.000)***	59.12 (0.000)***	68.63 (0.000)***	62.91 (0.000)***	66.10 (0.000)***	66.49 (0.000)***

Note: The first order autoregressive, AR(1) error process is defined as: $\varepsilon_{it} = \rho\varepsilon_{it-1} + z_{it}$, where $|\rho| < 1$ and z_{it} are iid errors; ***, **, * implies significance at 1%, 5% and 10% levels respectively; numbers in parentheses are the corresponding *p* values.

Table 5. Random-Effects Panel G2SLS Estimation (Dependent variable: NGO_{LOAN} in Stage 1 and *HHMEDIEXP* in Stage 2)

	Model 1		Model 2		Model 3		Model 4		Model 5	
	Stage 1	**Stage 2**	**Stage 1**	**Stage 2**	**Stage 1**	**Stage 2**	**Stage 1**	**Stage 2**	**Stage 1**	**Stage 2**
HHFLEXP	0.003 (0.070)*	0.036 (0.003)***	0.004 (0.076)*	0.0416 (0.001)***	0.003 (0.114)	0.037 (0.001)***	0.003 (0.127)	0.037 (0.001)***	0.003 (0.078)*	.036 (0.002)***
HHSIZE	-0.130 (0.002)***	0.905 (0.000)***	-0.156 (0.000)***	0.947 (0.000)***	-0.135 (0.001)***	0.943 (0.000)***	-0.138 (0.001)***	0.943 (0.000)***	-0.139 (0.001)***	0.927 (0.000)***
NGO_{LOAN}		-2.424 (0.054)**		-1.835 (0.091)*		-1.969 (0.099)*		-1.969 (0.099)*		-2.010 (0.102)*
EDUC	-0.0008 (0.807)	0.039 (0.042)**	-0.002 (0.598)	0.035 (0.056)*	-0.0007 (0.814)	0.038 (0.031)**	-0.001 (0.711)	0.038 (0.031)**	-0.0008 (0.802)	.037 (0.040)**
SEX	0.024 (0.715)	0.087 (0.825)	0.032 (0.645)	0.093 (0.810)	0.022 (0.724)	0.044 (0.902)	0.023 (0.722)	0.044 (0.902)	0.029 (0.651)	.051 (0.889)
AGE	2.387 (0.001)***	0.064 (0.838)	3.370 (0.000)***	0.010 (0.973)	2.408 (0.000)***	0.117 (0.617)	2.400 (0.000)***	0.117 (0.617)	2.329 (0.001)***	0.107 (0.656)
AGE^2	-0.384 (0.000)***		-0.540 (0.000)***		-0.388 (0.000)***		-0.387 (0.000)***		-0.376 (0.000)***	
BMI			0.089 (0.362)	0.627 (0.250)						
DEPEND	-0.038 (0.053)*	-0.021 (0.876)	-0.040 (0.046)**	-0.020 (0.873)	-0.037 (0.048)**		-0.036 (0.055)*		-0.038 (0.046)**	
INCOME	0.009 (0.003)***		0.011 (0.002)***		0.010 (0.003)***	-0.013 (0.548)	0.009 (0.005)***	-0.013 (0.548)	0.009 (0.006)***	-0.015 (0.512)
ASSET							0.003 (0.129)		0.002 (0.255)	0.010 (0.415)
GIFTR									-0.018 (0.000)***	-0.012 (0.738)
Constant	-3.320 (0.003)***	1.154 (0.419)	-5.078 (0.000)***	-0.650 (0.753)	-3.343 (0.002)***	0.939 (0.397)	-3.338 (0.002)***	0.939 (0.397)	-3.203 (0.003)***	0.965 (0.396)
N	2168 (723 HHs)	2168 (723 HHs)	1997 (702 HHs)	1997 (702 HHs)	2168 (723 HHs)	2168 (723 HHs)	2168 (723 HHs)	2168 (723 HHs)	2168 (723 HHs)	2168 (723 HHs)
Wald (χ^2)	42.00 (0.000)***	44.10 (0.000)***	49.00 (0.000)***	50.37 (0.000)***	44.00 (0.000)***	52.78 (0.000)***	46.00 (0.000)***	52.78 (0.000)***	60.00 (0.000)***	52.47 (0.000)***

Note: Variable Instrumented: NGO_{LOAN}; ***, **, * implies significance at 1%, 5% and 10% levels respectively; numbers in parentheses are the corresponding *p* values.

Table 6. Random-effects Panel TOBIT Estimation of the Proportion of Household Medical Expenditure Equation

Variable	**Dependent Variable: *PROPORTION***						
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
HHFLEXP	0.003 (0.000)***	0.003 (0.000)***	0.003 (0.000)***	0.003 (0.000)***	0.003 (0.000)***	0.003 (0.000)***	0.003 (0.000)***
HHSIZE	0.025 (0.050)**	0.029 (0.045)**	0.027 (0.077)*	0.027 (0.038)**	0.029 (0.042)**	0.031 (0.030)**	0.031 (0.031)**
NGO	-0.018 (0.028)**	-0.017 (0.038)**	-0.017 (0.043)**	-0.017 (0.036)**	-0.016 (0.055)**	-0.0158 (0.053)**	-0.016 (0.052)**
EDUC	0.0008 (0.446)	0.0009 (0.396)	0.0004 (0.678)	0.0006 (0.554)	0.0003 (0.787)	0.0008 0.411	0.0009 (0.408)
SEX	-0.050 (0.918)	0.010 (0.628)	0.008 (0.722)	-0.001 (0.961)	0.005 (0.829)	0.006 (0.761)	0.007 (0.758)
AGE	0.149 (0.623)	-0.256 (0.253)	0.040 (0.892)	-0.010 (0.414)	-0.018 (0.218)	-0.238 (0.288)	-0.239 (0.286)
AGE^2		0.038 (0.263)	-0.009 (0.842)			0.036 (0.297)	0.036 (0.296)
DEPEND		0.0007 (0.906)	0.0005 (0.942)			0.0001 (0.983)	0.0001 (0.987)
BMI			0.062 (0.074)*		0.061 (0.073)*		
INCOME				-0.002 (0.191)	-0.002 (0.240)	-0.001 (0.286)	-0.001 (0.285)
ASSET						-0.001 (0.206)	-0.001 (0.203)
GIFTR					0.061 (0.073)		-0.0003 (0.887)
Constant	-0.029 (0.606)	0.342 (0.335)	-.285 0.560	-0.021 (0.710)	-0.182 (0.123)	0.326 (0.359)	0.327 (0.357)
N	2183 (729 HHs)	2166 (723 HHs)	1995 (702 HHs)	2183 (729 HHs)	1995 (702)	2166 (723 HHs)	2166 (723 HHs)
Log-likelihood	76.931	77.125	60.448	77.785	61.132	78.601	78.615
Wald (χ^2)	27.11 (0.000)***	26.17 (0.001)***	28.33 (0.000)***	28.79 (0.002)***	29.63 (0.002)***	29.26 (0.001)***	29.27 (0.002)***

Note: The dependent variable (*PROPORTION*) is the household medical expenditure as a proportion of monthly household expenditure (HMEDIEXP/HHTOTEXP). ***, **, * implies significance at 1%, 5% and 10% levels respectively; numbers in parentheses are the corresponding *p* values.

Footnotes

[1] Bangladesh is located in the southern part of Asia with a total area of 147,570 square kilometers, most of Bangladesh lies within the broad delta formed by the *Ganges* and *Brahmaputra* rivers. The country is largely a flat, low-lying, alluvial plain traversed by innumerous rivers and has a coastline of about 580 kilometers along the Bay of Bengal. Over the last three decades, Bangladesh experienced more than 170 large-scale natural disasters, estimated to have killed half a million people and affected more than 400 millions. Over the past 30 years, the observed annual frequency of large scale disasters in Bangladesh has been about 6 per year, which is extremely high in comparison to other least developed countries (UNDP 2001). Out of all disasters in South and South-East Asia over the past 10 years, Bangladesh has witnesses nearly 90 percent (ECHO 1997).

[2] Gertler and Gruber (2002) list two different economic costs associated with sickness: (1) diagnosis and treatment; and (2) loss in income with reduced productivity.

[3] While microcredit and microfinance are used synonymously here, the term microfinance is used generally to incorporate other finance components (e.g. savings).

[4] The Microcredit Summit (2000) set a goal to serve 100 million of the world's poorest families with credit for self-employment and financial and business services by 2005.

[5] For instance, in Bangladesh the Department of Fisheries collaborates with five NGOs who form groups of fishermen and provide them with credit and other support, and work to develop effective institutions for managing the fisheries (Thompson, Islam, and Kadir 1998).

[6] One definition of social capital can be given as "the institutions, the relationships, the attitudes and values that govern interactions among people that contribute to the economic and social

development" (World Bank 1999). Coleman (1990, p. 304) defines social capital as: "When relations among persons change in ways that facilitate action."

[7] Stiglitz (1990) shows how group lending overcomes the moral hazard problem.

[8] Diseases caused by flood (e.g. diarrhea, cholera, hepatitis, typhoid) are very much curable with timely actions.

[9] A number of NGOs (including Grameen Bank) practice cross-reporting at village meetings where loans repayments are made (Rahman 1999). Rai and Sjostrom (2004) argue that cross-reporting substantially affects the success of microcredit programs.

[10] If mutual insurance is valued in monetary terms, the observed medical expenditure spent by a household can be considered as its potential medical expenditure (if no mutual insurance is received) minus the monetary value of mutual insurance.

[11] In Bangladesh, *thanas* are local administrative units covering roughly a 100 square-miles area. *Thanas* consist of several unions and the union in turn is a collection of several villages. A few *thanas* constitute a district. For surveying households, seven flood- affected *thanas* were selected using three main criteria. The first, is the severity of flood determined by the Water Board classifying *thanas* into 3 categories (1) not affected, (2) moderately affected and (3) severely affected, depending on the duration and depth of the floodwater. The second criterion used the percentage of poor people in the district in which the *thana* is located. *Thanas* with more than 70 percent of the population below the poverty line were classified as poor. The third criterion considered the *thanas* that were included in some other earlier survey studies and also gave a good regional and geographical balance throughout the six administrative divisions of the country. Based on these three criteria, 4 poor *thanas* (2 severely affected and 2 moderately affected) and 3 non-poor *thanas* (2 severely affected and 1 moderately affected) were selected

for household survey. The households were included based on a multi-stage probability sampling technique, resulting a final sample size of 757 households from 126 villages and 7 *thanas*. See del Ninno et al. (2001) for details regarding the data and sampling.

[12] Based on results from a Hausman specification test, the random-effects specification is preferred over the fixed-effects specification.

[13] It may be argued that households receiving a greater number of loans are a group of healthy people which leads to less spending in medical expenditures. The average body mass index of household members (*BMI*) is included to control for such a possibility.

[14] The NGO_{LOAN} is negative and significant at 15% level in models 3, 5, 6 and 7 (Table 3) in contrast to 10% level in Table 2.

[15] The first order autoregressive error process, AR(1) defined as: $\varepsilon_{it} = \rho\varepsilon_{it-1} + z_{it}$, where $|\rho| < 1$ and z_{it} are iid errors.

[16] The *INCOME* variable is no longer significant in second stage regressions in table 5. Since there is a positive relationship between NGO_{LOAN} and *INCOME,* and *INCOME* is used in instrumenting NGO_{LOAN}, the result in models 3, 4, and 5 (in table 5) implies that income reduces household medical expenditure mostly through NGO_{LOAN} further supporting the social capital hypothesis.